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AI-Driven Atrial Fibrillation Management: From Signal to Strategy

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Atrial fibrillation (AF) is the most common sustained cardiac arrhythmia worldwide and is associated with substantial morbidity, including ischemic stroke, heart failure, and cognitive decline. Despite established diagnostic and therapeutic strategies, AF remains frequently underdiagnosed and suboptimally managed, particularly in asymptomatic or paroxysmal cases, in which the episodic nature of the arrhythmia may make it difficult to detect using standard electrocardiography. Artificial intelligence (AI), including machine learning and deep learning, has emerged as a transformative technology across multiple aspects of AF care. AI-based electrocardiographic analysis and wearable technologies have demonstrated promising performance in detecting subclinical AF and facilitating scalable population screening. Multimodal models integrating clinical, imaging, and electrophysiological data have demonstrated improved accuracy in stroke prediction, recurrence risk estimation, and therapeutic planning. AI-assisted imaging has advanced atrial segmentation, fibrosis characterization, and ablation planning, whereas AI-driven mapping systems may enhance procedural efficiency and improve patient selection. Nevertheless, significant challenges remain, including limited external validation, data heterogeneity, concerns regarding interpretability, integration into clinical workflows, and ethical and regulatory considerations. Future efforts should prioritize explainable, clinically validated, and human-centered AI systems that are integrated into real-world clinical workflows. This review provides a comprehensive overview of current AI applications in AF management, including early detection, risk stratification, cardiovascular imaging, clinical decision support, and interventional electrophysiology.

INTRODUCTION

Atrial fibrillation (AF) is the most common sustained cardiac arrhythmia worldwide, affecting an estimated 60 million people, with the burden expected to rise further as populations age and comorbidities accumulate.[1,2] AF significantly increases the risk of ischemic stroke, heart failure, myocardial infarction, and dementia and also diminishes quality of life.[3,4] Despite established diagnostic and treatment strategies, AF often remains underdiagnosed, especially in asymptomatic or paroxysmal cases, in which intermittent arrhythmic episodes may not be captured by standard or opportunistic electrocardiography (ECG), thereby delaying diagnosis and appropriate treatment. Traditional methods, such as intermittent ECG screening and risk-scoring systems, have limitations in three distinct but complementary domains: first, predicting which individuals will develop AF (incident AF prediction); second, detecting subclinical AF in individuals who already have the condition but remain undiagnosed because of the asymptomatic or paroxysmal nature of their arrhythmia; and third, predicting post-ablation outcomes, specifically distinguishing patients who will maintain sinus rhythm from those who will experience arrhythmia recurrence. These three gaps have significant implications for stroke prevention, optimal patient selection for invasive therapies, and timely therapeutic intervention.[5,6]

The use of artificial intelligence (AI) in AF clinical applications is rapidly advancing across different areas of this disease.[7,8] Briefly, AI refers to computational systems that perform tasks that typically require human cognition, such as learning and reasoning; machine learning (ML) is a subset of AI in which algorithms learn patterns directly

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from data without explicit programming; and deep learning (DL) is a further subset that uses multilayered neural networks to model complex, high-dimensional inputs, such as raw ECG waveforms.[9] AI models analyzing ECG and wearable device data have demonstrated promising performance for early detection through long-term, low-cost, non-invasive screening.[10] AI models can improve stroke risk assessment beyond traditional scoring systems such as CHA_2DS_2-VASc by integrating complex clinical, laboratory, and imaging data to support individualized anticoagulation therapy.[11] Furthermore, AI shows increasing promise across all stages of AF ablation, including preprocedural planning, interpretation of complex AF signals during the procedure to optimize target identification, and prediction of postprocedural arrhythmia recurrence, thereby enabling more personalized patient follow-up, although its routine clinical adoption remains limited.[12] This review summarizes the current integration of AI into AF management, focusing on its potential and limitations in early detection, stroke risk assessment, anticoagulation personalization, patient selection, and procedural guidance for ablation and follow-up (Figure 1).

Literature search strategy

A structured literature search was conducted in PubMed, Embase, the Cochrane Library, and IEEE Xplore to identify studies published between January 2015 and April 2026. The following Medical Subject Headings and free-text terms were combined using Boolean operators (AND, OR): "atrial fibrillation," "artificial intelligence," "machine learning," "deep learning," "neural network," "convolutional neural network," "electrocardiogram," "photoplethysmography," "wearable device," "cardiac magnetic resonance," "catheter ablation," "electroanatomical mapping," "stroke risk," "risk stratification," and "clinical decision-support system." Studies were eligible if they reported original data or

