State of the Art of Artificial Intelligence in Clinical Electrophysiology in 2025. A Scientific Statement of the European Heart Rhythm Association (EHRA) of the ESC, the Heart Rhythm Society (HRS), and the ESC Working Group in e-Cardiology

E Svennberg (EHRA)[1], J K Han (HRS) [2] E G Caiani (ESC)[3,4], S Engelhardt (Independent expert)[5], S Ernst (EHRA) [6], P Friedman (HRS) [7], R Garcia (EHRA) [8], H Ghanbari (HRS)[9], G Hindricks (ESC)[10], S H Man (EHRA)[11], J Millet (e-Cardiology) [12], S M. Narayan (EHRA) [13], GA Ng (independent expert) [14], PA Noseworthy (EHRA) [15], FVY Tjong (EHRA) [16], J Ramírez (e-Cardiology) [17], JP Singh (HRS) [18], N Trayanova (HRS) [19], D Duncker D (EHRA) [20]

1 Karolinska Institutet, Department of Medicine (Med H) Karolinska University hospital, Stockholm, Sweden

2 Division of Cardiology and Cardiology Arrhythmia Service, VA Greater Los Angeles Healthcare Center and David Geffen School of Medicine at UCLA, Los Angeles, California, USA

3 Politecnico di Milano, Electronics, Information and Bioengineering Department, Milan, Italy.

4 IRCCS Istituto Auxologico Italiano, Ospedale S. Luca, Milan, Italy

5 Department of Cardiology, Angiology and Pneumology, Heidelberg University Hospital, Heidelberg, Germany

6 Division of Cardiology, Royal Brompton Hospital, Guys and St Thomas' Foundation Trust, London, United Kingdom

7 Department of Cardiovascular Medicine, Mayo Clinic, Rochester, Minnesota, USA

8 Cardiology department, University Hospital of Poitiers, Poitiers, France. Centre d'Investigations Cliniques, CIC-1402, University Hospital of Poitiers, Poitiers, France

9 University of Michigan, Department of Internal Medicine, Division of Cardiology, Section of Electrophysiology

10 Charité Hospital, Berlin, Germany

11 Department of Cardiovascular Sciences, University of Leicester, United Kingdom; Department of Cardiology, University Hospitals Plymouth NHS Trust, United Kingdom

12 EP Analytics Lab, Instituto ITACA, Universitat Politècnica de Valencia, & Center for Biomedical Network Research on Cardiovascular Diseases (CIBERCV), Spain

13 Department of Medicine, Cardiovascular Division, and Institute for Computational and Mathematical Engineering, Stanford University, Stanford, California, USA

14 Leicester British Heart Foundation Centre of Research Excellence, National Institute for Health and Care Research Leicester Biomedical Research Centre, Department of Cardiovascular Sciences, University of Leicester, United Kingdom

15 Division of Heart Rhythm Services, Department of Cardiovascular Medicine, Mayo Clinic, Rochester, Minnesota, USA

16 Heart Center, Department of Cardiology, Amsterdam UMC, location AMC, Amsterdam, The Netherlands

17 Aragon Institute of Engineering Research, University of Zaragoza, Zaragoza, Spain
Centro de Investigación Biomédica en Red, Biomateriales, Bioingeniería y Nanomedicina, Zaragoza, Spain
William Harvey Research Institute, Queen Mary University of London, London, United Kingdom

18 Massachusetts General Hospital, Harvard Medical School, Boston, Massachusetts, USA

19 Department of Biomedical Engineering and Alliance for Cardiovascular Diagnostic and Treatment Innovation, Johns Hopkins University, Baltimore, Maryland, USA.

20 Hannover Heart Rhythm Center, Department of Cardiology and Angiology, Hannover Medical School, Hannover, Germany

Reviewers

Prof. Jacob Tfelt Hansen (Review Coordinator):

1. Section of genetics, Department of Forensic Medicine, Faculty of Medical Sciences, University of Copenhagen, Denmark

2. The Department of Cardiology, The Heart Centre, Copenhagen University Hospital, Rigshospitalet, Copenhagen, Denmark.

Doctor Joseph Barker:

1. National Heart and Lung Institute, Imperial College London, United Kingdom.
2. Department of Cardiology, Imperial College Healthcare NHS Trust, London, United Kingdom.

Prof. Ruben Casado Arroyo:

Department of Cardiology, H.U.B.-Hôpital Erasme, Université Libre de Bruxelles, Brussels, Belgium.

Doctor Neal A. Chatterjee, MD MSc:

Associate Professor of Medicine Division of Cardiology, University of Washington Seattle, WA USA

Prof. Giulio Conte:

1. Department of Cardiology, Cardiocentro Ticino Institute, Ente Ospedaliero Cantonale, Lugano, Switzerland
2. Faculty of Biomedical Sciences, Università della Svizzera Italiana, Lugano, Switzerland

Doctor Søren Zöga Diederichsen:

Department of Cardiology, University Hospital Copenhagen – Rigshospitalet Copenhagen, Denmark

Prof. Dominik Linz:

Department of Cardiology, Cardiovascular Research Institute Maastricht (CARIM), Maastricht University Medical Centre, Maastricht, The Netherlands. Department of Biomedical Sciences, Faculty of Health and Medical Sciences, University of Copenhagen, Copenhagen, Denmark.

Doctor Arun Umesh Mahtani, MD, MS

Cardiology Fellow Department of Cardiology, Virginia Commonwealth University, Richmond, Virginia, USA

Assoc. Prof. Alessandro Zorzi:

Department of Cardiac, Thoracic and Vascular Sciences and Public Health , University of Padua, Italy

Acknowledgement

The authors thank the EHRA Scientific Document Committee:

Prof Katja Zeppenfeld, Prof. Jens Cosedis Nielsen, Dr. Luigi di Biase, Prof. Isabel Deisenhofer, Prof. Kristina Hermann Haugaa, Dr. Daniel Keene, Prof. Christian Meyer, Prof. Petr Peichl, Prof. Silvia Priori, Dr. Alireza Sepehri Shamloo, Prof. Markus Stühlinger, Prof. Jacob Tfelt Hansen, Prof. Arthur Wilde

Abstract

Aim

Artificial Intelligence (AI) has the potential to transform cardiac electrophysiology (EP), particularly in arrhythmia detection, procedural optimization, and patient outcome prediction. However, a standardized approach to reporting and understanding AI-related research in EP is lacking. This scientific statement aims to develop and apply a checklist for AI-related research reporting in EP to enhance transparency, reproducibility and understandability in the field.

Methods

An AI checklist specific to EP was developed with expert input from the writing group and voted on using a modified Delphi process, leading to the development of a 29-item checklist. The checklist was subsequently applied to assess reporting practices to identify areas where improvements could be made and provide an overview of the state of the art in AI-related EP research in three domains from May 2021 until May 2024: atrial fibrillation management, sudden cardiac death (SCD), and EP lab applications.

Results

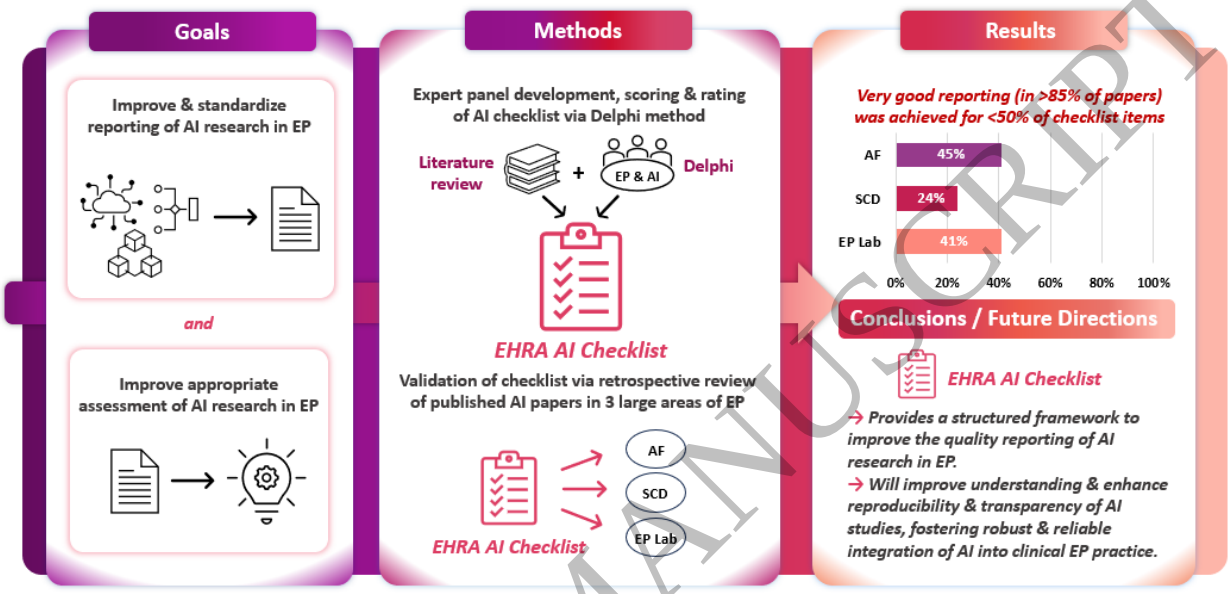
The EHRA AI checklist was applied to 31 studies in atrial fibrillation management, 18 studies in SCD, and 6 studies in EP lab applications. Results differed between the different domains, but in no domain reporting of a specific item exceeded 55 % of included papers. Key areas such as trial registration, participant details, data handling, and training performance were underreported (<20%). The checklist application highlighted areas where reporting practices could be improved to promote clearer, more comprehensive AI research in EP.

Conclusion

The EHRA AI checklist provides a structured framework for reporting AI research in EP. Its use can improve understanding but also enhance the reproducibility and transparency of AI studies, fostering more robust and reliable integration of AI into clinical EP practice.

Graphical Abstract

AI=Artificial Intelligence, EP=Electrophysiology, AF=Atrial Fibrillation, SCD=Sudden cardiac death



Introduction

Artificial intelligence (AI) is an emerging technology that holds great promise for the field of clinical electrophysiology (EP).[1] This includes early detection of arrhythmias like atrial fibrillation (AF), personalized diagnosis and risk prediction for sudden cardiac death (SCD), procedural optimization and guidance for EP procedures. The integration of AI into clinical practice has the potential to improve personalized treatment strategies and improve patient outcomes.

Over the past decade there has been a substantial increase in the number of publications reporting on the use of AI and machine learning (ML) in AF.[2-6] This is due to both the advancement in AI/ML techniques as well as the availability of open access databases, such as the PhysioNet repository and MIMIC-III which provide rich datasets for training and validating AI models in EP research.[7] As research in this field continues to grow, there is increasing potential for AI to provide real-time decision support, enhance diagnostic accuracy, and streamline workflow in EP laboratories, paving the way for more efficient and effective patient care.[8,9]

While the recently released TRIPOD (Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis) +AI statement[10] aims to improve the quality, reproducibility, and clinical relevance of AI research in general, there is a pressing need for an AI-specific reporting framework tailored to EP, as the field presents unique challenges, such as integrating complex algorithms into clinical workflows, ensuring transparency in model development and validation, addressing data heterogeneity, and managing the potential for bias. To facilitate the application of AI to the field of arrhythmia and to enhance understanding, reviewing and reporting of AI studies in EP, a checklist is proposed. This checklist explains essential terms for a novice reader of AI, helps guide studies on clinically relevant questions and provides scientists with a standardized approach to reporting and evaluating AI-related research.

We consequently developed an EHRA AI checklist tailored to EP and reviewed recent studies across three key areas: AF management, SCD, and AI applications in the EP lab. By applying the checklist, we assessed reporting practices, identified areas for improvement, and summarized the current state of the art in these relevant topics. A glossary of terms in the field of AI in EP is shown in table 1.

