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THE PRESENT AND FUTURE

JACC REVIEW TOPIC OF THE WEEK

Artificial Intelligence for Cardiovascular Care—Part 1: Advances

JACC Review Topic of the Week

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ABSTRACT

Recent artificial intelligence (AI) advancements in cardiovascular care offer potential enhancements in diagnosis, treatment, and outcomes. Innovations to date focus on automating measurements, enhancing image quality, and detecting diseases using novel methods. Applications span wearables, electrocardiograms, echocardiography, angiography, genetics, and more. AI models detect diseases from electrocardiograms at accuracy not previously achieved by technology or human experts, including reduced ejection fraction, valvular heart disease, and other cardiomyopathies. However, AI's unique characteristics necessitate rigorous validation by addressing training methods, real-world efficacy, equity concerns, and long-term reliability. Despite an exponentially growing number of studies in cardiovascular AI, trials showing improvement in outcomes remain lacking. A number are currently underway. Embracing this rapidly evolving technology while setting a high evaluation benchmark will be crucial for cardiology to leverage AI to enhance patient care and the provider experience. (J Am Coll Cardiol 2024;83:2472–2486) © 2024 by the American College of Cardiology Foundation.

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HIGHLIGHTS

- AI models can detect cardiovascular disorders including reduced ejection fraction, valvular heart disease, and cardiomyopathies from electrocardiograms with accuracy not previously achieved by human experts or technology.
- Despite an exploding number of studies of cardiovascular AI technologies and ongoing patient-oriented trials, evidence of improvement in outcomes is not currently available.
- All cardiac imaging modalities now have applications using AI, improving acquisition, measurement, and diagnostic capacity.

This review explores the current state of artificial intelligence (AI) applications in cardiology, highlights major breakthroughs, and identifies future directions. Although previous review articles have discussed AI methodology and some key studies in the field of cardiology,[1-3] the goal of this review is to provide a contemporary and comprehensive overview.

We have organized this review by efforts in the following domains: 1) electrocardiography, telemetry, and wearables; 2) echocardiography; 3) cardiovascular magnetic resonance (CMR), nuclear cardiology, and cardiac computed tomography; 4) advanced electrophysiology studies; 5) coronary angiography; and 6) genetics, multiomics, and other inputs. To aid the reader, we have included a glossary of terms relevant to AI (**Table 1**) plus a more detailed evaluation of studies within the field (**Table 2**). Our goal is to equip the cardiology community with an updated review of advancements at the intersection of AI and cardiology.

Although AI encompasses many technologies, we focus on deep learning AI technologies, given emerging evidence for their value in CV care. Physiologic waveforms and imaging are examples. To date, we often rely on human expert interpretation as a gold-standard for how accurately different diseases can be detected from such modalities. The emergence of deep learning methods like convolutional neural networks (CNNs) allows a new form of pattern recognition that may be complementary or even superior to human experts in certain cases.

ELECTROCARDIOGRAMS, TELEMETRY, AND WEARABLES

The electrocardiogram (ECG) is a cost-effective, noninvasive diagnostic tool that has endured across clinical medicine over a century after its advent. Efforts to automate ECG interpretation through rule-based algorithms have been ongoing for decades, because of its reproducible, standardized format. The construction of extensive digital waveform databases has opened the possibility of utilizing deep learning for a number of pathologies.

ARRHYTHMIA DETECTION. One area where this advance has demonstrated value is in arrhythmia classification. Despite reliable identification of sinus rhythm, conventional ECG algorithms displayed considerable inconsistencies with nonsinus rhythms and noise.[4-6] Newer deep learning techniques hold promise for better distinguishing significant arrhythmias from noise. Several groups have trained CNNs to diagnose several rhythm and conduction abnormalities.[7-9] Each model exhibited good diagnostic performance, with an AUC >0.97, comparable to experienced physicians. Recent work has demonstrated that CNNs are able to achieve such performance even on images of ECGs, instead of requiring less frequently available signal-based data.[10] Initial clinical implementation has shown promise in assisting with triage in an emergency setting.[11,12]

Neural networks have allowed not only the detection of rhythm and conduction disorders identifiable by clinicians, but also the prediction of paroxysmal atrial fibrillation from a 12-lead ECG acquired in normal sinus rhythm with high accuracy,[13,14] likely reflecting the ability to detect modest atrial perturbations not perceived by human readers (AUC >0.85). In a prospective study, AI effectively risk-stratified patients and enhanced detection compared with traditional risk factors.[15] In contrast, an analogous retrospective study assessed calculated risk in relation to the CHARGE-AF score used for atrial fibrillation and yielded equivalent though complementary predictions.[16]

CNNs have also improved upon traditional ECG criteria in diagnosing channelopathies and other arrhythmia disorders, such as long QT and Brugada syndromes.[17-19] Early incorporation of these models within wearable single-lead technology has been encouraging, exemplifying their ability to monitor transient conditions remotely.[20-22]