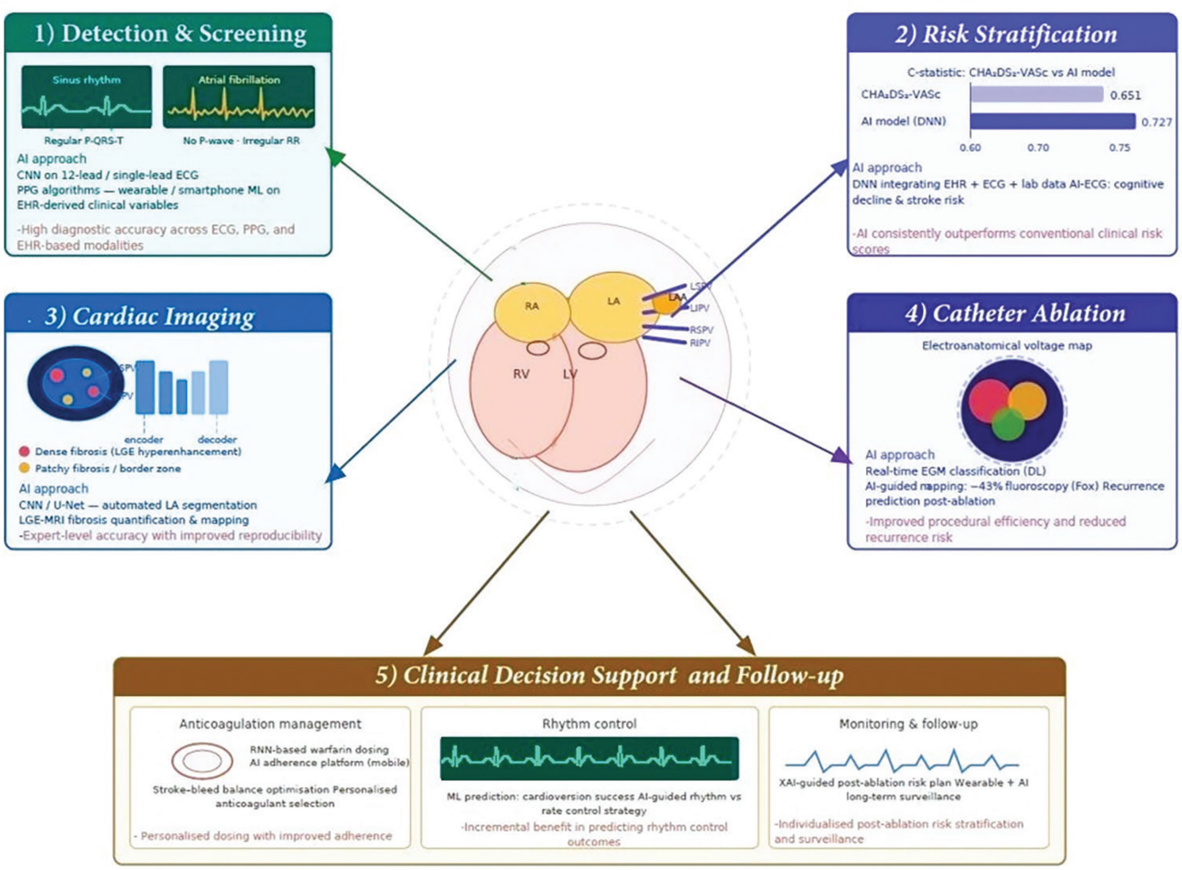

FIG. 1. AI applications across atrial fibrillation management. Structured overview of five principal domains of AI integration in AF care, organized around a central cardiac anatomical reference. (1) Detection and screening: CNN-based ECG analysis, PPG wearables, and EHR-derived models enable scalable AF identification across clinical and non-clinical settings. (2) Risk stratification: multimodal AI models integrating clinical, electrocardiographic, and laboratory data improve stroke and outcome prediction beyond conventional scoring systems. (3) Cardiac imaging: deep learning architectures automate left atrial segmentation and fibrosis quantification from cardiac MRI, improving reproducibility over manual interpretation. (4) Catheter ablation: AI-guided electroanatomical mapping and real-time signal classification enhance procedural efficiency and post-ablation recurrence prediction. (5) Clinical decision support and follow-up: AI tools support anticoagulation management, rhythm control strategy selection, and wearable-integrated long-term surveillance. CNN, convolutional neural network; DL, deep learning; ECG, electrocardiogram; EGM, electrogram; EHR, electronic health record; LA, left atrium; MRI, magnetic resonance imaging; LGE-MRI, late gadolinium-enhanced MRI; ML, machine learning; PPG, photoplethysmography; XAI, explainable artificial intelligence.

a structured synthesis of AI applications in any domain of AF management. The exclusion criteria included editorials, conference abstracts without full-text publications, non-peer-reviewed sources, and studies lacking quantitative outcome reporting. Representative studies across five clinical domains (ECG-based detection,[13-25] wearable monitoring,[26-30] risk stratification, catheter ablation,[31] and novel detection modalities) are summarized in Table 1, which provides an overview of the study design, patient population, AI methodology, and key quantitative findings. Throughout this review, we indicate the level of supporting evidence for each application—ranging from proof-of-concept and retrospective single-center analyses to prospective validation studies and randomized controlled trials (RCTs)—because these study designs differ substantially in methodological rigor and readiness for clinical adoption.

TABLE 1. Comprehensive Summary of Studies on AI Applications in Atrial Fibrillation Management.

Study/year	Study design	ECG/signal	Patients, n	AI approach	Key results/findings
Section A: ECG-based detection and prediction studies					
Attia et al., 2019[49]	Retrospective	12-lead ECG	180,922	CNN	AF detection during SR; AUC 0.87; opportunistic screening potential
Melzi et al., 2021[22]	Retrospective cohort	12-lead ECG	26,657	CNN-ResNet, CNN + LSTM, RNN, FCNN	AF prediction from SR ECG; demographics improved accuracy; feature visualization enhanced interpretability
Raghunath et al., 2021[51]	Retrospective cohort	12-lead ECG	~430,000 (1.6M ECGs)	CNN	New-onset AF within 1 year; AUC 0.85; sensitivity 69%, specificity 81%; 62% of future AF-related stroke patients identified
Rodrigo et al., 2022[37]	Prospective electrophysiology	Intracardiac EGMs (basket catheter)	86	CNN + RNN	AUC 0.97 (unipolar); novel AF signatures: timing variability > 15%, cycle length < 190 ms
Kaminski et al., 2022[33]	Retrospective cohort	12-lead ECG	1,403	CNN	AF risk in ED population; supports opportunistic screening; real-world implementation highlighted
Singh et al., 2022[38]	Retrospective multicenter	24-h Holter ECG	Int: 9,993 / Ext: 5,808	CNN + LSTM + Attention ensemble	Short-term AF prediction within 15 days; AUC 0.79 internal, 0.76 external
Yang et al., 2022[13]	Retrospective	12-lead ECG (P-wave)	460	SVM, RF, XGBoost, Perceptron	AUC 0.64; P-wave inter-lead dispersion key predictor; explainable approach
Suzuki et al., 2022[14]	Retrospective single-center	12-lead ECG	19,170 (2,172 derivation)	CNN	AUC up to 0.88; labeling strategy significantly impacted performance
Christopoulos et al., 2020[15]	Population-based cohort (Mayo Clinic Study of Aging)	12-lead ECG (sinus rhythm)	1,936	CNN (AI-ECG AF score)	AI-ECG predicted incident AF; > 50% probability → 21.5% AF at 2 yr, 52.2% at 10 yr; similar to CHARGE-AF
Khurshid et al., 2022[16]	Retrospective multicenter (3 cohorts)	12-lead ECG	> 80,000	DL + clinical risk factors (5-yr AF-free survival model)	AUC 0.823 for 5-yr AF-free survival; P-wave identified by saliency maps; ECG + risk factors identified highest-risk patients
Noseworthy et al., 2022 (Lancet)[17]	Prospective non-randomized interventional	12-lead ECG + EHR (NLP)	Screened high-risk patients	CNN (AI-ECG) + EHR clinical variables	High AI-ECG risk patients 5 × more likely to receive AF diagnosis on 30-day monitoring vs. low-risk controls
Gadaleta et al., 2023[18]	Retrospective cohort	Single-lead patch ECG (up to 14 days)	446,900	CNN + LSTM hierarchical model	Near-term AF (2 weeks); AUC 0.80; longer monitoring improved accuracy
Gruwez et al., 2023[19]	Retrospective + external validation	12-lead ECG	142,310	CNN (replication of Attia model)	AUC 0.87; consistent across external cohorts; confirmed generalizability
Hygrell et al., 2023[52]	Retrospective (prospective screening data)	Single-lead handheld ECG	14,831 (478,963 recordings)	CNN	AUC 0.62-0.80; performance varied with demographic heterogeneity
Kim et al., 2023[20]	Retrospective cohort	12-lead ECG	7,595	1D-CNN ResNet + Grad-CAM	AUC up to 0.864 for non-persistent AF (1-4 weeks); QRS and T-wave identified as key predictors
Kim et al., 2023[21]	Retrospective cohort	12-lead ECG (10 s)	134,447	ResNet-18, Conv1D + LSTM, Conv1D + Transformer	AUC up to 0.94; discrete heartbeat segmentation outperformed whole-ECG input

TABLE 1. Continued.