Table 1. European Heart Rhythm Association (EHRA) Artificial Intelligence in Electrophysiology glossary

EHRA AI in EP glossary	
Artificial intelligence (AI)	A branch of computer science focused on creating algorithms with the aim of performing tasks usually requiring human intelligence, such as recognizing patterns, making decisions and predicting outcomes. AI can supersede human level intelligence in domain specific tasks
Open science in AI	The practice of promoting transparency, reproducibility, and accessibility in artificial intelligence research through open sharing of data, code, and methodologies to enhance collaboration and accelerate innovation in the field.
Machine learning (ML)	A subset of AI where algorithms learn patterns from data to make predictions or perform classifications (binary or multi-class) without explicit programming for each task. ML includes supervised learning, where specific labels are defined by the user, as well as unsupervised learning, which identifies patterns and structures in data without predefined labels. In EP, ML models are used to diagnose arrhythmias, predict outcomes, and optimize arrhythmia treatment.
Deep learning (DL)	A subset of ML that uses artificial neural networks to process and analyze information, where the features of interest are learned directly from the data, and not defined by the user.
Artificial neural network (ANN)	A foundational method in AI that teaches computers to process data in a way that is inspired by the human brain, using interconnected nodes or "neurons" in a layered structure. It provides a means for dealing with complex pattern-oriented tasks, including classification, regression and pattern recognition. The nonparametric nature of ANN enables models to be developed without having any prior knowledge of the distribution of the data population or possible interaction effects between variables as required by commonly used parametric statistical methods.
Deep neural network (DNN)	A DNN is a neural network with multiple layers between the input and output layers required for high dimensional data analysis. DNNs encompass a variety of architectures designed for different tasks.

Convolutional neural network (CNN)	A specific type of DNN aiming to process spatial data using convolution layer and pooling layer, often used for image and signal analysis. In EP, CNNs can be applied to analyze ECG and imaging data to identify abnormalities.
Recurrent neural network (RNN)	A type of neural network designed for sequential data, such as time series and natural language. It retains memory of previous inputs to process sequences and produces outputs that depend on the entire input sequence.
Long short-term memory (LSTM)	A specialized type of RNN capable of learning long-term dependencies and patterns in sequential data, making it suitable for tasks requiring memory across many iterations.
Natural Language Processing (NLP)	NLP is a branch of AI that enables computers to process and interpret human language, both written and spoken. By combining computational linguistics with machine learning and deep learning, NLP can analyze unstructured data like clinical notes and electronic health records. In cardiology, it might help extract meaningful insights and identify patterns to potentially improve decision-making and patient outcomes.
Generative AI (GenAI)	A type of AI technology that uses algorithms and models, such as large language models (LLMs), to learn patterns from a dataset and then generate new data, including text, imagery, audio and synthetic data, that follows those patterns.
Transformer architecture	A neural network design at the basis of GenAI, especially effective for sequence data and NLP. By processing large volumes of text with the simple task of predicting the next word in every sentence, transformers give computers the power to understand language, learn facts, build abstract concepts about these facts.
Explainable AI (XAI)	Explainable AI is defined by a set of processes or methods for analyzing or complementing AI models to make their internal logic and output transparent and interpretable, so that the underlying process could be better understood and meaningful by a human user, to increase trust towards AI.

Multimodal AI	Multimodal AI is based on the concept of multimodal models, where several unimodal neural networks are processing information available in different data types (i.e., text, images, audio, and video) in order to perform complex tasks.
Supervised learning	A category of ML that uses labeled datasets (i.e., with a label provided by a gold standard human interpretation) to learn the relationship between the input features and the output labels and train algorithms to predict outcomes and recognize patterns.
Unsupervised learning	A type of ML that learns from unlabeled data (i.e., without the need for human supervision) and allows to discover potentially interesting patterns and insights without any explicit guidance or instruction making it useful for exploratory analysis.
Digital twin	A virtual representation of a patient, created by combining real-world data with computational models. In EP, a digital twin could simulate a heart's responses to ablation therapies or predict arrhythmia recurrence risk.[11]
Internal validation	The process of testing an AI model on data originating from the same source (i.e., hospital, equipment, patient group, …) as the data with whom it was trained on, to evaluate performance. This is an initial step to ensure the model can generalize within a single dataset.
External validation	The testing of an AI model on data originating from different sources (i.e., hospital, equipment, patient group, …) than those used in its training, thus ensuring the model's robustness and reliability across varied populations and settings. This is a critical step for wider clinical deployment.
Area Under the Receiver Operating Characteristic Curve (AUROC)	A metric used to evaluate the performance of a binary classification model. It measures the ability of a model to distinguish between classes by calculating the area under the ROC curve, where a value of 1 indicates perfect discrimination and 0.5 indicates no better than random guessing.
Area Under the Precision-Recall Curve (AUPRC)	A performance metric for evaluating binary classifiers, particularly in datasets with imbalanced class distributions. It measures the trade-off between precision (positive predictive value) and recall (sensitivity), with

	higher values indicating better performance in identifying true positives while minimizing false positives.
F1 Score	A harmonic mean of precision and recall, providing a single metric that balances the trade-off between the two. It is especially useful in evaluating classification models where there is an uneven class distribution. The F1 score ranges from 0 to 1, with higher values indicating better model performance.

Creation of the EHRA AI checklist

In alignment with the EQUATOR (Enhancing the QUAlity and Transparency Of health Research) project[12], and to enhance the quality of health research reporting in journal articles, several valuable manuscript checklists for reporting the evaluation of AI and ML models in medicine have been proposed (see Supplementary Table 1). These documents provide guidance to authors and reviewers, helping to standardize and validate content in a more reproducible way, ultimately enhancing transparency and completeness in reporting.

In the field of cardiovascular (CV) medicine, only one specific document currently exists, which focuses on proposed requirements for evaluating ML in CV imaging. [13] More recently, other publications have highlighted the need for quality evaluation criteria in prediction models for CV diseases, also proposing initial solutions. [14-16]

Checklist development

The members of the EHRA AI in EP Writing group were identified via nominations and recommendations from international professional CV EP societies, and first convened virtually to discuss and obtain consensus on aims and generating process of the scientific statement.

To define the items to be included into the dedicated checklist for group evaluation, a review of published literature proposing criteria or checklists relevant to AI [10, 13, 17-31], as well as recent systematic reviews on the topic was performed. [15, 32, 33] The proposing team (E.S., D.D., E.G.C.) identified the potential items that could be relevant with a focus on the need for clinical EP experts and listed them as candidate reporting items, including variables, definitions and rationale. This list was sent to the writing group for individual comment and refinement, thus resulting in the AI checklist that included 33 items (Supplementary). The development process is outlined in Figure 1.

To encourage robustness and completeness in AI research reporting within clinical EP, the EHRA AI in EP writing group decided to utilize a modified prospective Delphi method based on the RAND/UCLA process.[34]

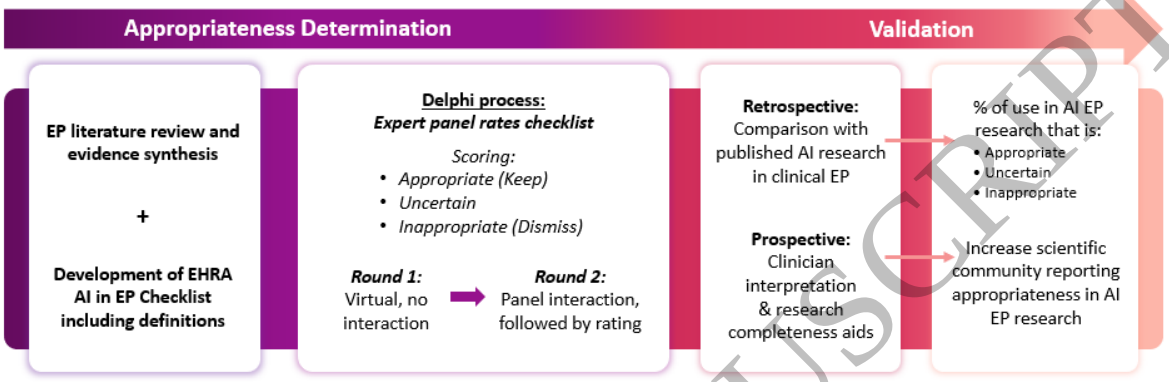


Figure 1. Workflow schematization of the Delphi process adopted to define the final European Heart Rhythm Association (EHRA) AI in EP checklist.

AI=Artificial Intelligence, EP=Electrophysiology, EHRA= European Heart Rhythm Association

Delphi process for consensus

In early 2024, the first round of virtual, electronic survey-based, individual Delphi voting was conducted, with no interaction amongst voting members. The survey included the initially selected 33 items, and for each of them participants were asked to vote on each item using a 5-point Likert scale, as follows: 1 to 2: not relevant, should not be included; 3: may be appropriate to include 4-5: appropriate to include. In addition, for each item, a question asking the need for further refinement (i.e., in case of an unclear description) was also proposed, for which an open-ended response was possible.

The working group reviewed responses for each checklist item, categorizing consensus levels based on the percentage of votes scoring 4 or 5. Consensus was defined as follows: weak for 50% to 75% agreement, moderate for 76% to 90%, strong for 91% to 99%, and unanimous for 100%. For items achieving a score of 1-2, ≥75% consensus was needed to exclude the item from the checklist. From this first Delphi round, 82% responses were received.

In April 2024, a combined in-person and virtual meeting of the EHRA AI in EP writing group members was convened during the EHRA 2024 congress in Berlin, where results of the first round of Delphi voting were revealed, including a distribution of their ratings. Based on these results, 8 items did not exceed the predefined 75% threshold for being directly included. Ratings and checklist items were discussed to better understand those that had poor consensus and/or conflicting votes, also considering the received open-ended responses, to further refine those items by proposing amendments. No attempt was made to force the panel to consensus during this meeting.

After further adjustment of the 8 items according to the discussions, a second round of virtual, electronic survey-based, individual Delphi voting was conducted between 25 April 2024 and 2 May 2024, with no interaction amongst voting members. For this round, 77% of the authors responded, where 6 reformulated items reached consensus while two items were finally discarded, thus resulting in the final consensus on the EHRA AI checklist shown in Table 2.

After finalization of the EHRA AI checklist, the checklist was validated retrospectively on papers on AI in EP having been published recently. Three representative topics from the field in EP were chosen to perform a structured review of articles connected to AI for 1) AF management, 2) SCD and 3) EP lab management.

For each section, studies of the respective topic were retrieved from PubMed by members of the author group. Only studies published between May 2021 and May 2024 were included to keep a contemporary focus, without intending to be exhaustive. For each study, the EHRA AI checklist was applied, and results were recorded for each item of the checklist. A summary of the results is presented in figure 2. A practical example of the extraction is provided in the Supplement, Supplement Table 3.

Detailed results of the checklist application are presented in Table 3.

Checklist Item	Intro		Methods													Regulatory				Open Science		Results							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
AI in Afib (n=31)	100%	100%	100%	87%	71%	90%	35%	100%	84%	100%	100%	87%	42%	65%	97%	45%	87%	87%	48%	35%	6%	45%	77%	100%	58%	100%	55%	97%	87%
AI in SCD (n=18)	44%	67%	94%	94%	100%	100%	78%	72%	78%	89%	100%	78%	56%	50%	56%	22%	61%	78%	94%	17%	28%	83%	39%	78%	28%	67%	50%	67%	94%
AI in the EP Lab (n=6)	100%	100%	100%	100%	67%	100%	67%	83%	100%	100%	100%	33%	17%	17%	83%	50%	67%	100%	100%	67%	33%	100%	83%	67%	17%	67%	50%	33%	100%

Figure 2. Overview of the application of the EHRA AI checklist in three different areas of electrophysiology. Each of the three areas are depicted in rows, and a summary of all the checklist items is provided in the

columns. In each area a literature review was performed, and the summary index of the reporting of each checklist item is provided. Items reported in > 85 % of the reviewed papers are reported in green; items reported in <20 % of the reviewed paper is reported in red, with items between 20% and 85% shown in yellow.

EHRA=European Heart Rhythm Association, AI=Artificial Intelligence

AI in atrial fibrillation management

Checklist application for AI studies on AF management

In total, 31 papers on AF management were identified (Table 3). Most focused on the use of AI for AF detection. The application of the EHRA AI checklist to all identified papers showed that 16 of 29 items (55%) were reported at a very good level (i.e., reported by ≥85% of papers). The most robust reporting was for checklist items under "methods" section with ≥85% papers reporting 8 of 13 items (61.5%). Reporting was least robust for checklist items under "open science"; notably, only 2 of 31 papers (6%) addressed trial registration (checklist item 21).