ABBREVIATIONS AND ACRONYMS

AI = artificial intelligence

CMR = cardiovascular magnetic resonance

CNN = convolutional neural network

CT = computed tomography

CTA = computed tomography angiography

ECG = electrocardiogram

LGE = late gadolinium enhancement

LV = left ventricular

LVEF = left ventricular ejection fraction

SPECT = single-photon emission computed tomography

TABLE 1 Glossary of Terms Related to Artificial Intelligence

Term	Definition
Algorithm	A set of mathematical procedures used to learn patterns from data.
Area under receiver operating characteristic curve	A metric to evaluate the performance of a binary classification model, representing the trade-off between true-positive rate and false-positive rate over different decision thresholds.
Artificial intelligence	The capability of a machine to imitate intelligent human behavior or perform tasks that typically require human intelligence.
Artificial neural networks	A generic architecture for a mathematical model to teach computers to learn, inspired by the human brain's neural structure, that is comprised of layers of "neurons," which calculate weights that ultimately inform a model if its current prediction is more or less accurate than prior iterations.
Classification	A type of machine learning task to predict a categorical label of an input.
Convolutional neural networks	A type of deep learning algorithm optimized for processing grid-like data such as images by learning unique features that distinguish them into different categories.
Deep learning	A subset of machine learning that uses artificial neural networks.
Features	Individual measurable properties of observed data that serve as input variables used by algorithms to learn patterns or make predictions.
Foundation models	Machine learning models trained on large amounts of unlabeled data that can be used for different tasks with very little fine-tuning.
Joint embedding	A technique where different types of data are transformed and mapped into a shared "embedding" or feature space, with the goal of identifying relationships between different data types.
Labels	The ground truth output for a given input data, often used to train supervised learning models.
Large language models	A type of machine learning model that has been trained on large amounts of text to recognize, summarize, translate, predict, and/or generate content.
Machine learning	A subset of artificial intelligence in which computers learn from experience without explicit programming.
Preprocessing	Preparing, cleaning, and organizing raw data to make it suitable as inputs for training AI models.
Reinforcement learning	A type of machine learning where agents learn to make decisions by taking actions in an environment to maximize cumulative reward.
Segmentation	Process of partitioning an image into multiple segments.
Semi-supervised Learning	A machine learning paradigm that uses both labeled and unlabeled data for training.
Structured data	Data that is organized into a predefined format.
Supervised learning	A machine learning paradigm where models are trained using labeled data, so that each example includes a paired input and output.
Unstructured data	A machine learning paradigm where a model is trained on data with provided labels, often with the goal of discovering hidden patterns or structure to the data.
Unsupervised learning	A machine learning paradigm that uses data without provided labels (unstructured data) to discover underlying structures or patterns.
Wearables	Electronic devices to collect data, track activities, and provide specific functionalities such as health monitoring.

STRUCTURAL HEART DISEASE. Deep learning models have also shown benefit in predicting structural heart disease from ECGs including models to detect composite endpoints such as a number of individual pathologies that fit under structural heart disease, as was done in the rECHOmmend study.[23] Models trained to discriminate asymptomatic systolic left ventricular (LV) dysfunction displayed good performance (sensitivity/specificity ≥85%) and additionally discovered patients at risk for worsening heart failure in the future.[24-28] A subsequent multicenter prospective validation demonstrated modest increase in diagnosis compared to usual care among all patients and those at high risk.[29] In comparison, implementation in emergency departments outperformed N-terminal pro-B-type natriuretic peptide at differentiating the cause of dyspnea.[30] Another prospective trial, applying CNNs to point-of-care single-lead tracings from ECG-enabled stethoscopes, showed similar performance in detecting reduced LV ejection fraction (LVEF) (AUC >0.85).[31] The detection of LV systolic dysfunction extends beyond the use of 12-lead raw voltage data to ECG images plus noisy 1-lead data obtained on portable and wearable devices.[32-34]

Screening for other cardiomyopathies has similarly been explored. Distinguishing hypertrophic cardiomyopathy from age- and sex-matched control subjects exhibited high accuracy (AUC; 0.95).[35,36] In cardiac amyloidosis, multiple independent studies have used CNNs to effectively classify patients with disease.[36-38] One study even predicted amyloidosis >6 months before diagnosis in over 50% of patients.[35] LV hypertrophy estimation correlated with magnetic resonance imaging-derived mass measurements and was superior to clinical assessment.[39,40]

Valvular heart disease has become more common in an aging population and contributes significantly to mortality, thus requiring early recognition.[41] Several algorithms have been designed to discern moderate-to-severe aortic stenosis with high accuracies (AUC ≥0.85) and negative predictive values,