Study/year	Study design	ECG/signal	Patients, n	AI approach	Key results/findings
Melzi et al., 2023[50]	Retrospective longitudinal	12-lead ECG (10 s)	AF: 3,761/SR: 22,896	Residual Network + demographics (longitudinal)	AUC up to 0.87; higher accuracy closer to AF onset; stable high-risk scores predicted future AF
Biton et al., 2023[23]	Retrospective multicenter	Long-term Holter (RR intervals)	Train: 2,147/ Ext: 402 (4 countries)	CNN + RNN (ArNet2; 60-beat RR windows)	AUROC up to 0.96; F1 up to 0.95; generalized across geography, age, sex
Dupulthys et al., 2024[24]	Retrospective cohort	Single-lead ECG (Lead I, 10 s)	68,880 patients (173,537 ECGs)	ResNet + EHR risk factors	AUC 0.74 (ECG alone), 0.76 with 6 risk factors; matched 12-lead ECG performance
Estrada-Magana et al., 2025[25]	Retrospective multicenter	12-lead ECG validated vs. ILR	2,523 (658 developed AF; follow-up 19 months)	DL-ECG vs. CHARGE-AF	AUC 0.73 vs. 0.69 (CHARGE-AF); high-risk subgroup: 46.8% vs. 14.8% AF incidence
Jo et al., 2021[43]	Retrospective	12-lead ECG	128,000+	Explainable DL (XAI: Grad-CAM, attention)	AUC 0.997-0.999; interpretable outputs linked to rhythm irregularity and P-wave absence; XAI aligned with cardiologist ECG features
Section B: wearable device studies					
Tison et al., 2018[55]	Prospective observational	Smartwatch (PPG)	9,750	Deep learning (PPG signal)	C-statistic ~0.97; feasibility of passive real-world AF screening
Perez et al., 2019[56]	Prospective pragmatic (Apple Heart Study)	Apple Watch PPG + ECG patch	419,297 enrolled/450 with ECG patches	Tachogram irregularity detection	PPV 0.84; 34% AF confirmed; 0.52% notification rate
Chen et al., 2020[26]	Prospective observational	Smart wristband (PPG + single-lead ECG)	401	SEResNet (PPG + ECG fusion)	PPG: sensitivity 88%, specificity 96%; ECG: specificity 99.2%, accuracy 94.76%
Guo et al., 2020 (mAFA)[57]	Prospective multicenter RCT	Mobile health app (mAFA platform)	3,324 AF patients (40 centers)	mHealth decision support	Composite outcome 1.9% vs. 6.0% (HR 0.39, $p < 0.001$); marked reduction in rehospitalization
Guo et al., 2021 (Huawei)[58]	Prospective population-based	PPG smartwatch/ wristband	Dev: 554/Val: 1,709/Prosp: 50	XGBoost (HRV + entropy; temporal integration)	AF onset prediction up to 4 h before: AUC 0.94 (dev), 0.83 (prospective); sensitivity 81.9%
Hiraoka et al., 2022[27]	Prospective observational (post-cardiac surgery)	Apple Watch (PPG; 14-day monitoring)	79	LightGBM (pulse rate features + clinical data)	AUC 0.94; sensitivity 90.9%, specificity 83.8%
Lubitz et al., 2022 (Fitbit Heart)[28]	Prospective single-arm	Fitbit PPG + ECG patch confirmation	455,699 enrolled/1,057 with ECG patches	PPG tachogram algorithm (11 consecutive irregular segments)	AF confirmed 32.2%; PPV 98.2%; sensitivity 67.6%, specificity 98.4%
Mannhart et al., 2023 (BASEL Wearable)[29]	Prospective observational	5 consumer wearables (Apple Watch 6, Samsung Galaxy Watch 3, Withings ScanWatch, Fitbit Sense, AliveCor KardiaMobile)	201	Device-specific proprietary algorithms + manual physician review	AF prevalence 31%; sensitivity 58-85% across devices; manual interpretation achieved 98-100% accuracy
Blok et al., 2025[30]	Prospective observational	Medical smartband PPG + concurrent ECG	72	SVM, statistical features, Markov modeling (3 algorithms)	Sensitivity 80.0-97.6%; specificity 90.6-96.9%; PPG-based AF detection confirmed feasible

TABLE 1. Continued.

Study/year	Study design	ECG/signal	Patients, n	AI approach	Key results/findings
Section C: AI for risk stratification and outcome prediction					
Jung et al., 2022[64]	Retrospective (Korean National Health Insurance)	EHR data (clinical variables)	AF: 754,949 patients (national database)	DNN vs. logistic regression (65 features)	AUROC 0.727 vs. 0.651 (CHA_2DS_2-VASc) for ischemic stroke prediction; superior to conventional score
Akbilgic et al., 2021[65]	Retrospective cohort (ARIC study)	12-lead ECG (10 s)	14,613 (803 developed HF within 10 yrs)	CNN (ECG-AI, ResNet-based) + LGBM ensemble	ECG-only AUC 0.756; with clinical variables AUC 0.818; ECG-AI output was the strongest HF predictor
Weil et al., 2022[66]	Population-based (Mayo Clinic Study of Aging)	12-lead ECG (AI-ECG AF score)	Cognition: 3,729/MRI: 1,373	CNN (AI-ECG AF probability score)	Higher AI-ECG-AF score → lower baseline cognition, faster decline in global cognition and attention; high score (> 0.5) associated with cerebral infarcts on MRI (OR 2.09, p = 0.03)
Vinter et al., 2020[67]	Retrospective cohort	Clinical + echocardiographic variables	332 women/790 men (electrical cardioversion)	ML + logistic regression (sex-specific)	AUC 0.56-0.60; only modest predictive performance for cardioversion success; ML did not outperform regression
Nuñez-Garcia et al., 2022[68]	Retrospective + validation	Clinical variables (cardioversion candidates)	429	ML prognostic model (vs. CHA_2DS_2-VASc, HATCH)	ML better predicted 6-month AF recurrence and rhythm control; less accurate than conventional scores for direct-current cardioversion success
Section D: AI-guided catheter ablation					
Deisenhofer et al. (TAILORED-AF), 2025[98]	Multicenter RCT	Intracardiac EGMs (spatio-temporal dispersion)	374 (1:1 randomized: AI-tailored vs. PVI-only)	AI algorithm detecting spatio-temporal electrogram dispersion (Volta software)	Freedom from AF at 12 months: 88% (AI-tailored) vs. 70% (PVI-only); significant benefit in AF duration ≥ 6 months subgroup; first large-scale RCT showing AI-guided ablation superiority
Fox et al., 2024[101]	Prospective (AI-guided arrhythmia mapping)	ECG + intracardiac signals	28	Forward-solution AI ECG mapping system	Time to first ablation -19%; procedure duration -22.6%; fluoroscopy -43.7%; 6-month arrhythmia-free survival 73.5%
Tang et al., 2022[31]	Retrospective (post-ablation prediction)	Intra-atrial EGMs + body surface ECG + clinical variables	165	CNN multimodal fusion model	AUC 0.859 for 1-year AF recurrence post-ablation; multimodal fusion outperformed single-modality models
Shade et al., 2020[96]	Retrospective (pre-procedural prediction)	LGE-MRI-based computational modeling + clinical data	Not specified	ML + personalized atrial simulation	AUC 0.82 for AF recurrence after PVI; outperformed imaging-alone models
Section E: novel AI detection methods (radiography, video)					
Matsumoto et al., 2022[60]	Retrospective	Chest radiograph (posteroanterior view)	13,868	CNN + saliency mapping	AUC 0.81 (95% CI 0.78-0.85); AI attended to upper left cardiac shadow (left atrial region); more sensitive for permanent vs. paroxysmal AF
Yan et al., 2020[61]	Proof-of-concept	Digital camera (facial PPG video)	20 AF/20 SR (5 simultaneous)	CNN (facial PPG signal extraction)	AUC 0.99; 80% of 1-min videos correctly classified 5 simultaneous patients; contactless, non-invasive AF detection