While reporting was generally good across methodological items, areas like open science, specifically trial registration, were poorly addressed. The lack of transparency regarding trial registration may limit the ability to track study protocols and outcomes, posing a barrier to reproducibility and potential bias in published results.

AF detection using photoplethysmography

The intermittent nature of AF can lead to low detection rates and inaccurate burden estimates with short-term monitoring.[35, 36] Photoplethysmography (PPG), readily available in wearables like smartphones and smartwatches, offers semi-continuous monitoring.[37, 38] Several consumer wrist-worn devices have been cleared by the US Food and Drug Administration (FDA) for PPG based AF detection and use AI in their algorithms.[38] Recent studies have evaluated the accuracy of PPG-based AI algorithms for detecting AF in ambulatory settings[39-42] and although PPG-based AF detection using smartphones was shown to be effective in different settings detecting or monitoring AF,[5, 43-46] a meta-analysis of data suggested that publication bias remained.[47] In international guidelines for the management of AF, an ECG is still required for diagnosis.[48, 49]

When evaluating studies focused on the detection of AF using PPG, several key areas need careful consideration to ensure clarity and precision, Figure 3.

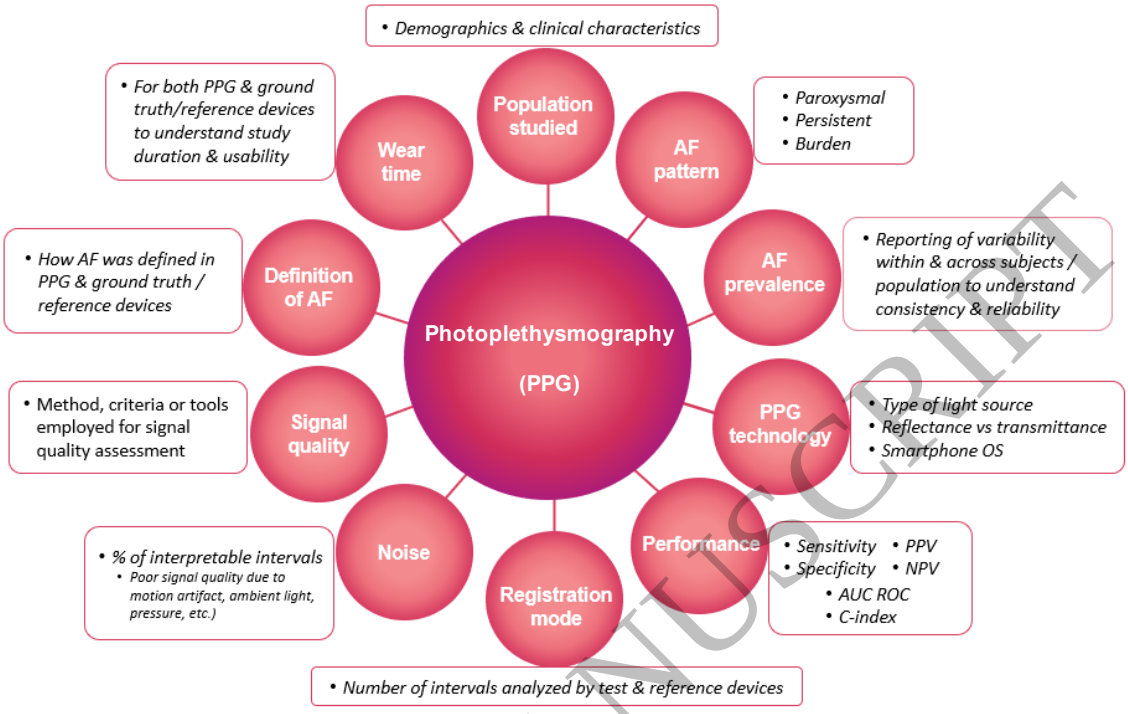


Figure 3. An overview of key issues to consider for the use of photoplethysmography within atrial fibrillation detection.

AF=Atrial Fibrillation PPG=Photoplethysmography PPV=Positive predictive value NPV= Negative predictive value AUC=Area under the curve ROC= Receiver Operating Characteristic OS=Operating System

ECG for detection and prediction of AF

Of the 31 identified papers, all covered the use of ECG for the detection of AF. Application of the EHRA AI checklist showed that 13 of the 29 items were reported by ≥85% of these papers.

ECG is a common source of data, and their increasing digitization is making computerized interpretation commonplace.[50, 51] Irregular RR intervals during AF serve as simple inputs that can train traditional ML models for automated AF detection.[3, 4] The loss of coordinated atrial activity in the form of 'f' waves with small voltages and the issue of noise poses greater technical challenges for which additional signal processing steps, optimization and AI-training may need to be introduced, for accurate definition and extraction. With the progression of AI/ML algorithms, including Deep Neural Networks (particularly Convolutional Neural Networks or more recent Transformer Architectures), there has been a reduction in the need for pre-processing steps and less emphasis on predefined features, which are now achieving impressive algorithm performance results.[50, 52]

Several independent research teams have now shown that an AI-enabled ECG using a convolutional neural network could detect signatures of AF present during sinus rhythm. [53] It is intriguing to conceptualize that, during sinus rhythm, factors that predispose to and eventually lead to AF could be identified using AI. These include substrate abnormalities, such as myocyte changes, fibrosis and electrical / structural remodeling, or trigger factors like atrial premature beats, autonomic signatures or multiple simultaneous non-linear signal changes not readily apparent to human readers like those seen in signal-averaged P wave properties.[54] This allows point of care assessment of the risk of developing AF and is particularly important, for instance, in patients with embolic stroke of undetermined source, where a positive diagnosis from documented AF poses challenges in prolonged recording, but an early AI-enhanced strategy would allow prompt appropriate treatment with anticoagulation.[55]

There are technical aspects of AI algorithms that need to be understood to appraise the output and their utility and clinical application. The confirmation of ground truth in the diagnostic labelling is a prerequisite so that data with high confidence may be used to train the AI-algorithm.

AI in sudden cardiac death

Checklist application for AI studies on sudden cardiac death

In total, 18 papers were identified for the field of AI in SCD. All papers focused on the use of AI for malignant arrhythmia or cardiac arrest prediction. Application of the EHRA AI checklist to all identified papers showed that 8 of 29 items (28%) were reported by ≥85% (very well reported). The most robust reporting was for checklist items under "methods" section with ≥85% papers reporting 6 of 13 items (46%). Reporting was less robust for checklist items under "open science"; notably, only 3 of 18 papers (17%) addressed data availability/sharing (checklist item 20).

The relatively low percentage of well-reported items across all sections raises concerns about the consistency and robustness of reporting practices. Poor reporting of data sharing and external validation is particularly concerning from a clinical perspective, as models that have not been validated externally may not perform well across diverse patient populations.

Data challenges in SCD studies present significant obstacles, particularly due to the rarity of events across diverse cardiovascular conditions and the prolonged time required for sufficient event accrual.[56] An underutilized resource in this context are historical datasets, which often include valuable ECG recordings constrained to paper formats. Ongoing efforts are focused on developing methodologies to extract and analyze data from image-based ECGs, unlocking the potential of these archival resources for predictive

modeling and research in ventricular arrhythmias and sudden cardiac arrest. [57] Current clinical criteria for implantable cardioverter-defibrillator (ICD) candidacy, left ventricular ejection fraction (LVEF) <30–35%, captures a mere 20% of patients at risk for SCDs. [58-62] New markers and methods for risk-stratification of SCD are urgently needed and there is an opportunity for AI, including machine and deep learning to move towards high yield, multiparametric scores to improve accuracy of prediction. [63] AI tools could enable personalized risk prediction of SCD by the customization of preventive strategies based on the unique characteristics of individual patients using subtle indicators and predictors of SCD that may be overlooked by traditional analytical methods. [64] Recent efforts by the international PROFID consortium, using multiparameter analysis with CMR data, failed to improve risk prediction. [65]

AI models for SCD prediction

Currently the use of AI for SCD risk prediction is a burgeoning field with fewer (but increasing) publications when compared to the use of AI for AF. As such it may be unsurprising that there was limited checklist item reporting for these papers, when compared to papers focusing on the use of AI in AF.

Screening for SCD could be performed differently depending on the population or setting:

a) In a low-risk population (general population) the 12-lead ECG holds significant potential as a non-invasive screening modality for evaluating arrhythmic risk, primarily due to its low cost and widespread availability. [66] An ECG-AI model developed using data from two prospective, community-based studies predicted SCD with an area under the receiver operating characteristic curve (AUROC) of 0.82 in an external validation cohort over a follow-up period of 1.6 ± 2.1 years. [67] When combined with clinical variables, the AUROC increased to 0.90, outperforming a conventional ECG risk score based on human-interpretable ECG parameters. [53 68-74] In ambulatory patients a deep learning (DL) analysis of ambulant 24h ECG-monitoring might capture a more comprehensive reflection of electrical instability over time, as a study showed good predictive score (AUROC 0.80) for SCD in a heterogeneous cardiac population. [75]

b) In a moderate risk population (heart failure patients without ICDs), ECG-AI models outperform current clinical criteria for primary ICD implantation and traditional ECG parameters despite only achieving moderate predictive abilities. [76, 77]

c) For high-risk patients (i.e. ICD carriers) ECG features alone do not suffice for accurate ventricular arrhythmia (VA)/ SCD prediction, possibly due to the extent of baseline abnormalities in their ECG. Dynamic ECG changes over time could reflect on the changing arrhythmic substrate, potentially providing a more powerful tool as shown in a model using a dynamic AI prediction model that

updated predictions with new ECG recordings which outperformed (AUROC 0.74) a static model that used baseline information alone (AUROC 0.64).[78] Moreover, a DL model using intracardiac electrograms from ICDs accurately predicted VA treated by the ICD 3 seconds before onset with an AUROC of 0.83.[79] However, this performance decreased significantly to an AUC 0.55 when attempting to predict beyond a 30-day timeframe. In addition, AI could aid improved ICD patient selection by predicting non-arrhythmic mortality combining ECG and clinical data (AUROC 0.8).[80] Another source of data is remote monitoring device data for prediction of VA and ICD therapy.[81, 82] A study demonstrated high accuracy in the real-time prediction of imminent ventricular arrhythmia (<30 days), using remote monitoring device data including device-derived parameters such as activity levels, thoracic impedance, atrial arrhythmia burden, and lead impedance. [83]

In addition, for patients admitted to general wards or ICUs, baseline 12-lead ECG, continuous monitoring of the heart rate and other vital signs provide opportunities for ML models to detect ventricular arrhythmias and cardiac arrest before its occurrence, providing critical advance notice. [66, 84]

Apart from ECGs, other data modalities, particularly cardiac imaging can provide anatomical and functional information that reflects on arrhythmic substrates. Several studies have assessed the value of cardiac magnetic resonance imaging (CMR) on VA and SCD prediction.[85, 86] Multimodal DL models have been developed, using late gadolinium enhancement (LGE)-CMR data combined with clinical covariates,.[87, 88]

Future holistic representations using AI for SCD prediction

The potential of AI may be maximized when multiple modalities are integrated to construct a comprehensive characterisation of the physiological cardiac state. This encompasses anatomical image features that reflect substrate-specific details such as tissue characteristics and 3D cardiac geometry, genome-wide associations studies to assess genetic predispositions, and the electrical conduction patterns and electrical physiology. Recent studies showed that neural networks can learn holistic representations across ECG and CMR, which may be associated with genetic variants.[89] An example is a multimodal AI approach (the DEEP RISK model) which integrated DL features from both ECG and LGE-CMR in patients with non-ischemic cardiomyopathy, along with clinical patient data, to predict the 1-year risk of ventricular arrhythmia (AUROC 0.84).[90] Personalized virtual heart models (Digital Twins) that integrate cardiac imaging and electrophysiological properties have also proven effective for assessing substrate complexity, guiding VT ablation, and predicting post-ablation arrhythmia recurrence [91-93 94, 95]Another promising avenue to explore is capturing temporal dynamics using telemonitoring and wearable devices. The risk of SCD is

dynamic and fluctuates over time due to factors such as lifestyle, hormones, medication changes, progression of underlying conditions, and acute cardiac events. [63]In addition to the information continuously captured by cardiac implantable electronic devices remote monitoring and wearable devices can register behavioral and electrophysiological data, activity patterns or stress levels. The high volumes of data that are collected through these digital tools can be analyzed through AI algorithms and leveraged for personalized prediction. Novel tools such as smartwatch-based loss of pulse detection to transform out-of-hospital cardiac arrest care by enabling early recognition and automated activation of emergency services through AI-driven algorithms.[96]

AI in the electrophysiology lab

Checklist application

Literature review identified a total of 6 papers on the use of AI within the EP lab. Applying the EHRA AI checklist to these papers showed that 13 of 29 items (45%) were reported by ≥85% of papers (very well reported). The most robust reporting was for checklist items under "regulatory", with ≥85% papers reporting 2 of 4 items (50%), followed by checklist items under "methods" section, with 6 of 13 items (46%) very well reported. Three items were reported poorly: balanced groups, missingness/poor data (items 13 & 14 under "methods") and external validation (item 25 under "results") which were reported by one paper (17%) each respectively. (Figure 3).