TABLE 2 Selected Studies Using Artificial Intelligence Within Cardiology

First Author, Year	Purpose	Input	Sites	Patients	Studies	AUC	Strengths	Limitations	Other Performance Metrics
Electrocardiograms, wearables, and telemetry									
Hannun et al, 2019[7]	Classification of rhythm and conduction abnormalities from patch-based ambulatory ECG monitor	Single-lead ECG	[a]	53,549	91,232	0.97	+ Single model looking at 12 rhythm classes + Comparison to consensus committee of 9 cardiologists	– Only included rhythms that are already diagnosed well by MDs and conventional computer algorithms	Average F_1 score of CNN (0.84) exceeded that of average cardiologists (0.78)
Attia et al, 2019[14]	Identification of atrial fibrillation from ECG in normal sinus rhythm	12-lead ECG	1	180,922	649,931	0.87	+ First study to demonstrate novel pattern recognition achievable with deep learning	– Significant differences in age, comorbidities between 2 comparator groups means model can learn from confounders	AUC increased to 0.90 when ECG obtained within 30 d of atrial fibrillation ECG
Attia et al, 2019[26]	Screening for asymptomatic LV dysfunction (LVEF ≤35%)	12-lead ECG	1	97,829	97,829	0.93	+ Large population with ECG and TTE done within 2 weeks of one another	– No race/ethnicity data, likely limited population diversity	Positive AI screen without ventricular dysfunction at 4× risk of developing LV dysfunction
Ko et al, 2020[35]	Identification of HCM	12-lead ECG	1	67,001	67,001	0.96	+ Largest HCM study population + ECGs from over 30 y	– HCM prevalence in data set was ∼4%, but real-world population of interest likely 10× lower.	AUC 0.95 within subgroup of patients with LVH
Cohen-Shelly et al, 2021[42]	Detection of AS	12-lead ECG	3	258,607	258,607	0.85	+ 3 tertiary referral centers in geographically distinct locations	– Population was 88% Caucasian – No external test set	False-positives had twice the risk for developing moderate-severe AS in 15 y
Giudicessi et al, 2021[20]	QTc interval estimation	6- and 12-lead ECGs	1	538,200	1,612,617	0.97	+ Compared to human over-reads + Prospectively tested in different device (mobile ECG)	– Only used to 2 leads of data to assess QTc – No comparison to conventional ECG algorithm to calculate QTc	Nominal difference between mobile ECG set-up (6-leads) and 12-lead ECG
Grogan et al, 2021[37]	Identification of cardiac amyloidosis	1-, 6-, and 12-lead ECGs	1	4,995	4,995	0.91	+ One of the largest cohorts of CA patients + Also conducts experiments with 1- and 6-lead ECG data	– Uses a case control approach with one-half of the patients positive for disease, not representative of screening population.	Predicted the presence of cardiac amyloidosis more than 6 months before clinical diagnosis in 59% of patients
Raghunath et al, 2021[13]	Identification of atrial fibrillation from ECG in normal sinus rhythm	12-lead ECG	1	430,000	1,600,000	0.85	+ Looked at number of preventable strokes in simulation	– Study population was 97% White – Single site with no external testing	Number needed to screen to find 1 new case of atrial fibrillation was 9. Deep learning outperformed the CHARGE-AF score (0.85 vs 0.77).
Elias et al, 2022[43]	Detection of AS, AR, and MR	12-lead ECG	4	77,163	260,811	0.84	+ Tested and validated at 4 hospitals, mix of academic/community	– Performance dropped by 9% in hospital not included in training data	AUC for AS; AUC for AR 0.77 and MR 0.83
Sangha et al, 2023[28]	Screening for asymptomatic LV dysfunction (LVEF ≤40%)	12-lead ECG	7	116,210	385,601	0.91	+ Validated externally and on ECG images that can be uploaded to web-app	– Trained on patients with ECG /echo, who differ from intended screening population.	AUC range 0.88 to 0.95 across external sets. Positive screen with >27-fold higher odds of LV dysfunction

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TABLE 2 Continued

First Author, Year	Purpose	Input	Sites	Patients	Studies	AUC	Strengths	Limitations	Other Performance Metrics
Yao et al, 2023[29]	Screening for asymptomatic LV dysfunction (LVEF ≤50%)	12-lead ECG	45	22,641	22,641	–	+ One of the only pragmatic clinical trials in the field	– Clinicians notified by e-mail, clinical decision support delivery may not replicate	Use of ECG-AI associated with OR 1.32 for diagnosis compared with usual care
Guo et al, 2019[130]	Detection of atrial fibrillation on wearable smartwatch	PPG	[a]	187,912	–	–	+ Translation of 12-lead ECG model to popular consumer device	– High selection bias for patients with Apple Watch, MyChart, research compliance	87% of patients with suspected AF notification and follow-up had confirmed AF
Perez et al, 2019[131]	Detection of atrial fibrillation on wearable smartwatch	PPG	[a]	419,297	–	–	+ Large study with popular consumer device + Tackled implementation challenges of real-world population with low disease prevalence	– No follow-up to determine stroke benefit – Depended on participant adherence to follow-up measures, potentially introducing bias	0.5% of patients received irregular pulse notification and follow-up; 34% had confirmed AF
Lubitz et al, 2022[132]	Detection of atrial fibrillation on wearable smartwatch	PPG	[a]	455,699	–	–	+ Large study with popular consumer device + Included medical/social history data	– Detection during active motion remains significant challenge	1% of patients received irregular pulse notification and follow-up; 32% had confirmed AF
Echocardiography									
Zhang et al, 2018[61]	Identification of echocardiographic views; quantification of chamber volumes, LVEF, and strain	Complete 2D TTE	1	14,035	14,035	–	+ Included view classification, pathology evaluation, and segmentation performance	– Single site, no external validation	84% accuracy for echocardiographic views; LVEF with MAE 9.7%; cardiac volumes with MAE between 15% and 17%
Ouyang et al, 2020[60]	Estimation of LVEF and assessment for heart failure	2D A4C TTE	1	10,030	10,030	0.96	+ Released entire data set and model weights alongside paper	– Single site, no external validation – Only uses A4C	AUC for cardiomyopathy identification in external data set; predicts LVEF with MAE 6.0%
Duffy et al, 2022[67]	Diagnosis of HCM and CA from other causes of LVH. Quantification of LV wall thickness	2D PLAX and A4C TTE	3	23,745	23,745	0.89	+ One of the first examples of precision phenotyping pipeline using deep learning	– Referral bias may exist as data comes from specialty care clinics	AUC for HCM in external validation data set; AUC 0.79 for CA; intraventricular wall thickness with MAE 1.2 mm
Narang et al, 2021[56]	Evaluation of DL-based software to assist novice users with obtaining echocardiographic views	Real-time 2D TTE	2	240	240	–	+ Innovative study of 8 novice nurses each completing 30 clinically indicated TTEs with AI guidance	– Small sample size, not representative of ongoing daily practice performance	98.8% of studies met diagnostic quality for left ventricular size and function
He et al, 2023[133]	LVEF assessment compared with sonographer estimation	Complete 2D TTE	1	3,495	3,495	–	+ One of the only prospective trials of AI segmentation compared to standard of care	– Single site, may be dependent on quality of sonographers or local echocardiography laboratory practices	Change in LVEF assessment less common (−10.4%) and smaller in magnitude (−0.97%) for AI vs sonographer