AF, atrial fibrillation; AUC, area under the curve; CNN, convolutional neural network; DL, deep learning; DNN, deep neural network; ECG, electrocardiogram; EGM, electrogram; EHR, electronic health record; HF, heart failure; HRV, heart rate variability; ILR, implantable loop recorder; LGE-MRI, late gadolinium enhancement MRI; LSTM, long short-term memory; ML, machine learning; PPG, photoplethysmography; PPV, positive predictive value; PVI, pulmonary vein isolation; RCT, randomized controlled trial; RNN, recurrent neural network; SR, sinus rhythm; SVM, support vector machine; XAI, explainable artificial intelligence. Reported AUC values ≥ 0.99 or those derived from very small cohorts (e.g., Yan et al.,[61] 2020, n = 40; Hiraoka et al.,[27] 2022, n = 79) should be interpreted with caution, as these figures often reflect small sample sizes or limited external validation rather than robust real-world performance.

FOUNDATIONS OF AI IN CARDIOVASCULAR MEDICINE

Core concepts: ML and DL in AF

AI involves simulating human intelligence in computers or machines, enabling them to perform tasks that normally require cognitive abilities, such as learning, reasoning, and problem-solving. In AI, ML is a subset in which algorithms learn from data to make predictions or decisions without explicit programming. There are two main approaches to ML: supervised and unsupervised learning.[32] In supervised learning, the target outcome is predefined, and a labeled dataset is used to train the algorithm to predict the outcome using various statistical techniques. Supervised learning approaches rely on labeled ECG datasets to train predictive models that identify AF-associated patterns and distinguish them from normal or noisy signals. By learning hierarchical representations of ECG morphology, ML-based supervised models can achieve improved classification performance and generalizability in AF-related signal analysis.[33] In contrast, unsupervised learning identifies intrinsic patterns within unlabeled datasets without predefined outcomes by leveraging diverse data sources, including ECG, imaging, and EHR data.[34,35]

A more specialized area of ML is DL, which uses layered neural networks modeled after the human brain. These models can handle complex, high-dimensional data, such as continuous ECG signals or imaging data, and are particularly effective at detecting subtle features that may be imperceptible to human clinicians. DL approaches enable end-to-end analysis of electrocardiographic signals by automatically learning hierarchical feature representations from raw data.[36] Convolutional and recurrent neural network architectures can capture both waveform morphology and temporal rhythm dynamics, allowing accurate discrimination between AF and normal sinus rhythm.[37] Unlike traditional machine-learning pipelines, these models jointly perform feature extraction and classification, enabling the identification of complex non-linear patterns within ECG signals (Figure 2).[38]

Explainable AI and clinical trust

As AI adoption in cardiology increases, clinician trust becomes a critical determinant of real-world implementation. The growing availability of multisource cardiac data, including cardiac magnetic resonance (CMR), ECG, and EHR data, has enabled the development of advanced AI models; however, the "black-box" nature of many ML algorithms limits clinical trust and adoption.[39-42]

Explainable AI (XAI) is a framework designed to increase transparency by providing human-understandable insights into model predictions. In healthcare, XAI aims to clarify which features, signal segments, or imaging regions most strongly influence an

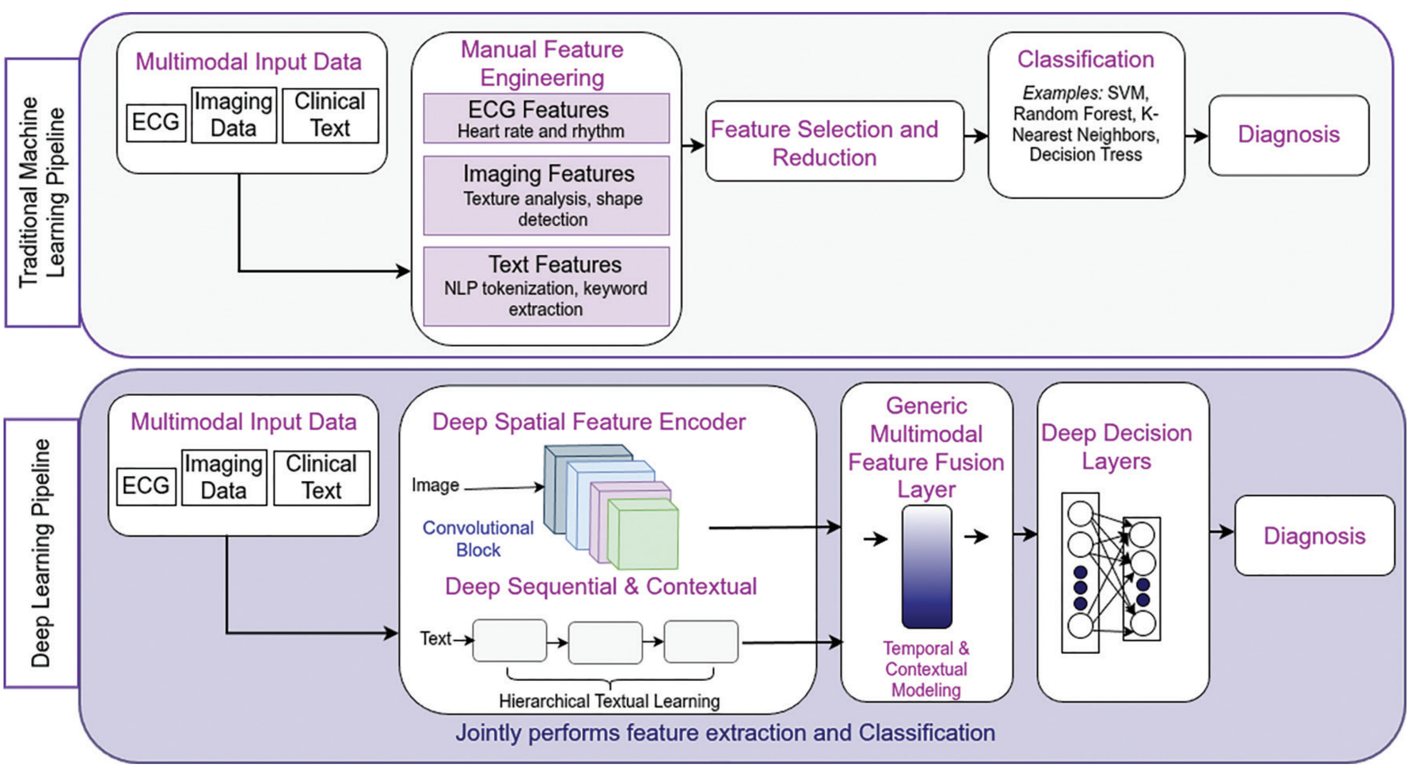

FIG. 2. Traditional machine learning vs. deep learning pipelines for multimodal AF analysis. Schematic comparison of two computational approaches to multimodal cardiovascular data processing. The upper panel depicts the traditional machine learning pipeline, in which ECG, imaging, and clinical text inputs undergo manual feature engineering followed by feature selection and conventional classification algorithms. The lower panel illustrates the end-to-end deep learning pipeline, in which convolutional spatial encoders and hierarchical sequential modules jointly extract features and perform classification via a multimodal fusion layer and deep decision layers, eliminating the need for manual intermediate steps. CNN, convolutional neural network; ECG, electrocardiogram; KNN, k-nearest neighbors; NLP, natural language processing; SVM, support vector machine.