In this field, regulatory items were reported more consistently, reflecting growing awareness of regulatory considerations for AI tools used in clinical environments. However, poor reporting on missing data and balanced groups suggests a need for better guidance on handling and reporting missingness, as this can significantly impact model performance and clinical utility. Similarly, external validation remains a concern, as AI models used in procedural settings must be robust across different populations and settings to ensure safe clinical application.

Overall, the ability of ML and DL to learn and automate pattern recognition of biological signals relevant to arrhythmias such as ECGs, bipolar electrograms (EGM) has the potential to reduce both human feature engineering and inter-observer variability in identification of arrhythmia substrates as well as improve precision of ablation targets.[97] New classification features of arrhythmia substrates have emerged, complementing existing electrical and imaging parameters that previously required manual or semi-automated annotation on 3D electroanatomical mapping systems during catheter ablation. [98]

The concept of creating a "digital twin" of individual patients, based on personalized computational modelling, enables simulations to be performed before and after treatment of arrhythmias and prediction of response to treatment strategies, to inform and optimize pre-procedural clinical decision making. [99] This methodology offers the potential for *in silico* clinical trials comparing treatment strategies without subjecting patients to the potential risk of procedural complications of catheter ablation and potentially reducing the need for further procedures if the first ablation guided by an AI method was effective.

AI for AF ablation

Of the 6 identified papers in the review, 5 covered the use of AI in AF ablation. Of these, none reported ≥85% of EHRA AI checklist items (range 52-83%).

An example of one of the studies is showcased in Figure 4 and supplemental Table 1. In the study a DL-based architecture for automated assessment of triggers as targets for AF ablation. [100]

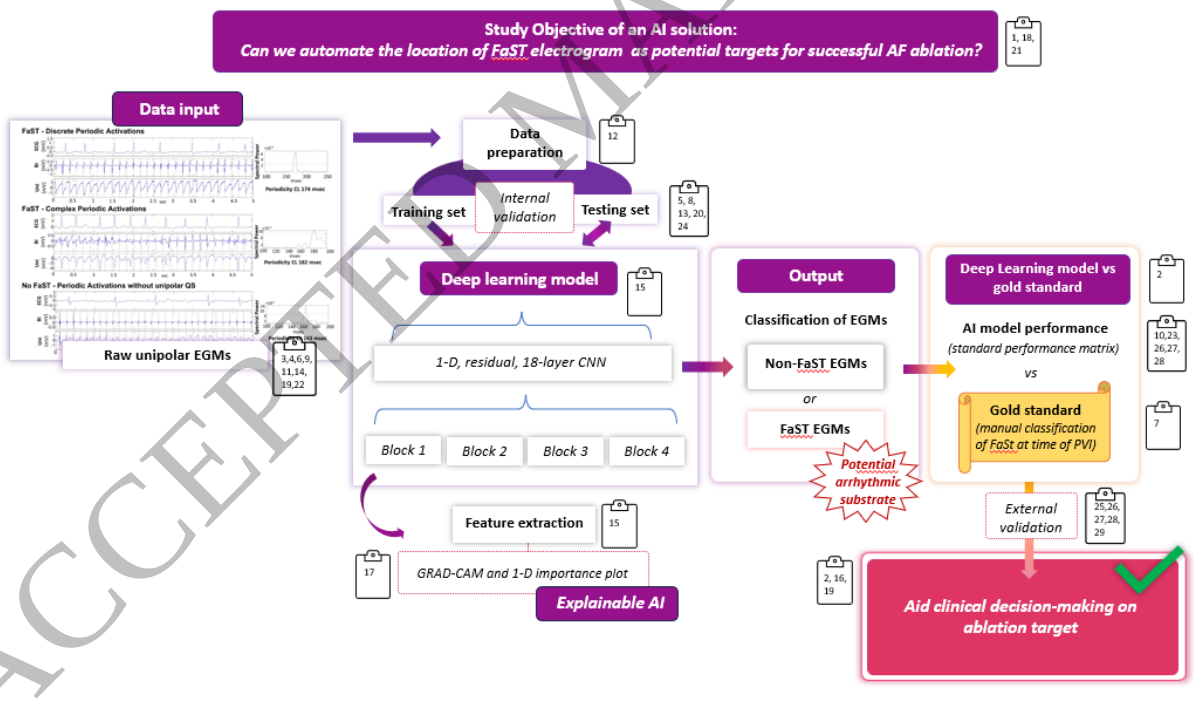


Figure 4. The Figure illustrates the process of evaluating scientific publications on the use of AI methods in EP, based on the 29-items checklist. The numbers shown correspond with the individual checklist item numbers and where in the evaluation process they should theoretically be applied. In this example based on a study by Liao et al.[100], intracardiac electrograms (EGMs) serve as data input into a deep learning (DL) model of AI involving convolutional neural network (CNN) with the output as classification of EGMs into focal source and triggers (FaST) to identify and ablation targets. After data preparation, the data is split into a training set and a testing set for internal validation. In the training set a DL model is developed

extracting features of EGMs to differentiate FaST from non-FaST EGMs. The model then undergoes internal validation using the testing data set. The results of the internal validation are used to fine-tune the AI model to improve its accuracy. The final AI model is compared with manual classification of FaST EGMs during an AF ablation as gold standard. The accuracy of the AI model is then assessed using a standard performance matrix (AUC on ROC analysis, specificity, sensitivity, NPV, PPV and F1 score).. If the model shows good performance against a gold standard, it may provide additional clinical benefit over existing methods in automating the location of arrhythmia substrates to target AF ablation. Note that not all items on the AI checklist were reported in the study., for example, external validation, trial registration and legal framework were not described, Supplement Table 1.

AI=Artificial Intelligence, EP=Electrophysiology, AF=Atrial Fibrillation, FaST=Focal source and triggers, EGMs=Intracardiac electrograms, CNN= Convolutional neural network, PVI=Pulmonary vein isolation PPV=Positive predictive value NPV= Negative predictive value AUC=Area under the curve ROC= Receiver Operating Characteristic

In contrast to other studies using ML methods using retrospectively processed data off-line, the proprietary Volta software (Volta Medical) classifies intracardiac EGMs during mapping in real time with high probability of atrial spatial-temporal dispersion (DISPERS) as drivers of AF can guide catheter ablation in addition to pulmonary vein isolation (PVI) in treatment of persistent AF. [101, 102] A recent study analyzed the outcome and safety of catheter ablation guided by the Volta VX1 software in patients with long-standing persistent AF [103]. Among 50 consecutive patients undergoing catheter ablation for persistent AF, recurrence of any atrial arrhythmia was documented in 26 patients (52%) after a 6-week blanking period.

Tailored-AF was a multicenter RCT, using the AI-based Volta AF-Xplorer™ software, that was recently presented (ClinicalTrials.gov NCT04702451).[103]AI-guided ablation in addition to PVI showed higher freedom from AF at 12 months than the PVI only arm (88% vs 70% and 66% vs 15%).

The proof-of-concept OPTIMA (Optimal Target Identification via Modelling of Arrhythmogenesis) pilot study used digital twins from imaging data to identify and refine optimal ablation targets for AF, improving treatment precision and outcomes. [99] The process was repeated until the substrate was no longer inducible and the final set of targets were imported into the 3D electro anatomical navigation system to successfully guide ablation.[104] An RCT of PVI and non-PVI substrates guided by OPTIMA is ongoing (NCT04101539).

ML methods have also been applied to imaging data to identify features that may predict AF recurrence after AF ablation, including a study using DL method based on pre-ablation pulmonary vein computed tomography image that has been shown to predict recurrence of AF from non-pulmonary vein (NPV) triggers in patients who received catheter ablation for paroxysmal AF. In additional studies, ML that combine LGE-CMR [95, 105], CT, clinical features and the body surface ECG have been shown to predict

recurrence of AF after PVI better than a variety of clinical risk scores. [106, 107] Further prospective studies are needed to validate these findings.[108]

AI for VT ablation

Of the 6 identified papers, 2 covered the use of AI in VT ablation. One paper reported 18 of 29 (62%) and the other paper reported 15 of 29 (52%) of EHRA AI checklist items, neither meeting the ≥ 85% threshold of very good reporting.

ML methods have been applied to predict from 12 lead ECGs the site of origin of focal VT or the site of VT exit in scar-related re-entrant VT, with the aim of enabling pre-procedural planning and improving the accuracy and efficiency of localizing VT target for ablation. [109] Patient-specific virtual heart models reconstructed from CMR data, including LGE, have shown promise in improving VA ablation outcomes. These models can localize arrhythmogenic substrates and predict ablation targets pre-procedurally by simulating VT induction, helping to reduce unnecessary ablation and associated complications. Additionally, by enabling precise target localization and effective pre-procedural planning, these models can shorten procedure durations, reduce operator fatigue, and optimize resource utilization. This integration of predictive tools into clinical workflows enhances patient outcomes and represents a significant advancement in personalized EP care. [110]

AI-aided 3D image integration for EP procedures

There have been significant advances in development of computing software which can process and analyze raw image data acquired from CMR and CT scans to enable pre-procedural planning of catheter ablation. AI-guided software can quantify total scar volume, predict acute hemodynamic decompensation, [111]predict post-infarct VT isthmuses[112, 113] for successful VT ablation. Heterogeneous tissue channels can be defined and classified automatically as sub-endocardial, sub-epicardial and transmural using AI-guided image analysis and further guide ablation.[114]

Recently, in a single center pilot study "Ablate by LAW", it was shown that a personalized AF ablation strategy with titration of ablation index, based on left atrial wall thickness obtained from multidetector computed tomography post-processed with a software tool and integrated into a mapping system resulted in reduction in duration of procedure and fluoroscopy time, with similar rates of first pass PVI and AF recurrence to conventional catheter ablation. [115] There is currently an ongoing multi-center clinical trial using this approach to optimize AF ablation (NCT04218604).

Application of AI in guiding left ventricular lead placement for cardiac resynchronisation therapy (CRT)

Of the 6 identified papers a single paper covered the use of AI for guidance of CRT lead placement. This paper reported 23 of 29 (79%) of EHRA AI checklist items.

Recent advancements in patient-specific cardiac modeling and machine learning (ML) have demonstrated significant potential to optimize left ventricular lead placement in cardiac resynchronization therapy (CRT). Personalized heart models derived from MRI and CT imaging enable in silico simulations of electrical activation patterns under intrinsic rhythm and biventricular pacing, providing insights into optimal pacing strategies.

In one study, supervised ML classifiers were trained on model-derived ventricular activation characteristics combined with clinical data to predict CRT response with an accuracy of 0.77 (ROC AUC = 0.84). The ML approach identified an optimal LV pacing site that improved the predicted CRT response by 17% compared to the clinical pacing site. Additionally, 20% of non-responders were reclassified as responders when paced at the ML pacing site, demonstrating the technique's ability to refine patient stratification.