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TABLE 2 Continued

First Author, Year	Purpose	Input	Sites	Patients	Studies	AUC	Strengths	Limitations	Other Performance Metrics
Cardiovascular magnetic resonance, nuclear cardiology, and cardiac computed tomography									
Bai et al, 2018[76]	Chamber segmentation of LV, RV, and atria	Short- and long-axis cine CMR images	[b]	4,875	93,500	–	+ Large publicly available data set utilized (UK Biobank) to allow further innovation	– Homogenous population of mostly healthy subjects in middle age – Largely based on 1 magnetic resonance imaging protocol	Dice metric for all metrics ranging from 0.88-0.96 comparable to human interpretation
Oikonomou et al, 2018[92]	Evaluation of the prognostic value of perivascular fat attenuation index	Coronary CTA	2	3,912	3,912	0.84	+ First to show incremental value of quantifying perivascular fat	– Low number of fatal events – Unclear benefit in asymptomatic patients	Optimal cutoff (−70.1 Hounsfield units) showed HR of 5.6 for cardiac mortality and 3.7 for all-cause mortality
Choi et al, 2021[87]	Characterization of coronary vessel morphology and stenosis	Coronary CTA	4	232	232	–	+ Multicenter international study + Adjudication with 3 advanced imaging MDs	– No gold-standard validation with invasive approaches (IVUS/OCT)	Performance for >70% stenosis; agreement between expert readers and AI on maximal stenosis with mean difference within 1%
Hu et al, 2021[79]	Assessment of ML-based approach for SPECT MPI rest scan cancellation	SPECT MPI, clinical variables	5	20,414	20,414	0.80	+ Comparison to number of current clinical selection rules for scanning	– Simulation only, no actual cancellation of rest scans	AUC for MACE prediction; ML approach identified patients for rest cancellation with lower MACE rates than physician selection
Zhang et al, 2021[77]	Evaluation of virtual native enhancement as replacement for LGE. Validation on HCM registry	Matched CMR T_1 maps, cines, and LGE data sets	44	1,378	4,093	–	+ One of first studies of virtual native enhancement + Included comprehensive quality controls	– Still lacks mapping to T_2 and other modalities	Improved image quality compared to LGE. High visuospatial agreement with LGE in HCM ($r = 0.77$-0.79 in hyperintensity lesions)
Lin et al, 2022[86]	Measurement of plaque volume and stenosis severity. Prognostic value assessment for MI	Coronary CTA	11	2,757	2,757	0.70	+ Comprehensive data from range of different study sites	– Limited race/ethnicity data – Did not include studies of poor image quality	Performance for >50% stenosis. Plaque volume >238.5 μL associated with HR 5.4 for MI

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thereby serving as ideal screening tools.[42-44] Conversely, aortic regurgitation has been more challenging to distinguish (AUC: 0.77).[43] Similar approaches were then employed for mitral valve pathologies, demonstrating utility in discriminating moderate-to-severe regurgitation yet weaker performance for prolapse.[36,43,45]

OTHER CONDITIONS. Outside of cardiac abnormalities, CNNs have been implemented to investigate novel applications and systemic conditions with characteristic ECG manifestations. Investigators have developed noninvasive methods of detecting hyperkalemia with high sensitivities.[46-48] Anemia could also be effectively identified from a single-lead ECG, suggesting the possibility for future monitoring techniques.[49] Other innovative approaches have illustrated the considerable prognostic information that neural networks can extract from ECGs with an ability to estimate physiologic age and predict 1-year all-cause mortality.[50,51]