algorithm's output. XAI techniques, such as Shapley Additive Explanations, Local Interpretable Model-Agnostic Explanations, Grad-CAM, and attention-based attribution methods, have been developed to address this need by providing both local and global explanations of model behavior. These methods help clinicians identify which variables, image regions, or signal segments influence a prediction, making otherwise opaque algorithms more understandable as clinical tools. By using interpretable architectures and attribution techniques, recent studies have demonstrated that AI systems can highlight clinically meaningful electrocardiographic features, such as rhythm irregularity, the absence of P waves, and changes in waveform morphology, when identifying AF.[43] An explainable DL model trained on more than 128,000 ECG recordings achieved excellent diagnostic performance for AF detection while simultaneously providing interpretable outputs related to rhythm irregularity and P-wave absence, two core electrophysiological markers of AF.[43] Similarly, gradient-based attribution methods applied to arrhythmia classification models have shown that AI-generated explanations often align with cardiologist-recognized ECG features, such as P waves, Q, R, and S wave complexes, R peaks, and rhythm intervals.[44,45]

AI-BASED AF DETECTION AND POPULATION SCREENING

AI has greatly enhanced the ability to detect, predict, and screen for AF, especially in cases in which the arrhythmia remains hidden or occurs sporadically. Traditional screening methods that rely on intermittent ECG recordings often miss silent AF episodes, creating a significant opportunity for AI-driven strategies to improve early detection. In interpreting these approaches, it is useful to distinguish three clinically distinct scenarios that carry different levels of evidence and regulatory implications: opportunistic screening (a single, one-time rhythm assessment in at-risk individuals), continuous or prolonged monitoring (e.g., wearable- or implantable-device surveillance for paroxysmal AF), and diagnostic confirmation,[12] which, under current guidelines, still requires ECG documentation of AF.[46] ML models applied to EHR data can combine hundreds of clinical variables, including demographic information, comorbidities, and laboratory results, to estimate an individual's risk of developing AF. Beyond clinical risk prediction, DL-enhanced ECG analysis has become one of the most promising tools for AF detection.[47,48] Attia et al.[49] demonstrated that a convolutional neural network (CNN) applied to standard 12-lead ECGs can identify patients with prevalent AF during sinus rhythm with high accuracy [area under the curve (AUC) ≈ 0.87], highlighting the potential of AI-based ECG analysis for opportunistic screening and early detection. In a subsequent externally validated study, a DL-based ECG model trained to predict future or occult paroxysmal AF from ECGs recorded during normal sinus rhythm maintained robust performance (AUC ≈ 0.87), supporting its generalizability across diverse populations.[48] Similarly, Melzi et al.[50] showed that DL models integrating ECG signals with demographic variables can improve the prediction of incident AF during sinus rhythm, while feature visualization techniques enhance the interpretability of model outputs. Raghunath et al.[51] demonstrated that a CNN trained on approximately 430,000 12-lead ECGs predicted new-onset AF within 1 year with an AUC of 0.85, additionally identifying 62% of patients who subsequently experienced AF-related stroke, underscoring the clinical relevance of AI-ECG screening beyond arrhythmia detection alone. In contrast, Hygrell et al.[52] demonstrated that AI applied to single-lead ECG recordings can predict incident AF with more variable performance (AUC 0.62-0.80), with results influenced by population characteristics, particularly age heterogeneity. Comprehensive reviews have similarly cataloged the rapid expansion of AI-based ECG analysis for AF detection and prediction while cautioning that most reported models still require prospective, multicenter validation before routine clinical use.[53] AI-driven screening has also expanded beyond conventional clinical settings through wearable technologies and consumer devices.

The ECG remains the gold standard for AF diagnosis; however, the increasing prevalence of consumer-grade wearable devices has introduced a paradigm shift in AF detection.[54] Photoplethysmography (PPG) technology enables real-time, automated rhythm assessment in non-clinical settings by utilizing wearable devices and smartphones to facilitate continuous cardiac monitoring. Early proof-of-concept work by Tison et al.[55] demonstrated that DL applied to passive smartwatch PPG data could detect AF with a C-statistic of approximately 0.97 in a real-world ambulatory population, establishing the foundational feasibility of consumer wearable-based AF screening. Large-scale studies have evaluated both the diagnostic accuracy of wearable-based PPG algorithms and their potential role in identifying previously undiagnosed AF. Perez et al.[56] enrolled more than 400,000 participants; 34% of those notified of an irregular pulse were subsequently diagnosed with AF, and 84% of notifications were confirmed by ECG. Guo et al.[57] demonstrated that PPG-based wearable monitoring enables large-scale AF screening with high diagnostic accuracy (positive predictive value, 91.6%) while facilitating integration into a structured care pathway and improving anticoagulation uptake in high-risk patients.[58,59] Together, these studies highlight both the diagnostic potential of consumer-grade wearable technology and the logistical challenges of translating algorithmic accuracy into scalable, real-world AF detection.

Implantable cardiac devices often misclassify atrial flutter, atrial tachycardia, or even premature atrial ectopic beats as AF because of the rate or irregularity of the intracardiac signals. Rodrigo et al.[37] developed a DL algorithm to distinguish AF from other tachycardias using intracardiac electrogram (EGM) features. The algorithm demonstrated excellent performance, achieving an AUC of 0.95-0.97, depending on whether unipolar or bipolar EGMs were used, compared with traditional single-EGM features, which achieved an AUC of 0.67-0.75. These findings support the continued evaluation of DL as a tool for improving the identification of AF from other arrhythmias using EGMs obtained from cardiac implantable electronic devices.

Beyond ECG- and wearable-based approaches, emerging AI methods have demonstrated the ability to detect AF from unconventional data sources. Matsumoto et al.[60] showed that a CNN applied to standard posteroanterior chest radiographs could identify AF with an AUC of 0.81. Saliency mapping revealed that the model primarily focused on the left atrial region, consistent with the known structural remodeling associated with AF. In a separate proof-of-concept study, Yan et al.[61] demonstrated contactless AF detection from facial PPG videos using CNN-based signal extraction, achieving an AUC of 0.99 in a small cohort. Although these findings require large-scale prospective validation, they suggest that AI may enable AF screening using ubiquitous, non-invasive data sources, particularly in resource-limited or remote settings.