These findings underscore the utility of combining ML and personalized heart modeling to enhance CRT outcomes, improve patient selection, and refine lead placement strategies, addressing the high non-response rate in CRT. [116]

Future role of AI in EP lab

It is expected that AI will enhance several aspects of the treatment of cardiac arrhythmias in the near future. This includes refining patient selection, improving pre-procedural target identification and substrate analysis, optimizing the intraprocedural mapping process, and enabling precise assessment of ablation lesions as the chosen energy is delivered to the arrhythmia's origin (Figure 5). [117] Ideally, this approach will allow for the use of fewer catheters, enhancing patient safety and comfort while ultimately leading to better clinical outcomes. [118]

Looking ahead, the future role of AI in the EP lab holds significant promise. Beyond the procedural enhancements mentioned, AI has the potential to reduce procedural complexity and risk, shorten procedural durations, enhance ablative durability, and improve downstream health outcomes. Additionally, it is conceivable that data from AI-derived ECG analyses and other biological metrics could be integrated into multiparametric databases. These databases would provide a comprehensive platform for predicting arrhythmia substrates, facilitating more effective and precise catheter ablation strategies.

To realize this vision, it is essential to adhere rigorously to standards like the EHRA checklist, which promotes reproducibility and reliability in AI-based studies. By combining visionary innovation with rigorous methodology, AI can truly transform the art and science of managing cardiac arrhythmias.

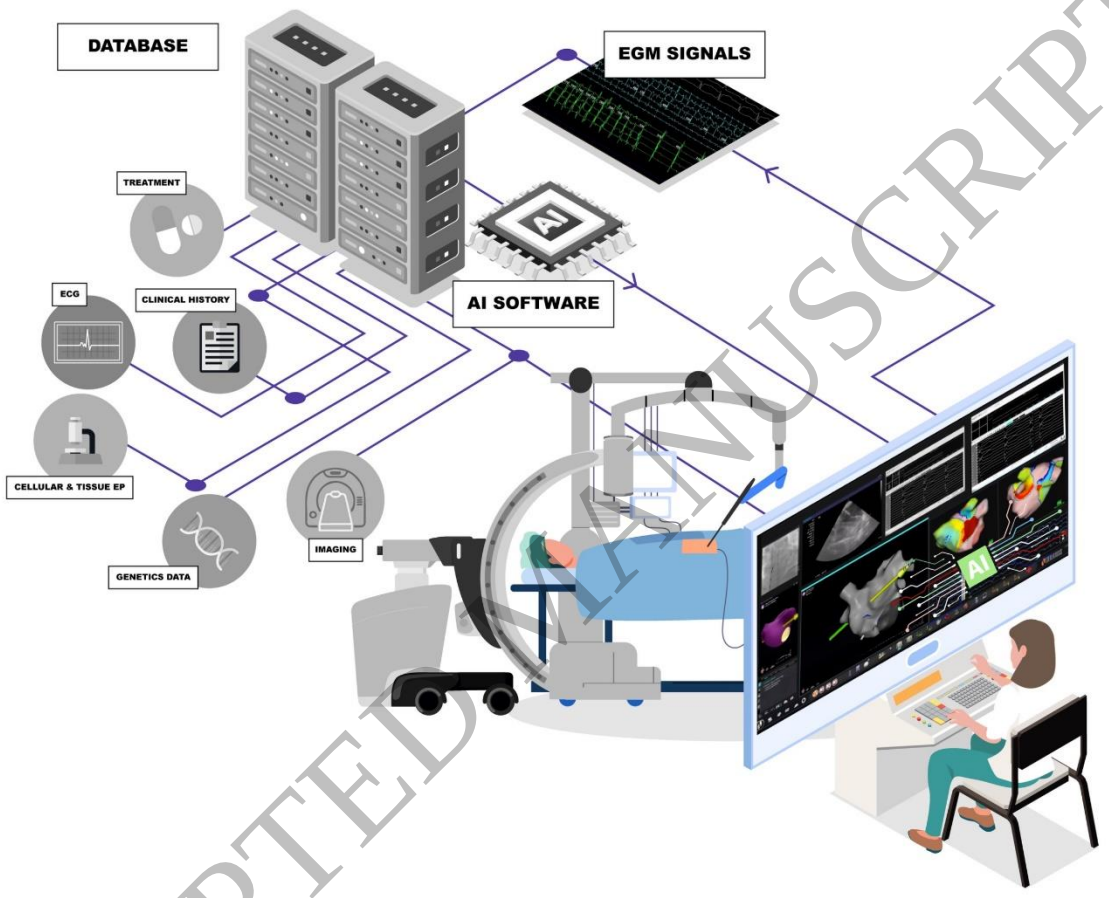


Figure 5. A future vision of the use of artificial intelligence to guide robotic catheter ablation of atrial fibrillation in the EP lab using computer software that processes and analyses intracardiac electrograms in real time to indicate ablation targets.

EGM= electrograms, EP=Electrophysiology, ECG=Electrocardiogram, AI=Artificial Intelligence

Limitations and gaps in evidence

The current body of evidence regarding AI models in the field EP is growing but still remains limited, necessitating further research and validation. There is wide heterogeneity between studies in terms of

study population, incidence of the endpoint and input data used. It is therefore critical to establish and follow standards for reporting AI studies in the field.

The application of the checklist within three key areas of EP suggests that while there is increasing awareness of methodological rigor, there are key gaps in open science and validation practices. To improve the quality of AI studies in EP, several steps could be taken:

- **Journals and reviewers** should emphasize the importance of trial registration, data availability, and external validation.
- **Research institutions and funding bodies** could incentivize these practices through funding and recognition mechanisms.
- **Authors** could be encouraged to adhere to reporting guidelines like the EHRA AI checklist to improve the transparency and reproducibility of their work.

The observed reporting gaps, particularly in external validation, data sharing, and missing data handling, have direct implications for clinical care. AI models that are not externally validated may perform well in research settings but fail in real-world clinical practice, leading to potential risks for patients. Similarly, a lack of data availability limits the ability of other researchers to replicate findings or improve existing models, ultimately slowing the translation of AI innovations into clinical practice. Addressing these gaps through improved reporting standards would therefore contribute to safer, more effective deployment of AI tools in EP.

A further limitation of this study is the use of a threshold of >85% as a benchmark for a "good level" of reporting, which was selected based on practical considerations but lacks a universally established justification in the context of reporting standards. While this threshold provides a useful point of comparison, further research is needed to validate its appropriateness and to explore whether alternative thresholds might better reflect optimal reporting practices. Addressing this limitation in future efforts could help refine reporting benchmarks and provide more nuanced guidance for quality improvement in study designs.

Since the field is rapidly evolving, it could be necessary to adapt the list of items in the future. The writing group will reassess the need for adaptation at regular intervals.

AI models are not automatically the solution for all challenges in clinical EP. AI algorithms can lack transparency, making it difficult for clinicians to understand the rationale behind a model's clinical

decision. Furthermore, AI models trained on specific patient populations or device types may not generalize well across diverse patient groups, EP labs, or specific catheters or devices. For example, the outcome SCD is heterogenous and includes proxies for SCD such as sustained ventricular arrhythmia, ICD therapy (shock or anti-tachycardia pacing), out-of-hospital cardiac arrest, in-hospital cardiac arrest or any unexpected death. An AI framework trained on an imperfect ground truth, such as poorly defined or unadjudicated outcomes, inevitably compromises the reliability of the model. Many of the studies reviewed lacked proper external validation, potentially resulting in overfitting and optimistically biased model performance.

To be accurate, AI models require large, high-quality datasets for training and external validation. Effective deployment of AI in cardiac EP must therefore include rigorous validation, a collaborative approach between research groups and careful consideration of ethical and privacy concerns.

Conclusions

This scientific statement on the state of art of AI in clinical EP underscores the importance of a structured and standardized approach to reporting AI-related studies. The introduction of the EHRA AI checklist for EP will improve the quality, transparency, reproducibility and understandability of research in this rapidly advancing field. By standardizing reporting elements – such as study design, participant demographics, trial registration, AI model specifics, and evaluation metrics – the checklist seeks to address current gaps in how AI studies are reported.

Applying the EHRA AI checklist across the three areas of AF management, SCD, and the EP lab revealed several key trends. First, we observed that reporting practices are generally more robust for methodological items. This suggests that researchers in the field of AI in EP are aware of the importance of methodological rigor. However, the notably weaker reporting in areas such as "open science" (e.g., trial registration and data availability) highlights critical gaps that need attention to improve transparency and reproducibility in AI studies. These gaps may hinder broader validation and implementation of AI tools in clinical practice, as key information about data sharing, reproducibility, and trial registration is essential to build trust and foster collaboration across institutions.

This scientific statement emphasizes that adopting this checklist widely can support the critical evaluation and validation of AI tools in clinical EP. The authors advise using this EHRA AI checklist for AI in EP studies for submission processes of manuscripts and for critical appraisal during peer review, as well as for readers of AI in EP studies for personal assessment.

Continuous validation of the checklist will ensure that it remains relevant and robust as AI applications in EP evolve. Reevaluation and refinement of the checklist may be appropriate in some years.

In conclusion, the EHRA AI checklist serves as a foundational tool for improving AI research quality in EP, fostering better collaboration, and supporting evidence-based AI implementation in clinical settings.

COI

Dr Svennberg is supported by the Stockholm County Council (Clinical researcher appointment), the Swedish Research Council (DNR 2022-01466), the Swedish Heart and Lung foundation, CIMED, and has received institutional lecture fees from Abbott, Astra Zeneca, Bristol-Myers Squibb, Pfizer, Johnson & Johnson

Prof. Caiani reports a grant in the form of a <1K€ payment to his institution from the Advisory Board on digital Health of Medtronic USA; honoraria for presentations or educational events (total <10k€) from Servier, Summeet Srl, Dynamicom Education Srl, UVET GBT Spa, Sanofi; support for attending meetings and/or travel from the European Society of Cardiology

S Engelhardt is supported by research grants from German Center for Cardiovascular Research (DZHK), the Carl-Zeiss Foundation in the project Multi-dimension AI, and received honoraria (<10kEuro) from Boehringer-Ingelheim for educational events.

S Ernst (EHRA) is a consultant for Stereotaxis Inc, Biosense Webster and Catheter Precision and is receiving research funds from Abbott Medical

P Friedman reports research grants from Medtronic, Abbott, and has received honoraria/speaking/consulting fees from Boston Scientific, and has intellectual property rights in AliveCor, Anumana, iRhythm, Medoc, Eko, Marani, and XAI health

R Garcia reports research grants from Boston Scientific, Medtronic, and Microport

H Ghanbari reports consulting engagements with Medtronic, Boston Scientific, Verily Life Sciences, Happitech, and Huxley Medical

J K Han (HRS) , Consulting engagements with Abbot, iRhythm, Medtronic, and Vector Remote

G Hindricks (ESC)

S H Man (EHRA) , nil

J Millet (e-cardiology) reports grant support PID2022-142514OB-I00 from Spanish Research Agency.

S M. Narayan (HRS), reports grant support from the National Institutes of Health (NIH R01 HL149134, HL166260, HL83359), equity from PhysCade Inc., Lifesignals.ai, consulting from Uptodate and TDK Inc and intellectual property owned by University of California Regents and Stanford University.

Professor GA Ng reports grant support from the British Heart Foundation [Research Excellence Award (RE/24/13003) and Healthcare Innovation Fund (HI/C2/24/360038)], the National Institute for Health and Care Research Invention for Innovation Award (NIHR204553); consultancy fees from AliveCor and Biosense Webster; institutional research grant support from Abbott Medical and Boston Scientific; and intellectual property owned by the University of Leicester.

P Noseworthy (HRS) reports filed patents related to the application of AI to the ECG for diagnosis and risk stratification and has licensed (anlong with Mayo Clinic) several A-ECG algorithms to Anumana. Dr. Noseworthy and Mayo Clinic are involved in potential equity/royalty relationship with AliveCor.

F Tjong is supported by personal research grants from the Dutch Research Council (NWO), Amsterdam Cardiovascular Sciences, and Health Holland. She has received institutional lecture fees from Daiichi Sankyo, Abbott and Boston Scientific, and received unrestricted research funding from Abbott.

J Ramirez acknowledges funding from the European Union-NextGenerationEU, fellowship RYC2021-031413-I from MCIN/AEI/10.13039/501100011033, and from the European Union ''NextGenerationEU/PRTR'' and from grants PID2021-128972OA-I00, CNS2023-143599 and PID2023-148975OB-I00, funded by MCIN/AEI/10.13039/501100011033. She has no conflict of interest.