CURRENT USE AND FUTURE DIRECTIONS. Despite these promising studies, implementing AI-supported ECG models into practice is nascent, and findings from the first few prospective trials have not matched the expected clinical utility. The EAGLE (ECG AI-Guided Screening for Low Ejection Fraction) trial evaluated an AI model to detect reduced LVEF prospectively. Notifying clinicians that the AI model was positive for low EF increased echocardiogram acquisition from 38.1% to 49.6%, while diagnosis of low EF increased from 1.6% to 2.1%.[29] Although CNNs can differentiate complex patterns, performance may be

TABLE 2 Continued

First Author, Year	Purpose	Input	Sites	Patients	Studies	AUC	Strengths	Limitations	Other Performance Metrics
					Coronary angiography				
Du et al, 2021[112]	Segmentation of coronary arteries and recognition of lesion morphology	Coronary angiography	1	10,073	20,612	0.80	+ Comprehensive data set with segment and lesion morphology data	− Only uses single frame of video − Single site, single vendor	AUC for stenosis; AUC for CTO 0.76, calcification 0.80, thrombus 0.78, dissection 0.86. 98% accuracy for segment prediction
Moon et al, 2021[109]	Classification of coronary artery stenosis >50%	Coronary angiography	4	452	452	0.97	+ First fully automated stenosis recognition algorithm	− Still requires key frame detection which failed 7.5% of the time	External validation with AUC 0.93
Neleman et al, 2021[134]	Prognostic evaluation of coronary calcium quantification	IVUS	1	408	408	–	+ Range of subsequent treatment plans in patient + Median follow-up data of 6 y	− Small sample size, single site, IVUS technique may vary − No atheroma volume calculation	HR: 1.51 for all-cause mortality, stroke, MI, or revascularization
Hong et al, 2022[114]	Prediction of MACE based on plaque morphology	OCT	1	604	604	0.84	+ 2-y follow-up data + Utilizes comprehensive prospective OCT registry	− Small sample size, single site, OCT technique may vary	Lipid-to-cap ratio and optical flow ratio were superior to minimal lumen area at predicting nonculprit vessel MACE at 2 y.
Park et al, 2022[116]	Diagnosis of plaque erosion with acute coronary syndromes	OCT	8	873	302,415	0.96	+ One of the only comparisons of CNN vs transformer architectures	− Less common pathologies (nodule, dissection, hemorrhage) not included	Integration of adjacent frames showed superior performance
Avram et al, 2023[107]	Coronary artery stenosis localization and estimation	Coronary angiography	2	11,972	13,843	0.86	+ External validation with different vendor/ operator	− Ground truth was physician visual estimation − Low number of severe stenoses	Performance for internal validation
Avram et al, 2023[118]	Prediction of LVEF and identification of LV dysfunction (LVEF <40%)	Coronary angiography	2	3,679	4,042	0.91	+ First study to determine ability to predict LVEF from the modality	− Does not provide information on regional wall motion abnormalities	AUC for LVEF <40% in internal validation; LVEF predicted with MAE 8.5%

We conducted a narrative review of deep learning methods applied to physiologic waveform, imaging, and multiomics data with clinical applications in cardiology. Each subsection working group consisted of cardiac artificial intelligence (AI) investigators recognized for their expertise in the individual modalities. Each group utilized MeSH terms in PubMed to identify relevant studies. They also conducted backward and forward citation reviews of the studies, consistent with known narrative review practices. Studies were then discussed within each subsection's working group to select studies based to their merits in size, number of sites, degree of retrospective/prospective validation, number of citations, and perceived importance to the field by subject matter experts on each subsection. The recommended list was reviewed and approved by the lead and senior authors (P.E., S.J., J.d.S., T.M.). [a]Patient or imaging studies were not recruited at a centralized site. [b]Data derived from UK Biobank, number of unique sites contributing was not disclosed.

A4C = apical 4-chamber; AR = aortic regurgitation; AS = aortic stenosis; CMR = cardiac magnetic resonance; CNN = convolutional neural network; CTA = computed tomography angiogram; CTO = chronic total occlusion; HCM = hypertrophic cardiomyopathy; IVUS = intravascular ultrasound; LGE = late gadolinium enhancement; LV = left ventricle; LVEF = left ventricular ejection fraction; MACE = major adverse cardiovascular events; MAE = mean absolute error; MI = myocardial infarction; ML = machine learning; MR = mitral regurgitation; OCT = optical coherence tomography; PLAX = parasternal long axis; PPG = photoplethysmography; SPECT MPI = single-photon emission computerized tomography myocardial perfusion imaging; TTE = transthoracic echocardiography.

intrinsically limited by ECG signals themselves with common features existing across multiple conditions. There is additional concern that algorithms may not be generalizable to diverse patient populations, which will require more rigorous validation across health care systems.[52] Last, models built on patients with both ECGs and echocardiograms are then being prospectively tested on patients with only ECGs, an inherently different population. These population shifts and their accompanying changes in disease prevalence make performance estimation of predictive models challenging.