These AI-based detection tools should be considered within the context of current clinical practice guidelines. The 2024 ESC/EACTS and 2023 ACC/AHA/ACCP/HRS AF guidelines acknowledge the emerging role of AI and ML and recommend opportunistic screening in older adults while clearly distinguishing systematic population-based screening from opportunistic detection.[62] Crucially, however, a definitive diagnosis of AF still requires ECG documentation. PPG- and other non-ECG-based tools are regarded as adjunctive screening aids rather than diagnostic instruments, and the quality of evidence supporting consumer PPG applications is explicitly acknowledged as limited.[6] No current guideline endorses AI-derived diagnostic or risk algorithms for routine standalone clinical use, reflecting the gap between promising algorithmic performance and the prospective, outcome-based validation required for formal recommendation.[63]

AI-BASED RISK STRATIFICATION AND CLINICAL OUTCOME PREDICTION

Risk stratification is essential in AF management to identify patients at high-risk of stroke, heart failure, or disease progression. Traditional clinical risk scores, such as CHA_2DS_2-VASc, are widely used to estimate stroke risk; however, they rely on relatively simple empirical factors (e.g., age and stroke history), and their discriminative performance remains modest (C-statistic approximately 0.60).[11] Recent advances in AI-driven stroke prediction have focused on integrating multimodal data, including demographic, clinical, and electrocardiographic variables, to overcome the limitations of traditional risk stratification scores. Jung et al.[64] demonstrated that a deep neural network using national health data predicted ischemic stroke in patients with AF with superior discriminative performance compared with CHA_2DS_2-VASc (AUROC 0.727 vs. 0.651). Similarly, Akbilgic et al.[65] showed that a DL model using only 12-lead ECG signals could predict future heart failure with an AUC of 0.756 and that integrating AI-derived ECG features with clinical variables further improved predictive performance to an AUC of 0.818. AI-based ECG has also shown promise in identifying broader AF-related systemic risks. In a population-based cohort, Weil et al.[66] reported that an AI-derived ECG probability score for AF was associated with lower baseline cognitive performance, accelerated decline in global cognition and attention, and a higher prevalence of cerebral infarcts detected on brain magnetic resonance imaging (MRI). These findings suggest that AI-derived ECG features may capture subtle electrophysiological signatures reflecting underlying atrial cardiopathy and systemic vascular vulnerability beyond those identified by traditional clinical predictors.

Beyond risk stratification, AI- and ML-based approaches have also been explored to predict therapeutic outcomes in AF. Vinter et al.[67] demonstrated that ML models showed only modest predictive performance for successful electrical cardioversion in patients with AF (C-statistic ≈ 0.56-0.60), highlighting the ongoing challenge of accurately identifying patients most likely to benefit from rhythm-control strategies. Nuñez-Garcia et al.[68] demonstrated that ML models improved the prediction of sinus rhythm restoration and maintenance after electrical cardioversion compared with traditional risk scores (AUC up to 0.80 vs. 0.66), although performance remained limited for predicting successful direct-current cardioversion. Two important caveats apply across this body of literature. First, improved discriminative performance does not necessarily translate into better patient outcomes. Second, most of these models remain investigational because they have largely been derived from retrospective cohorts, have undergone limited external validation, and have not yet been shown to influence clinical management.[69] Future prospective studies must demonstrate that AI-guided risk prediction improves clinical decision-making and ultimately reduces stroke, bleeding, or mortality before routine clinical adoption can be justified.[70,71]

AI APPLICATIONS IN CARDIAC IMAGING FOR AF

Cardiac imaging plays a crucial role in the assessment and management of AF. It helps identify conditions such as left ventricular dysfunction, left atrial enlargement, three-dimensional (3D) atrial and pulmonary vein geometry for ablation planning, and valvular heart disease, all of which increase the risk of AF development and persistence.[72] Imaging modalities such as echocardiography, computed tomography (CT), and CMR imaging enable detailed assessment of atrial anatomy, fibrosis burden, and thrombus formation, all of which are critical for risk stratification and procedural planning. However, conventional interpretation of these imaging modalities is time-consuming, operator dependent, and subject to interobserver variability. In this context, AI has emerged as a transformative tool for enhancing image analysis, improving reproducibility, and enabling more precise phenotyping of AF.[73,74] Lyu et al.[75] highlighted that AI-based image analysis can automate complex workflows in AF care, reducing reliance on manual interpretation while maintaining accuracy comparable to that of expert readers.

A fundamental application of AI in AF imaging is the automated segmentation of cardiac structures, particularly the left atrium (LA), pulmonary veins, and left atrial appendage. DL-based segmentation models, especially CNNs and U-Net–derived architectures, can learn complex spatial features directly from raw imaging data, eliminating the need for handcrafted feature extraction and significantly improving efficiency and consistency in clinical workflows.[76] Xiong et al.[77] developed a dual-path DL model (AtriaNet) that achieved highly accurate LA segmentation by combining local and global feature extraction. Borra et al.[78] demonstrated 3D U-Net architectures outperformed traditional two-dimensional approaches in volumetric LA segmentation, whereas Baraboo et al.[79] demonstrated the feasibility of AI-based delineation of LA boundaries for automated LA blood flow quantification.

Beyond the technical performance of these segmentation architectures, their clinical value lies in improving reproducibility, reducing reporting time, facilitating more consistent procedural planning, predicting ablation outcomes, and enabling objective quantification of atrial fibrosis, all of which are highly relevant to clinical practice.[80]

Beyond segmentation, AI has shown substantial potential for classifying and predicting AF using imaging data. ML and DL algorithms can integrate imaging-derived features with clinical variables to identify patients at increased risk of AF onset, recurrence after ablation, or thromboembolic events. Unlike conventional approaches that rely on a limited number of imaging biomarkers, AI models can capture complex, non-linear relationships within high-dimensional imaging datasets, enabling more accurate and individualized risk prediction.[48,81] Importantly, these approaches facilitate the transition from qualitative to quantitative imaging, thereby supporting precision medicine in AF management.

AI has also significantly advanced the assessment of atrial fibrosis, a key substrate underlying the initiation and maintenance of AF. Late gadolinium-enhanced CMR visualizes atrial fibrosis; however, its interpretation is technically challenging and requires expert-level analysis.[80] AI-based models can automate fibrosis quantification and spatial mapping, improving the identification of arrhythmogenic substrates and enabling more effective patient selection for catheter ablation. Razeghi et al.[82] demonstrated that automated segmentation-based approaches can reproducibly quantify atrial fibrosis from imaging data, whereas Gunawardhana et al.[80] highlighted that DL-based segmentation, particularly using CNN and U-Net architectures, enables accurate and reproducible delineation of left atrial structures and fibrosis from late gadolinium-enhanced MRI (LGE-MRI), overcoming the limitations of manual segmentation. In addition, emerging AI-based image reconstruction techniques have shown promise in reducing image noise and improving spatial resolution, thereby helping to overcome the limitations of conventional late gadolinium-enhanced CMR.[83-85] Furthermore, AI-driven analysis of CT and CMR datasets can provide detailed anatomical reconstructions of the LA and pulmonary veins, facilitating procedural planning and potentially improving ablation outcomes.[86]

AI-INTEGRATED CLINICAL DECISION SUPPORT IN AF MANAGEMENT

AI is increasingly being integrated into clinical decision-support systems (CDSSs), with the potential to enhance clinical decision-making in AF management. By leveraging large-scale datasets, including EHRs, imaging data, and continuous monitoring signals, AI-based CDSSs can assist clinicians with diagnosis, risk stratification, and therapeutic decision-making. These systems aim to reduce human error, improve efficiency, and support personalized treatment strategies.[87,88] As Moazemi et al.[89] highlighted, AI-driven CDSSs are particularly valuable in complex cardiovascular settings, where large volumes of data and time-sensitive decisions challenge conventional clinical workflows.