JP Singh is a consultant for Abbott Inc, Biotronik Inc, Boston Scientific, Carelog, Cardiologs Inc, COreDio Inc, CVRx Inc, EBR Inc, DocGo Inc, Impulse Dynamics, Implicity Inc, I-Rhythm Inc, Medtronic Inc, Medscape Inc, Microport Inc., Notal Vision, Orchestra BioMed Inc, Oura Inc, Phillips Inc, Sanofi Inc, Smart Cardia Inc and Vektor Medical Inc Research – Senti-AR, Cardiologs Inc and EBR.

N Trayanova (HRS) is supported by NIH grants R01HL166759 and R01HL174440 and a grant from the Leducq Foundation

Dr Duncker received modest lecture honorary, travel grants and/or a fellowship grant from Abbott, Astra Zeneca, Bayer, Biotronik, Boehringer Ingelheim, Boston Scientific, Bristol Myers Squibb, CVRx, Medtronic, Microport, Pfizer, Sanofi, and Zoll.

Table 2. The EHRA AI checklist. The table presents the final checklist, with the items that reached >75% consensus after the two rounds of the Delphi process.

THE EHRA AI checklist for reporting, reading and understanding AI studies in clinical EP				
Item #	**Category/Section**	**Explanation**	**Rationale**	**Page #**
	TITLE			
i)	***Title***	Include clear terms to identify the study as using artificial intelligence, machine learning or other specific terms	To facilitate paper retrieval the terms artificial intelligence/machine learning/neural network in the context of EP should be used	
	INTRODUCTION			
1	**Intended clinical use**	Clearly describe the intended use and where in clinical workflow the model can be used and the objective of the study	To provide clear information of the clinical context in which to use the suggested AI solution in the context of EP	
2	**Clinical benefit**	Added benefit of AI compared to standard clinical care (gold standard)	To explain how the AI is performing compared to clinical care (gold standard/standard practice) to better evaluate the performance of the AI model and its potential added benefit	
	METHODS			
3	**Data Collection**	Describe how data was collected	To provide a clear description of the dataset generation process, for example was data retrospectively of prospectively collected, from a single center, or multicenter?	
4	**Source (of data)**	Describe the study design or source of input data and how it was acquired	To describe how the input data was acquired including the study design - for example RCT, cohort, registry data	
5	**Development data set (model training data set)**	Describe the data set	To describe the data set that was used for training of the model (i.e 12-lead ECGs from a specific population)	

6	**Participants**	Describe the participants in the data sets, including eligibility criteria (inclusion and exclusion criteria).	Flow chart of participants (or table) suggested	
7	**Comparator**	Provide clear definition of how the gold standard was collected. Clearly describe the gold standard and ground truth including limitations.	To describe in detail how ground truth the model was trained on was established - human interaction, consensus, review type). For example, how was the diagnosis of atrial fibrillation established (12 lead ECG interpreted by independent electrophysiologists)	
8	**Testing data set**	Describe the testing data set, in particular defining the data set split.	To describe in detail the data set that was used for testing the model, and the rationale bases on which the whole dataset was split and how.	
9	**Sample Size**	Explain how the study size was arrived at.	For supervised models: Focus in particular on the training set including number of positives/negatives and the use of data augmentation/reduction (legitimization). For unsupervised models: focus on the number of participants	
10	**Outcome**	Clearly define standardized and reproducible outcome of clinical relevance.	To clearly describe the outcome, for example the accuracy of a specific algorithm	
11	**Data type (source)**	Clearly describe the data type for the study, including pre-processing	To describe the data used (i.e., ECG, image, EGM, omics, EHR..) and its specification used to train and validate the model (i.e., was the information from an ECG in a image or a digital format)	
12	**Data Preparation**	*Input data handling, data augmentation and selection prior to analysis by the AI system, application of techniques to prevent data leakage.*	To describe every step of handling the data (i.e., was the data reused at any time in the model, like using one ECG to provide several data points)	
13	**Balanced groups**	Clearly state how/if groups were balanced	To describe in detail the data set that was used for validating the model, and the rationale bases on which the whole dataset was split and how.	
14	**Data issues (missingness / poor data / duplication / outliers)**	Describe how handling of data of poor quality/noise/missing data was performed	To provide information about possible issues in the utilized data, as well as how these were identified and handled. It should also be specified if there was a minimum standard for quality required for the input data, and where this standard was not achieved, how this was handled	
15	**Feature engineering (extraction /**	If features are used, feature selection should be described including by whom features were extracted.	To describe the process of feature selection (i.e., handcrafted or automatically generated), as well as the strategy adopted to reduce their number (i.e., threshold on cumulative explained variance)	

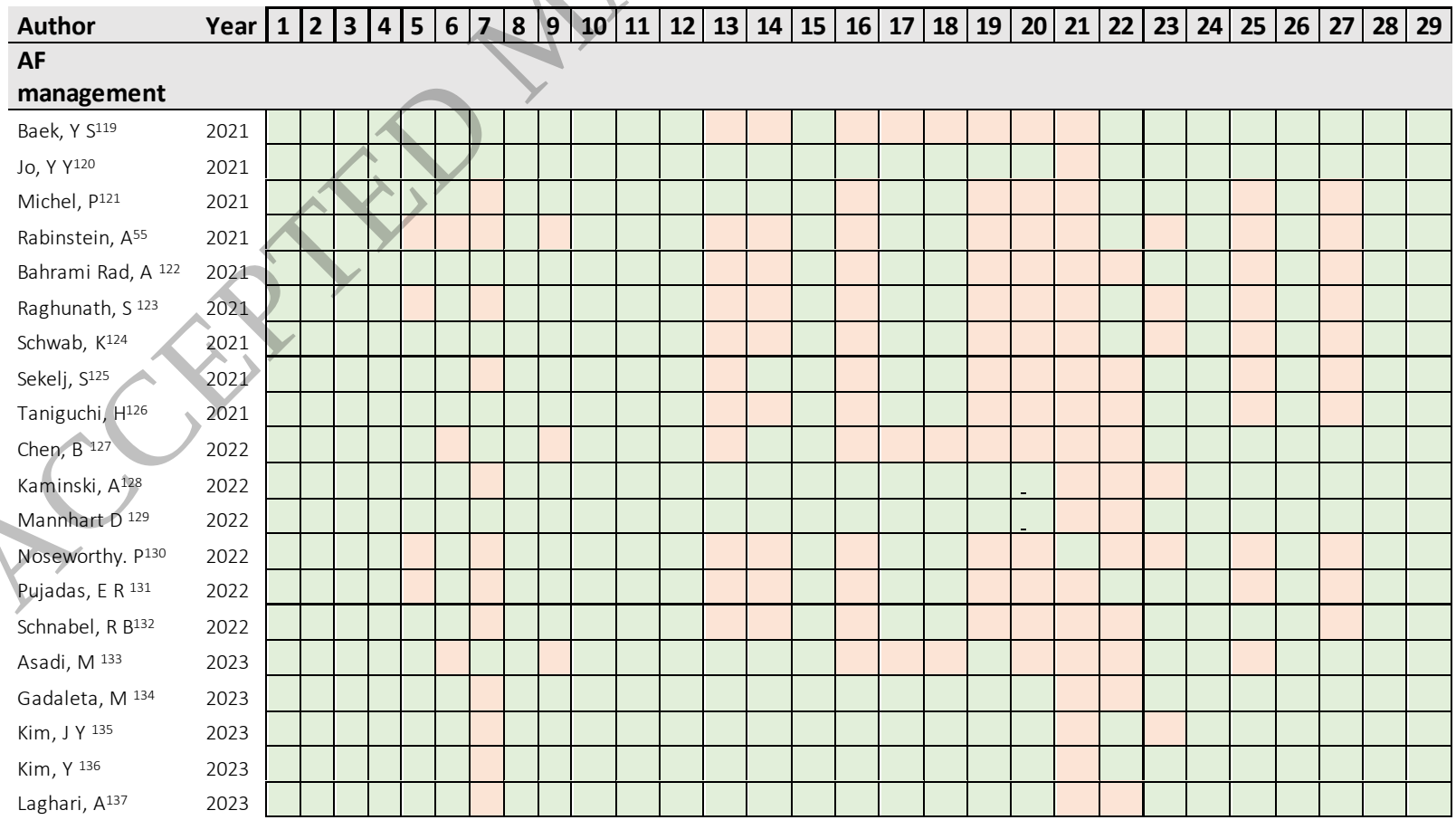
	selection / reduction)			
	REGULATORY			
16	**Legal framework**	Clearly state if the software has been approved by legal authorities, e.g. Certificate of conformity (EU) or FDA approval or other, and add further details, where appropriate (e.g. risk class).	To provide information about the certification process undergone by the AI software specific version, and associated risk class for its use as declared by the manufacturer	
17	**Explainability**	Is the AI model explainable on the patient level or on a global or local level.	To provide a description of the methodology used to provide model explainability	
18	**Ethical approval**	Provide information on ethical approval of the study.	To clearly describe which entity evaluated and released the ethical approval for the study	
19	**Fairness**	Describe inclusion of relevant groups in the dataset	To describe the efforts made to ensure fairness in the study, including for example age, ethnicity and gender	
	OPEN SCIENCE			
20	**Data availability/ Code sharing**	Is the data available on a public website? Is the code available?	To provide details on how to access the anonymized data used for training/validating the model, as well as code sharing	
21	**Trial registration**	In case of a trial, clearly state if and where the trial is registered.	Provide the number and the reference for the trial registration.	
	RESULTS			
22	**Participants**	Baseline demographics (internal and external validation data).	To clearly describe the participant demographics in the study/trial/inclusion to perform internal validation of the AI model, as well as the dataset used for external validation."	
23	**Training performance**	Provide results from the training data set	To provide results using proper metrics describing the model performance when applied to the training set, in order to provide a reference for the expected model performance and allow overfitting assessment in non-externally validated studies	

24	**Internal validation**	The results from the testing data set	To provide results using proper metrics describing the model performance when applied to the validation set, as obtained from the same population/hospital/study/equipment	
25	**External validation**	The results from the external validation data set	To provide results using proper metrics describing the model performance when applied to a validation set obtained from a different population/hospital/study/equipment	
26	**Model performance Internal and external validation**	Choose appropriate metric selection for reporting	"To provide appropriate metrics (threshold dependent or independent), for example: AUC/Sensitivity/Specificity/NPV/PPV/F1/Uncertainty Failing cases"	
27	**Performance errors**	Analysis of performance errors and how they were identified	To provide description about how errors in the model were detected, possible explanations, and potential corrections taken	
28	**Performance compared to classic statistical methods**	What did the model add?	To provide a comparison with a regular statistical model if applicable, potentially using net reclassification indices (i.e., what would have been the results of a regression model compared to the AI-algorithm)"	
29	**Generalizability**	Discuss the level of generalizability of the results obtained.	To discuss how and within which limits the obtained results could be generalized to a more general population, with regards to internal and external validation data sets	
	CONCLUSION			
ii)	**Conclusion**	Is the conclusion supported by the dataset?		