Despite these barriers, meaningful progress seems possible in the near future. Multiple clinical trials are underway with potential to expedite structural heart disease diagnosis. The U.S. Food and Drug Administration just granted its first de novo approval of an AI software in cardiology in August 2023—a hypertrophic

cardiomyopathy detection algorithm for ECG.[53] Another approval has since been granted for detecting low ejection fraction.[54] The rising popularity of wearables increases screening accessibility along with expansive data sets that necessitate automation. Some models having been recently validated using wrist-based wearables.[33,34] Similarly, integration with real-time telemetry in emergency care can enhance monitoring while simultaneously facilitating screening. Last, multimodal architectures, using ECG, echocardiogram, and computerized tomography (CT) data in a single model, are under development.[55]

ECHOCARDIOGRAPHY

Echocardiography is used for a range of diagnostic purposes, from screening to risk stratification. AI applications include advancements in image acquisition and interpretation.

IMAGE ACQUISITION. Although comprehensive echocardiography is typically performed by trained sonographers, AI efforts in the space of image acquisition have focused primarily on more limited point-of-care use cases. Multiple AI platforms are being developed to aid novice users in obtaining standard echocardiography views with built-in automated tools for limited image interpretation, such as assessment of the LVEF.[56,57] Deployment of these platforms may improve point-of-care disease diagnosis in primary care and emergency department settings and increase echocardiography availability in resource limited locations.

Echocardiography presents unique challenges for AI interpretation caused by its heterogeneous and unstructured nature, featuring high variability across patients and images. In contrast to the consistent acquisition process of ECGs and the structured protocols of CT and magnetic resonance imaging, echocardiograms include a variable array of stills and videos without standard annotations, making view classification a critical first step for further analysis such as segmentation or disease detection.

IMAGE INTERPRETATION. Once views have been appropriately classified, AI has been proposed to automate the measurements and assessments with a particular focus on automating or expediting image segmentation tasks.[58-63] These segmentation technologies may reduce the time needed for echocardiography technicians and cardiologists to make measurements such as LV wall thickness, atrial size, and LVEF. These technologies may yield improvements in intraobserver and interobserver variability, a common issue in echocardiography.[64,65] Following segmentation, AI has been developed to measure and predict important diagnoses made by echocardiography, including heart failure and valvular heart disease.[66-69]

Recently, large language models have been trained for multimodality with medical imaging[70,71] and text.[72] However, a critical bottleneck for their application in medicine has been the availability and access to large data sets necessary for training. Echocardiography provides a high number of complex images, which makes it well suited to train foundation models.[73]

FUTURE DIRECTIONS. AI in echocardiography will likely focus on easing image acquisition through image guidance tools. It will also focus on increasing the efficiency and reliability of image interpretation via AI assistance with a growing capacity for AI-assisted disease identification.

CMR, NUCLEAR CARDIOLOGY, AND CARDIAC CT

Advanced cardiac imaging offers detailed assessments of anatomy, physiology, and pathology. There is growing clinical adoption of AI techniques from enhanced image acquisition to AI-based radiomics to unlock latent information.[74]

CMR IMAGING. In CMR imaging, AI has the potential to transform the field from acquisition to disease diagnosis. Multiple vendors implement CNN-based denoising for image reconstruction, which can result in higher-quality image reconstruction with shorter acquisition times.[75] AI has also revolutionized CMR image segmentation, with nearly all postprocessing vendors utilizing CNN-based approaches for segmenting the LV, RV, and atria on cine images,[76] plus T_1/T_2 mapping, late gadolinium enhancement (LGE), and phase-contrast velocity encoding, greatly simplifying postprocessing workflow. AI is also used to quantify CMR images including assessment of strain, myocardial motion, and perfusion. Generative models have been used with precontrast images to predict LGE, potentially obviating the need for contrast.[77]

NUCLEAR CARDIOLOGY. In nuclear cardiology, AI has been used to improve prognostication in patients with suspected coronary artery disease undergoing single-photon emission computerized tomography (SPECT) myocardial perfusion imaging. For example, machine learning (ML)-based prediction of early coronary revascularization outperformed expert interpretation and automatic quantitation.[78] Similarly, ML using clinical and stress imaging data

obviated the need for rest imaging, with higher prognostic safety than current clinical approaches.[79] The diagnostic performance of DL-based interpretation of SPECT myocardial perfusion imaging was comparable to conventional approaches.[80] Abnormal cardiac uptake on Technetium-99m pyrophosphate scintigraphy can also be identified using AI.[81] AI is also being used to integrate CT information from attenuation correction scans, such as coronary artery calcium scoring and epicardial adipose tissue volume.[82] AI can also perform attenuation correction without requiring a CT scan.[83]