One of the most impactful applications of AI in AF management is stroke and thromboembolic risk stratification. Accurate risk assessment is essential for identifying patients with AF who require anticoagulation to prevent thromboembolic events. The next challenge is personalizing anticoagulation therapy to balance stroke prevention against bleeding risk. Beyond individualized treatment decisions, medication adherence remains a significant challenge in anticoagulation management for patients with AF. Labovitz et al.[90] evaluated an AI-based mobile platform designed to improve adherence to anticoagulation therapy among patients with ischemic stroke by managing medication schedules and sending reminders. The ongoing REACT-AF trial is assessing the safety and efficacy of using an AI-driven PPG algorithm on a smartwatch to deliver a "pill-in-the-pocket" anticoagulation strategy for patients with infrequent paroxysmal AF.[91]

In addition to risk prediction and therapy planning, AI-based CDSSs have shown promise for real-time patient monitoring and the early detection of clinical deterioration. Continuous data streams from wearable devices, implantable monitors, and intensive care unit systems can be analyzed using advanced algorithms, including recurrent neural networks and reinforcement learning models. These approaches enable dynamic risk assessment and timely intervention, particularly for high-risk patients.[92,93] At present, however, few AI-based CDSSs have progressed beyond retrospective development or single-center pilot studies. Most lack prospective external validation, and none has yet demonstrated improvements in hard clinical outcomes.[94] Their current role should therefore be regarded as supportive and investigational rather than established, a distinction that is particularly important for clinical decision support and risk prediction.

AI IN CATHETER ABLATION AND INTERVENTIONAL AF MANAGEMENT

Catheter ablation requires precise substrate identification and real-time decision-making and has traditionally been highly operator dependent; however, this field is increasingly being enhanced by AI-driven tools.[95] A key application of AI in interventional AF management is preprocedural planning and patient selection. ML models can integrate clinical, imaging, and electrophysiological data to identify patients most likely to benefit from catheter ablation and predict procedural success. Shade et al.[96] demonstrated that combining ML with personalized LGE-MRI-based computational modeling predicts AF recurrence after pulmonary vein isolation (PVI) with good accuracy (AUC 0.82), outperforming models based on imaging alone. Similarly, Roney et al.[97] showed that integrating ML with patient-specific simulations, imaging, and clinical data significantly improved the prediction of AF recurrence after ablation (AUC $\approx$ 0.85), outperforming models based on clinical or imaging data alone. However, these preprocedural models are largely retrospective, single-center studies derived from computational simulations and should therefore be regarded as proof-of-concept. Consequently, their level of evidence remains considerably lower than that of the randomized tailored ablation for persistent (TAILORED)-AF trial discussed below.[98]

During procedures, AI-driven tools have shown substantial potential to improve electroanatomical mapping and real-time guidance.

Advanced algorithms can analyze intracardiac signals and surface ECG data to localize arrhythmia sources with high precision. In particular, AI-based arrhythmia mapping systems can identify focal drivers and critical substrates more efficiently than conventional mapping techniques. Honarbakhsh et al.[99] demonstrated that a novel mapping approach stochastic trajectory analysis of ranked signals mapping identifies early activation sites that drive AF and that targeted ablation of these regions resulted in arrhythmia termination or significant cycle-length slowing in most patients, with approximately 80% freedom from AF/AT during follow-up. Complementing these findings, Alhusseini et al.[100] showed that DL models can accurately classify complex intracardiac activation patterns with near-expert performance, highlighting AI's ability to interpret electrophysiological complexity in real time. The strongest clinical evidence supporting AI-guided ablation to date comes from the TAILORED-AF RCT,[98] in which 374 patients were randomly assigned to AI-guided ablation targeting spatiotemporal EGM dispersion in addition to PVI or to PVI alone. The AI-guided strategy resulted in significantly higher freedom from AF at 12 months (88% vs. 70% in the modified intention-to-treat analysis), with the greatest benefit observed in patients with long-standing persistent AF. However, the secondary endpoint of freedom from any atrial arrhythmia did not reach statistical significance in the per-protocol analysis.[98] This trial represents the first large-scale RCT to demonstrate the superiority of an AI-guided ablation strategy over standard PVI, marking an important step toward the evidence-based integration of AI into interventional electrophysiology. Furthermore, Fox et al.[101] demonstrated that AI-based ECG mapping significantly improved procedural efficiency, resulting in a 19% reduction in time to first ablation, a 22.6% reduction in total procedure duration, and a 43.7% reduction in fluoroscopy exposure without compromising clinical outcomes. Nevertheless, these procedural efficiency endpoints, including fluoroscopy time and total procedure duration, should be interpreted cautiously because they are surrogate measures. Durable rhythm control and patient-centered outcomes remain the most clinically meaningful endpoints for evaluating AI-guided ablation. Overall, these findings highlight AI's potential to enhance both procedural safety and efficiency in electrophysiology laboratories.

After AF ablation, AI has shown promise in improving outcome assessment, predicting AF recurrence, and facilitating long-term follow-up.[48] Bifulco et al.[102] demonstrated that explainable ML models can accurately predict AF recurrence after ablation while identifying individualized risk factors, thereby supporting personalized post-ablation follow-up strategies.

LIMITATIONS AND BARRIERS TO CLINICAL TRANSLATION

Despite rapid advances in AI applications for AF, several important challenges and limitations continue to hinder widespread clinical adoption. Although AI has demonstrated promising performance in detection, risk stratification, imaging, and interventional planning, its integration into routine clinical workflows remains limited. One of the most significant barriers to the clinical implementation of AI in AF is the lack of external validation and generalizability across diverse patient populations. Many AI models are developed using retrospective datasets from single centers or highly selected cohorts, which may not adequately reflect the variability encountered in real-world clinical practice. Consequently, concerns remain regarding model robustness, reproducibility, and generalizability when these models are applied to broader populations. These concerns are further compounded by publication bias, as positive AI performance is reported far more frequently than negative or null findings, and many models that perform well during internal validation show substantially reduced performance on external validation.[98] Consistent with this observation, AI applied to single-lead ECGs predicted incident AF with markedly variable accuracy across populations (AUC 0.62-0.80), whereas machine-learning models for predicting cardioversion success demonstrated only modest discrimination (C-statistic ≈ 0.56-0.60). These examples underscore the importance of reporting and learning from underperforming or poorly generalizable models rather than emphasizing successful models alone.[36] Moazemi et al.[89] reported that a substantial proportion of AI-based clinical decision-support studies lack external validation, highlighting a critical barrier to translating these models into clinical practice. Another major challenge is the "black-box" nature of many ML and DL models. These models often lack transparency, making it difficult for clinicians to understand how their predictions are generated. This limited interpretability can reduce clinician trust and hinder adoption in high-stakes clinical environments. In response, XAI techniques have been proposed to improve transparency; however, their implementation remains inconsistent and is often insufficiently validated. Moreover, only a minority of studies systematically evaluate the quality and clinical relevance of AI-generated explanations, emphasizing the urgent need for a standardized assessment framework.[42]