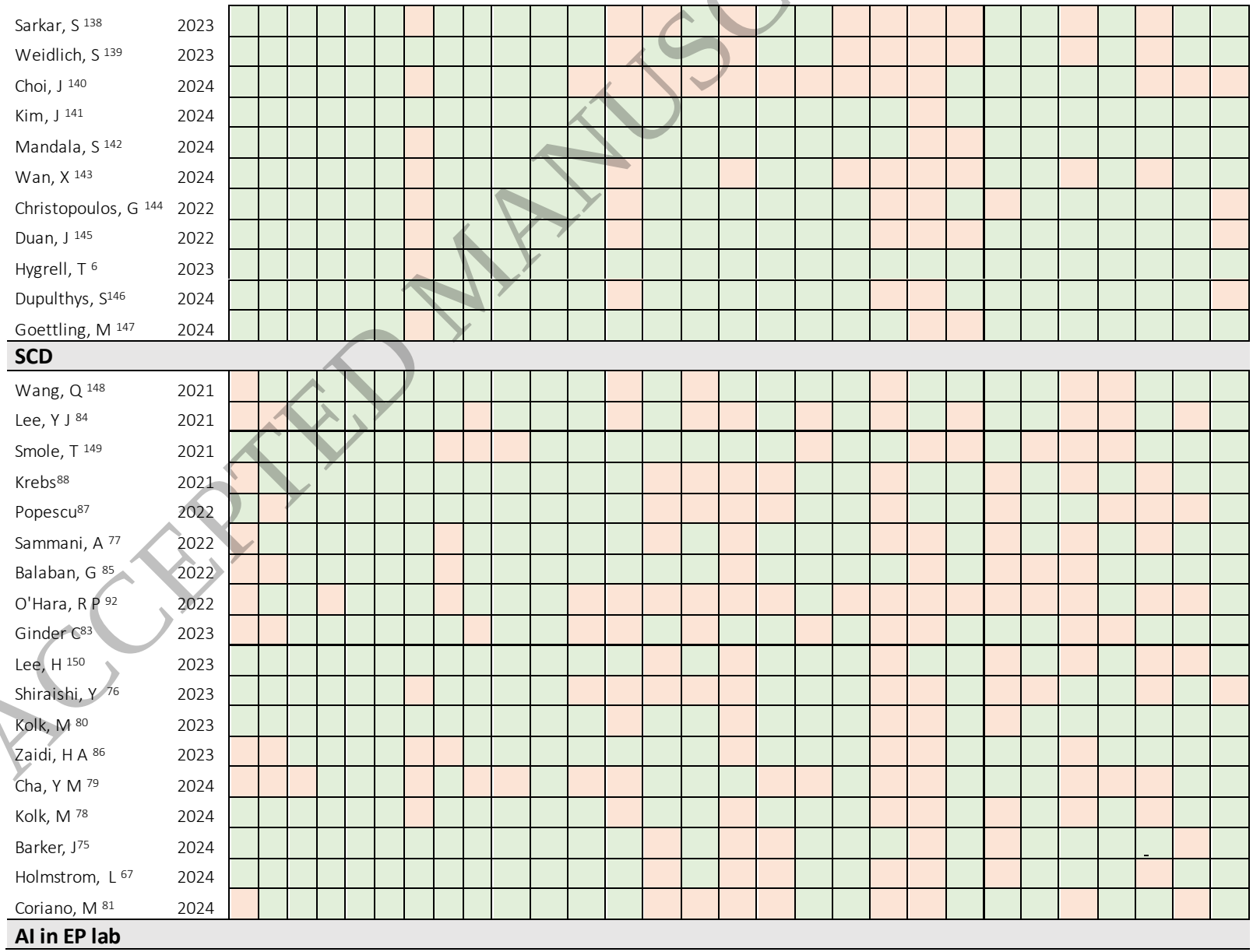
1

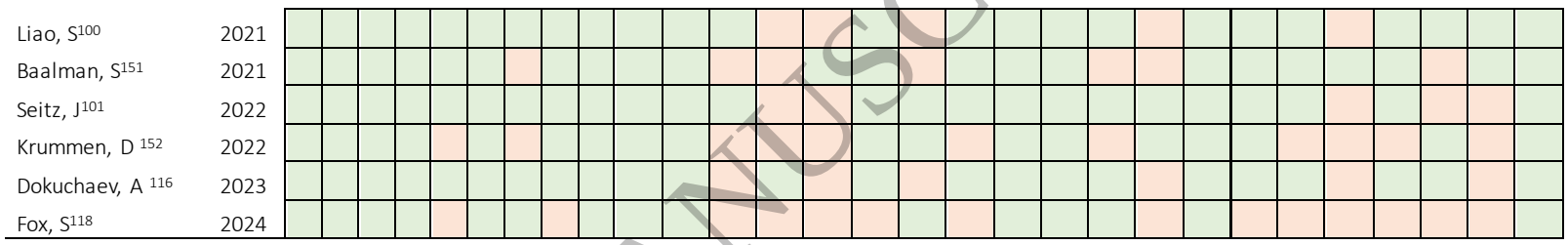
Table 3 Overview of checklist items for each extracted paper

The extracted papers, categorized by topic area, were further divided into three distinct review areas. For each checklist item (#1–29), a color code was assigned: green to indicate that relevant information was provided in the study, and red to indicate that relevant information was not provided.



Author	Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
AF management																														
Baek, Y S[119]	2021																													
Jo, Y Y[120]	2021																													
Michel, P[121]	2021																													
Rabinstein, A[55]	2021																													
Bahrami Rad, A [122]	2021																													
Raghunath, S [123]	2021																													
Schwab, K[124]	2021																													
Sekelj, S[125]	2021																													
Taniguchi, H[126]	2021																													
Chen, B [127]	2022																													
Kaminski, A[128]	2022																													
Mannhart D [129]	2022																													
Noseworthy. P[130]	2022																													
Pujadas, E R [131]	2022																													
Schnabel, R B[132]	2022																													
Asadi, M [133]	2023																													
Gadaleta, M [134]	2023																													
Kim, J Y [135]	2023																													
Kim, Y [136]	2023																													
Laghari, A[137]	2023																													





1

References

[1] Svennberg E, Caiani EG, Bruining N, Desteghe L, Han JK, Narayan SM, et al. The digital journey: 25 years of digital development in electrophysiology from an Europace perspective. *Europace : European pacing, arrhythmias, and cardiac electrophysiology : journal of the working groups on cardiac pacing, arrhythmias, and cardiac cellular electrophysiology of the European Society of Cardiology* 2023; **25**.

[2] Olier I, Ortega-Martorell S, Pieroni M, Lip GYH. How machine learning is impacting research in atrial fibrillation: implications for risk prediction and future management. *Cardiovascular research* 2021; **117**: 1700-1717.

[3] Faust O, Kareem M, Ali A, Ciaccio EJ, Acharya UR. Automated Arrhythmia Detection Based on RR Intervals. *Diagnostics (Basel)* 2021; **11**.

[4] Keidar N, Elul Y, Schuster A, Yaniv Y. Visualizing and Quantifying Irregular Heart Rate Irregularities to Identify Atrial Fibrillation Events. *Front Physiol* 2021; **12**: 637680.

[5] Fernstad J, Svennberg E, Åberg P, Kemp Gudmundsdottir K, Jansson A, Engdahl J. Validation of a novel smartphone-based photoplethysmographic method for ambulatory heart rhythm diagnostics: the SMARTBEATS study. *Europace : European pacing, arrhythmias, and cardiac electrophysiology : journal of the working groups on cardiac pacing, arrhythmias, and cardiac cellular electrophysiology of the European Society of Cardiology* 2024; **26**.

[6] Hygrell T, Viberg F, Dahlberg E, Charlton PH, Kemp Gudmundsdottir K, Mant J, et al. An artificial intelligence-based model for prediction of atrial fibrillation from single-lead sinus rhythm electrocardiograms facilitating screening. *Europace : European pacing, arrhythmias, and cardiac electrophysiology : journal of the working groups on cardiac pacing, arrhythmias, and cardiac cellular electrophysiology of the European Society of Cardiology* 2023; **25**: 1332-1338.

[7] Batra G, Aktaa S, Camm AJ, Costa F, Di Biase L, Duncker D, et al. Data standards for atrial fibrillation/flutter and catheter ablation: the European Unified Registries for Heart Care Evaluation and Randomized Trials (EuroHeart). *Eur Heart J Qual Care Clin Outcomes* 2023; **9**: 609-620.

[8] Boriani G, Mei DA, Lip GYH. Artificial intelligence in patients with atrial fibrillation to manage clinical complexity and comorbidities: the ARISTOTELES project. *European heart journal* 2025; **46**: 775-777.

[9] Ortega-Martorell S, Olier I, Ohlsson M, Lip GYH. TARGET: A Major European Project Aiming to Advance the Personalised Management of Atrial Fibrillation-Related Stroke via the Development of Health Virtual Twins Technology and Artificial Intelligence. *Thrombosis and haemostasis* 2025; **125**: 7-11.

[10] Collins GS, Moons KGM, Dhiman P, Riley RD, Beam AL, Van Calster B, et al. TRIPOD+AI statement: updated guidance for reporting clinical prediction models that use regression or machine learning methods. *BMJ (Clinical research ed)* 2024; **385**: e078378.

[11] Bhagirath P, Strocchi M, Bishop MJ, Boyle PM, Plank G. From bits to bedside: entering the age of digital twins in cardiac electrophysiology. *EP Europace* 2024; **26**.

[12] Altman DG, Simera I, Hoey J, Moher D, Schulz K. EQUATOR: reporting guidelines for health research. *Lancet* 2008; **371**: 1149-1150.

[13] Sengupta PP, Shrestha S, Berthon B, Messas E, Donal E, Tison GH, et al. Proposed Requirements for Cardiovascular Imaging-Related Machine Learning Evaluation (PRIME): A Checklist: Reviewed by the American College of Cardiology Healthcare Innovation Council. *JACC Cardiovasc Imaging* 2020; **13**: 2017-2035.

[14] Lüscher TF, Wenzl FA, D'Ascenzo F, Friedman PA, Antoniades C. Artificial intelligence in cardiovascular medicine: clinical applications. *European heart journal* 2024; **45**: 4291-4304.

[15] van Smeden M, Heinze G, Van Calster B, Asselbergs FW, Vardas PE, Bruining N, et al. Critical appraisal of artificial intelligence-based prediction models for cardiovascular disease. *European heart journal* 2022; **43**: 2921-2930.
[16] van Royen FS, Asselbergs FW, Alfonso F, Vardas P, van Smeden M. Five critical quality criteria for artificial intelligence-based prediction models. *European heart journal* 2023; **44**: 4831-4834.
[17] Elvidge J, Hawksworth C, Avşar TS, Zemplenyi A, Chalkidou A, Petrou S, et al. Consolidated Health Economic Evaluation Reporting Standards for Interventions That Use Artificial Intelligence (CHEERS-AI). *Value in health : the journal of the International Society for Pharmacoeconomics and Outcomes Research* 2024; **27**: 1196-1205.
[18] Tejani AS, Klontzas ME, Gatti AA, Mongan JT, Moy L, Park SH, et al. Checklist for Artificial Intelligence in Medical Imaging (CLAIM): 2024 Update. *Radiol Artif Intell* 2024; **6**: e240300.
[19] Snell KIE, Levis B, Damen JAA, Dhiman P, Debray TPA, Hooft L, et al. Transparent reporting of multivariable prediction models for individual prognosis or diagnosis: checklist for systematic reviews and meta-analyses (TRIPOD-SRMA). *BMJ (Clinical research ed)* 2023; **381**: e073538.
[20] Debray TPA, Collins GS, Riley RD, Snell KIE, Van Calster B, Reitsma JB, et al. Transparent reporting of multivariable prediction models developed or validated using clustered data: TRIPOD-Cluster checklist. *BMJ (Clinical research ed)* 2023; **380**: e071018.
[21] Klement W, El Emam K. Consolidated Reporting Guidelines for Prognostic and Diagnostic Machine Learning Modeling Studies: Development and Validation. *J Med Internet Res* 2023; **25**: e48763.
[22] Vasey B, Nagendran M, Campbell B, Clifton DA, Collins GS, Denaxas S, et al. Publisher Correction: Reporting guideline for the early-stage clinical evaluation of decision support systems driven by artificial intelligence: DECIDE-AI. *Nat Med* 2022; **28**: 2218.
[23] Olczak J, Pavlopoulos J, Prijs J, Ijpma FFA, Doornberg JN, Lundström C, et al. Presenting artificial intelligence, deep learning, and machine learning studies to clinicians and healthcare stakeholders: an introductory reference with a guideline and a Clinical AI Research (CAIR) checklist proposal. *Acta Orthop* 2021; **92**: 513-525.
[24] Schwendicke F, Krois J. Better Reporting of Studies on Artificial Intelligence: CONSORT-AI and Beyond. *J Dent Res* 2021; **100**: 677-680.
[25] Kwong JCC, McLoughlin LC, Haider M, Goldenberg MG, Erdman L, Rickard M, et al. Standardized Reporting of Machine Learning Applications in Urology: The STREAM-URO Framework. *Eur Urol Focus* 2021; **7**: 672-682.
[26] Cruz Rivera S, Liu X, Chan AW, Denniston AK, Calvert MJ. Guidelines for clinical trial protocols for interventions involving artificial intelligence: the SPIRIT-AI extension. *Lancet Digit Health* 2020; **2**: e549-e560.
[27] Liu X, Cruz Rivera S, Moher D, Calvert MJ, Denniston AK. Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: the CONSORT-AI extension. *Lancet Digit Health* 2020; **2**: e537-e548.
[28] Hernandez-Boussard T, Bozkurt S, Ioannidis JPA, Shah NH. MINIMAR (MINimum Information for Medical AI Reporting): Developing reporting standards for artificial intelligence in health care. *J Am Med Inform Assoc* 2020; **27**: 2011-2015.
[29] Stevens LM, Mortazavi BJ, Deo RC, Curtis L, Kao DP. Recommendations for Reporting Machine Learning Analyses in Clinical Research. *Circulation Cardiovascular quality and outcomes* 2020; **13**: e006556.
[30] Norgeot B, Quer G, Beaulieu-Jones BK, Torkamani A, Dias R, Gianfrancesco M, et al. Minimum information about clinical artificial intelligence modeling: the MI-CLAIM checklist. *Nat Med* 2020; **26**: 1320-1324.