CARDIAC CT. In cardiac CT, AI has shown promise to potentially improve the ability to predict major adverse cardiovascular events.[84] AI can accurately determine coronary calcium scores from ECG-gated calcium scoring scans and estimate it from other scans,[85] and quantify stenosis plus plaque burden from coronary CT angiograms with close agreement to expert readers.[86,87] On nongated CT scans, AI can identify patients with incidental findings of coronary calcium to initiate cardiovascular disease prevention management.[88-90] Although most clinical CT-based fractional flow reserve estimation is based on computational fluid dynamics, alternative approaches use deep learning.[91] Peri-coronary fat attenuation on CT using AI is a radiomic metric of coronary inflammation that serves as a marker of increased cardiac mortality.[92] AI also addresses technical issues such as image reconstruction, segmentation, and motion correction. All major vendors now offer AI-based image reconstruction algorithms, and newer approaches improve spatial resolution of coronary CT angiograms by training standard acquisition data with that obtained using an ultra-high-resolution scanner.[93]

FUTURE DIRECTIONS. We expect that future developments will improve the speed or quality of data acquisition and exploit latent information in the scans to assist with downstream prognostication. There are also ongoing efforts to use AI for novel radiomics, extracting previously unmeasured information such as cardiovascular age and disease susceptibility.[94]

ADVANCED ELECTROPHYSIOLOGY STUDIES

Electrophysiology lends itself well to utilizing AI given its need to integrate complex data sources such as electrocardiography, intracardiac signals, 3-dimensional cardiac reconstruction, and multiple imaging modalities. The use of AI has extended to all parts of electrophysiology studies, encompassing preprocedural, intraprocedural, and postprocedural applications.

PREPROCEDURAL APPLICATIONS. As described in the previous text, AI applications within advanced cardiac imaging such as CMR imaging has included the identification areas of myocardial inflammation, scar, and edema using both T_1 mapping and T_2-weighted images.[95-98] These data can be impactful on preprocedural planning for ablation of both atrial and ventricular arrhythmias while risk stratifying arrhythmic risk in cardiomyopathy patients.

INTRAPROCEDURAL APPLICATIONS. Intraprocedural use cases include the advent of using extended reality in the electrophysiology laboratory through a head-mounted display, allowing the electrophysiologist to have 3-dimensional patient specific anatomies with catheter locations to assist in the procedure while manipulating the data in a sterile environment.[99,100] AI tools incorporate intracardiac electrical signals in real time to identify rotors that may be effective targets for ablation.[101] These allow operators to review a greater amount of electrical signals taken in 3-dimensional space to identify regions of interest for ablation in a way that would be challenging for human operators alone. Clinical trials have not shown improvement in outcomes (as measured by freedom from recurrent atrial fibrillation) compared with usual treatment, but subgroup analyses have shown potential benefit.[102,103]

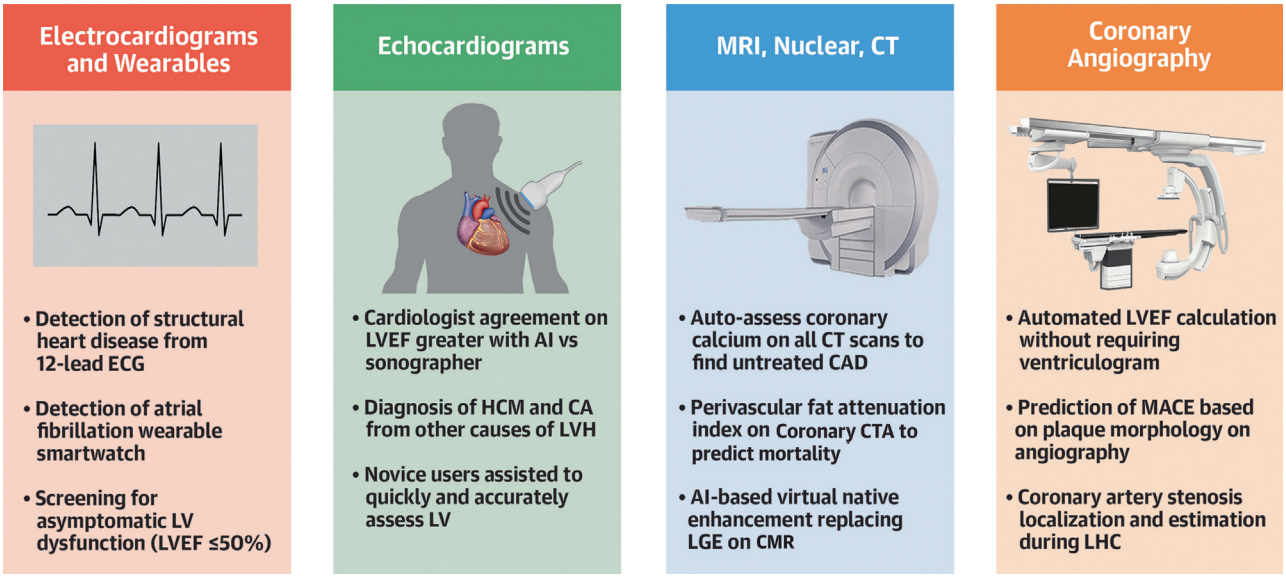
POSTPROCEDURAL APPLICATIONS. Postprocedural prediction use cases are early in their development. However, one potential use case is personalized noninvasive electrophysiology models to predict an individual's response to cardiac resynchronization therapy[104,105] and atrial fibrillation ablation.[106]

CORONARY ANGIOGRAPHY

In the field of coronary angiography, AI has shown promise in assisting with image acquisition, image interpretation, and risk stratification.