Data-related challenges also represent a major limitation to the clinical implementation of AI. AI models require large volumes of high-quality, well-annotated data for training and validation. However, clinical datasets are often incomplete, imbalanced, or affected by measurement variability and missing values. Furthermore, biases within training datasets, including demographic imbalances and institution-specific practices, may result in biased predictions and potentially exacerbate existing healthcare disparities.[103] Integration into clinical workflows represents another significant barrier. AI systems must be seamlessly integrated into existing healthcare infrastructure, including EHRs and CDSSs, without disrupting established clinical workflows. However, interoperability challenges, the lack of standardized data formats, and limited capabilities for real-time implementation remain substantial obstacles. In addition, clinicians may be reluctant to adopt AI tools because of concerns regarding their reliability, usability, and medico-legal responsibility.[104]

Regulatory and ethical considerations further complicate the adoption of AI in AF management. Unlike traditional medical devices, AI systems are dynamic and may evolve over time through continuous learning, creating challenges for regulatory approval and postmarket surveillance. Issues related to patient privacy, data security, and informed consent are also critical, particularly when large-scale datasets are used. Moreover, the potential for overreliance on AI systems raises concerns about the erosion of clinical judgment. As noted in recent reviews, maintaining a human-in-the-loop approach is essential to ensure that AI serves as a supportive tool rather than a replacement for clinician expertise.[105,106]

ETHICAL, LEGAL, AND REGULATORY CONSIDERATIONS

The rapid integration of AI into AF management introduces substantial ethical and regulatory challenges that must be addressed to ensure safe, equitable, and clinically meaningful implementation. Although AI-driven tools have demonstrated promising capabilities in AF detection, risk stratification, and therapeutic decision-making, their deployment raises important concerns regarding data privacy, algorithmic bias, transparency, accountability, and regulatory oversight.

One of the foremost ethical challenges is ensuring data privacy and security, particularly because AI systems rely on large-scale, and often continuous, patient data streams from EHRs, imaging, and wearable devices.[107] AI-based wearables, such as smartwatches that use PPG or ECG-based monitoring, continuously collect sensitive physiological data, increasing the risk of data breaches and unauthorized access if appropriate safeguards are not implemented. Furthermore, the integration of third-party platforms further complicates data governance, necessitating strict adherence to regulatory frameworks such as the General Data Protection Regulation and the Health Insurance Portability and Accountability Act, together with transparent informed consent processes.[108]

Another major concern is algorithmic bias and fairness. AI models trained on non-representative datasets may demonstrate unequal performance across different demographic groups, potentially exacerbating existing healthcare disparities. In cardiology, where AF prevalence and outcomes vary according to age, sex, and ethnicity, biased algorithms may contribute to underdiagnosis or suboptimal treatment in vulnerable populations.[109] Ensuring diversity in training datasets, conducting external validation across heterogeneous populations, and implementing bias-detection mechanisms are essential to mitigate these risks.

A further concern, particularly for generative AI models, is the risk of hallucinations, in which models generate plausible but factually incorrect or clinically unsupported outputs.[110] In high-stakes settings such as AF management, hallucinated risk predictions or treatment recommendations could directly compromise patient safety, underscoring the need for rigorous output validation and continued human oversight before generative AI tools are deployed in clinical practice.[12,111]

Closely related is the challenge of accountability and liability. When AI-driven recommendations contribute to adverse clinical outcomes, determining responsibility remains challenging. The respective responsibilities of clinicians, developers, and healthcare institutions are not yet clearly defined within existing legal frameworks. Current consensus emphasizes that AI should function as a clinical decision-support tool rather than a replacement for clinical judgment, with ultimate responsibility remaining with the treating physician. However, evolving regulatory policies must address this ambiguity by establishing clear guidelines for liability and risk management.[112,113] Two additional issues warrant explicit consideration. First, adaptive (“continuously learning”) algorithms that evolve after deployment challenge traditional one-time regulatory approval processes and require new frameworks for continuous performance monitoring and change control, such as predetermined change-control plans. Second, reimbursement pathways for AI-based diagnostic and clinical decision-support tools remain poorly defined in most healthcare systems, and the absence of clear coding and reimbursement mechanisms represents a practical barrier to sustainable clinical adoption.[114,115]

Finally, excessive reliance on AI may undermine individualized patient care; therefore, maintaining a human-in-the-loop approach is essential to preserve patient-centered decision-making in AF management.[108]

FUTURE DIRECTIONS AND EMERGING PERSPECTIVES

Future directions in AI-driven AF management are increasingly focused on shifting from detection to prediction, expanding wearable ecosystems, and integrating multimodal and XAI models into clinical workflows. Recent advances suggest that AI may enable earlier identification of individuals at risk of AF by leveraging multimodal data, including ECG, imaging, and wearable-derived signals, thereby supporting preventive strategies before the onset of clinical disease.[71] In particular, AI-based wearable technologies have demonstrated substantial potential for scalable AF screening. Large studies, such as those summarized by Papalamprakopoulou et al.,[116] highlight the growing diagnostic capabilities of smartwatch-based PPG and single-lead ECG systems, although challenges related to signal quality and clinical integration remain. Similarly, Francisco et al.[117] emphasized that wearable devices, when combined with AI algorithms, may facilitate early AF detection and improve clinical outcomes through the timely initiation of anticoagulation and rhythm-control strategies, reinforcing their role in preventive cardiology. Beyond detection, emerging paradigms such as federated learning, which enables model training across institutions without sharing raw patient data, and large-scale foundation models pretrained on multimodal cardiovascular data hold considerable promise for addressing current limitations in generalizability, data scarcity, and cross-institutional applicability. Together, these approaches represent an important next frontier for AI in AF management.[118] Future research is expected to focus on multimodal DL frameworks and XAI approaches to improve interpretability and clinician trust, both of which are essential for widespread clinical adoption. Furthermore, integration into EHR-based CDSSs and validation through prospective, real-world studies will be critical for demonstrating meaningful clinical benefit, including reductions in stroke and mortality. Importantly, the continued evolution toward human-in-the-loop models, in which AI augments rather than replaces clinical decision-making, may shape the next generation of AF management and accelerate the transition toward personalized, continuous, and preventive cardiovascular care.[116,119]

CONCLUSION

AI is rapidly transforming the landscape of AF management by offering new opportunities across the entire continuum of care, from early detection and risk stratification to imaging, clinical decision support, and interventional guidance. As demonstrated in recent studies, AI-based models, particularly those leveraging ECG, multimodal data integration, and wearable technologies, have shown strong potential for identifying subclinical AF, improving stroke risk prediction, and personalizing therapeutic strategies. These advances have the potential to overcome key limitations of traditional approaches, enabling more precise, scalable, and preventive cardiovascular care. However, despite these promising developments, significant challenges remain, including limited external validation, data heterogeneity, limited interpretability, and barriers to clinical integration. Ethical and regulatory considerations, particularly those related to data privacy, algorithmic bias, and accountability, further underscore the need for cautious and responsible implementation. Future progress will require prospective multicenter validation, federated data infrastructures, and regulatory frameworks adapted to continuously learning AI systems. Collectively, these advances may usher in a new era of precision, preventive AF care.

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