IMAGE ACQUISITION AND INTERPRETATION. AI has been applied to automate critical aspects of coronary angiogram interpretation, including coronary artery stenosis detection. Various investigators have developed AI algorithms to identify stenosis from angiograms,[107-111] often using fewer than 500 annotated examinations to train and validate models. An investigator group trained 2 AI models to accomplish coronary artery stenosis detection, one model to

CENTRAL ILLUSTRATION **Key Studies in Cardiovascular Artificial Intelligence by Imaging Modality**



Elias P, et al. J Am Coll Cardiol. 2024;83(24):2472–2486.

Recent advances in the capabilities of AI exist across a range of modalities. These include making imaging easier and safer to acquire, improving accuracy of interpretation, and even detecting diseases normally not assessed using the given modality. AI = artificial intelligence; CA = cardiac amyloidosis; CMR = cardiac magnetic resonance imaging; CT = computed tomography; CTA = computed tomography angiography; ECG = electrocardiogram; HCM = hypertrophic cardiomyopathy; LGE = late gadolinium enhancement; LHC = left heart catheterization; LVEF = Left ventricular ejection fraction; LVH = left ventricular hypertrophy; MACE = major adverse cardiac event.

identify the coronary artery segment, and another model to identify stenotic regions in the coronary artery.[112] They reported an accuracy of 98.4% in vessel segment identification and an AUC of 0.801 to detect stenoses ≥50% in severity. However, the study lacked external validation and a gold standard such as quantitative coronary angiography as a comparator, and its use of a ≥50% stenosis threshold rather than the clinically used threshold of ≥70% to define obstructive stenosis. A more recent study described a sequential pipeline of neural networks that provides a broad foundation for coronary angiogram interpretation.[107] Each algorithm achieves a distinct task necessary for coronary angiogram interpretation. The model mitigates some inherent limitations of predicting stenoses using visual estimation, including interobserver and intraobserver variability, thereby showcasing superiority of a quantitative approach.

ADDITIONAL CORONARY IMAGING MODALITIES. AI has also been used to develop models for various angiogram-adjacent tasks. AI has been used for intravascular imaging to identify plaque characteristics,[108] vulnerable plaque,[113] and perform risk stratification for future cardiovascular events.[108,114] One study described a method for automatically computing the fractional flow reserve in 303 patients using AI, achieving an accuracy of 93% in identifying hemodynamically significant stenoses.[115] Another investigator group trained and validated an algorithm using optical coherence tomography to distinguish acute coronary syndrome from plaque erosion, rupture, and other conditions, achieving an AUC of 0.96, comparable to core laboratory standards.[116] The tool enhanced sensitivity among novice readers, aligning with the proficiency of experienced analysts. AI was also employed to generate a dynamic coronary overlay ("roadmap") by tracking the catheter tip.[117] This technology allows coronary artery visualization without contrast.

Another study predicted LVEF from angiograms of the left coronary artery, information usually only

attained with a ventriculogram that significantly increases contrast load and procedural risk to the patient.[118] It was also accurate among patients presenting with acute coronary syndromes, where recent LVEF values may not be available to guide procedures.

FUTURE DIRECTIONS. Ongoing efforts are targeting integration of AI within the catheterization laboratory. A current study is examining the accuracy of an AI algorithm in patients admitted for ACS, using echocardiograms as the reference standard. The model is tested directly in the catheterization laboratory during angiography providing clinical workflow efficiencies (NCT05317286).

GENETICS, MULTIOMICS, AND OTHER INPUT MODALITIES

Recent studies have shown that ML can exploit nonlinear and complex relationships in genomic data, leading to improved risk prediction across diverse ancestries.[119] Additionally, the interpretation of genomic variants is crucial for the diagnosis and risk assessment of cardiovascular disease. Thousands of genetic variants can be identified for a single patient by next-generation sequencing technologies. However, only a few of these variants might be pathogenic in the individual patient. Novel AI methods can lead to improved variant identification of pathogenic variants.[120,121] Improved pathogenicity identification and clarity around variants of unknown significance are key for improving integration into clinical care.

AI has been used to interpret many other inputs,[122] including video-based detection for vital signs and atrial fibrillation,[123,124] audio-based heart rhythm analysis,[125] and electronic medical record-based evaluation for cardiovascular disease risk and diagnosis of a variety of cardiovascular diseases.[126-129]

Future directions involve a focus on higher quality and quantity of labeling, more diverse training data, rigorous evaluation of model generalizability, and education to promote adoption.

CONCLUSIONS

AI in cardiovascular medicine has advanced in recent years, with particular progress in analysis of waveform, imaging, and genetic data. These advancements touch every step of the patient journey. Our **Central Illustration** highlights key advances in 4 modalities where some of the most impactful advancements have occurred. AI technologies have shown early promise in screening for disease, integrating disparate imaging data sources into composite assessments, providing workflow efficiencies through preprocessing of images, and assisting clinicians with more accurate diagnoses. These applications begin to show how AI can serve not only as "artificial intelligence," but also as "augmented intelligence" for our clinicians.

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