[31] Luo W, Phung D, Tran T, Gupta S, Rana S, Karmakar C, et al. Guidelines for Developing and Reporting Machine Learning Predictive Models in Biomedical Research: A Multidisciplinary View. *J Med Internet Res* 2016; **18**: e323.
[32] Friedrich S, Groß S, König IR, Engelhardt S, Bahls M, Heinz J, et al. Applications of artificial intelligence/machine learning approaches in cardiovascular medicine: a systematic review with recommendations. *Eur Heart J Digit Health* 2021; **2**: 424-436.
[33] de Hond AAH, Leeuwenberg AM, Hooft L, Kant IMJ, Nijman SWJ, van Os HJA, et al. Guidelines and quality criteria for artificial intelligence-based prediction models in healthcare: a scoping review. *NPJ Digit Med* 2022; **5**: 2.
[34] Kathryn Fitch SJB, María Dolores Aguilar. The RAND/UCLA Appropriateness Method User's Manual. In: Commission E, ed. 2001.
[35] Lip GYH, Proietti M, Potpara T, Mansour M, Savelieva I, Tse HF, et al. Atrial fibrillation and stroke prevention: 25 years of research at EP Europace journal. *Europace : European pacing, arrhythmias, and cardiac electrophysiology : journal of the working groups on cardiac pacing, arrhythmias, and cardiac cellular electrophysiology of the European Society of Cardiology* 2023; **25**.
[36] Doehner W, Boriani G, Potpara T, Blomstrom-Lundqvist C, Passman R, Sposato LA, et al. Atrial fibrillation burden in clinical practice, research, and technology development: a clinical consensus statement of the European Society of Cardiology Council on Stroke and the European Heart Rhythm Association. *Europace : European pacing, arrhythmias, and cardiac electrophysiology : journal of the working groups on cardiac pacing, arrhythmias, and cardiac cellular electrophysiology of the European Society of Cardiology* 2025; **27**.
[37] Pereira T, Tran N, Gadhoumi K, Pelter MM, Do DH, Lee RJ, et al. Photoplethysmography based atrial fibrillation detection: a review. *NPJ Digit Med* 2020; **3**: 3.
[38] Svennberg E, Tjong F, Goette A, Akoum N, Di Biaise L, Bordachar P, et al. How to use digital devices to detect and manage arrhythmias: an EHRA practical guide. *Europace : European pacing, arrhythmias, and cardiac electrophysiology : journal of the working groups on cardiac pacing, arrhythmias, and cardiac cellular electrophysiology of the European Society of Cardiology* 2022.
[39] Lubitz SA, Faranesh AZ, Selvaggi C, Atlas SJ, McManus DD, Singer DE, et al. Detection of Atrial Fibrillation in a Large Population Using Wearable Devices: The Fitbit Heart Study. *Circulation* 2022: 101161circulationaha122060291.
[40] Perez MV, Mahaffey KW, Hedlin H, Rumsfeld JS, Garcia A, Ferris T, et al. Large-Scale Assessment of a Smartwatch to Identify Atrial Fibrillation. *The New England journal of medicine* 2019; **381**: 1909-1917.
[41] Poh MZ, Battisti AJ, Cheng LF, Lin J, Patwardhan A, Venkataraman GS, et al. Validation of a Deep Learning Algorithm for Continuous, Real-Time Detection of Atrial Fibrillation Using a Wrist-Worn Device in an Ambulatory Environment. *Journal of the American Heart Association* 2023; **12**: e030543.
[42] Wasserlauf J, Vogel K, Whisler C, Benjamin E, Helm R, Steinhaus DA, et al. Accuracy of the Apple watch for detection of AF: A multicenter experience. *Journal of cardiovascular electrophysiology* 2023; **34**: 1103-1107.
[43] McManus DD, Chong JW, Soni A, Saczynski JS, Esa N, Napolitano C, et al. PULSESMART: Pulse-Based Arrhythmia Discrimination Using a Novel Smartphone Application. *Journal of cardiovascular electrophysiology* 2015.
[44] Brasier N, Raichle CJ, Dörr M, Becke A, Nohturfft V, Weber S, et al. Detection of atrial fibrillation with a smartphone camera: first prospective, international, two-centre, clinical validation study (DETECT AF PRO). *Europace : European pacing, arrhythmias, and cardiac electrophysiology : journal of the working groups on cardiac pacing, arrhythmias, and cardiac cellular electrophysiology of the European Society of Cardiology* 2019; **21**: 41-47.

[45] Gruwez H, Ezzat D, Van Puyvelde T, Dhont S, Meekers E, Bruckers L, et al. Real-world validation of smartphone-based photoplethysmography for rate and rhythm monitoring in atrial fibrillation. *Europace : European pacing, arrhythmias, and cardiac electrophysiology : journal of the working groups on cardiac pacing, arrhythmias, and cardiac cellular electrophysiology of the European Society of Cardiology* 2024; **26**.
[46] Mol D, Riezebos RK, Marquering HA, Werner ME, Lobban TCA, de Jong J, et al. Performance of an automated photoplethysmography-based artificial intelligence algorithm to detect atrial fibrillation. *Cardiovasc Digit Health J* 2020; **1**: 107-110.
[47] Gill S, Bunting KV, Sartini C, Cardoso VR, Ghoreishi N, Uh HW, et al. Smartphone detection of atrial fibrillation using photoplethysmography: a systematic review and meta-analysis. *Heart (British Cardiac Society)* 2022; **108**: 1600-1607.
[48] Van Gelder IC, Rienstra M, Bunting KV, Casado-Arroyo R, Caso V, Crijns H, et al. 2024 ESC Guidelines for the management of atrial fibrillation developed in collaboration with the European Association for Cardio-Thoracic Surgery (EACTS). *European heart journal* 2024; **45**: 3314-3414.
[49] Joglar JA, Chung MK, Armbruster AL, Benjamin EJ, Chyou JY, Cronin EM, et al. 2023 ACC/AHA/ACCP/HRS Guideline for the Diagnosis and Management of Atrial Fibrillation: A Report of the American College of Cardiology/American Heart Association Joint Committee on Clinical Practice Guidelines. *J Am Coll Cardiol* 2024; **83**: 109-279.
[50] Siontis KC, Noseworthy PA, Attia ZI, Friedman PA. Artificial intelligence-enhanced electrocardiography in cardiovascular disease management. *Nature reviews Cardiology* 2021; **18**: 465-478.
[51] Wu H, Patel KHK, Li X, Zhang B, Galazis C, Bajaj N, et al. A fully-automated paper ECG digitisation algorithm using deep learning. *Sci Rep* 2022; **12**: 20963.
[52] Ansari Y, Mourad O, Qaraqe K, Serpedin E. Deep learning for ECG Arrhythmia detection and classification: an overview of progress for period 2017-2023. *Front Physiol* 2023; **14**: 1246746.
[53] Attia ZI, Kapa S, Lopez-Jimenez F, McKie PM, Ladewig DJ, Satam G, et al. Screening for cardiac contractile dysfunction using an artificial intelligence-enabled electrocardiogram. *Nat Med* 2019; **25**: 70-74.
[54] Fukunami M, Yamada T, Ohmori M, Kumagai K, Umemoto K, Sakai A, et al. Detection of patients at risk for paroxysmal atrial fibrillation during sinus rhythm by P wave-triggered signal-averaged electrocardiogram. *Circulation* 1991; **83**: 162-169.
[55] Rabinstein AA, Yost MD, Faust L, Kashou AH, Latif OS, Graff-Radford J, et al. Artificial Intelligence-Enabled ECG to Identify Silent Atrial Fibrillation in Embolic Stroke of Unknown Source. *Journal of stroke and cerebrovascular diseases : the official journal of National Stroke Association* 2021; **30**: 105998.
[56] Natale A, Zeppenfeld K, Della Bella P, Liu X, Sabbag A, Santangeli P, et al. Twenty-five years of catheter ablation of ventricular tachycardia: a look back and a look forward. *Europace : European pacing, arrhythmias, and cardiac electrophysiology : journal of the working groups on cardiac pacing, arrhythmias, and cardiac cellular electrophysiology of the European Society of Cardiology* 2023; **25**.
[57] Sau A, Ahmed A, Chen JY, Pastika L, Wright I, Li X, et al. Machine learning-derived cycle length variability metrics predict spontaneously terminating ventricular tachycardia in implantable cardioverter defibrillator recipients. *Eur Heart J Digit Health* 2024; **5**: 50-59.
[58] Al-Khatib SM, Stevenson WG, Ackerman MJ, Bryant WJ, Callans DJ, Curtis AB, et al. 2017 AHA/ACC/HRS Guideline for Management of Patients With Ventricular Arrhythmias and the Prevention of Sudden Cardiac Death: Executive Summary: A Report of the American College of Cardiology/American Heart Association Task Force on Clinical Practice Guidelines and the Heart Rhythm Society. *J Am Coll Cardiol* 2018; **72**: 1677-1749.

[59] Zeppenfeld K, Tfelt-Hansen J, de Riva M, Winkel BG, Behr ER, Blom NA, et al. 2022 ESC Guidelines for the management of patients with ventricular arrhythmias and the prevention of sudden cardiac death. *European heart journal* 2022; **43**: 3997-4126.
[60] Stecker EC, Vickers C, Waltz J, Socoteanu C, John BT, Mariani R, et al. Population-based analysis of sudden cardiac death with and without left ventricular systolic dysfunction: two-year findings from the Oregon Sudden Unexpected Death Study. *J Am Coll Cardiol* 2006; **47**: 1161-1166.
[61] Fishman GI, Chugh SS, Dimarco JP, Albert CM, Anderson ME, Bonow RO, et al. Sudden cardiac death prediction and prevention: report from a National Heart, Lung, and Blood Institute and Heart Rhythm Society Workshop. *Circulation* 2010; **122**: 2335-2348.
[62] Albert CM, Chae CU, Grodstein F, Rose LM, Rexrode KM, Ruskin JN, et al. Prospective study of sudden cardiac death among women in the United States. *Circulation* 2003; **107**: 2096-2101.
[63] Marijon E, Narayanan K, Smith K, Barra S, Basso C, Blom MT, et al. The Lancet Commission to reduce the global burden of sudden cardiac death: a call for multidisciplinary action. *Lancet* 2023; **402**: 883-936.
[64] Marijon E, Garcia R, Narayanan K, Karam N, Jouven X. Fighting against sudden cardiac death: need for a paradigm shift-Adding near-term prevention and pre-emptive action to long-term prevention. *European heart journal* 2022; **43**: 1457-1464.
[65] Peek N, Hindricks G, Akbarov A, Tijssen JGP, Jenkins DA, Kapacee Z, et al. Sudden cardiac death after myocardial infarction: individual participant data from pooled cohorts. *European heart journal* 2024.
[66] Lin C-S, Liu W-T, Tsai D-J, Lou Y-S, Chang C-H, Lee C-C, et al. AI-enabled electrocardiography alert intervention and all-cause mortality: a pragmatic randomized clinical trial. *Nature Medicine* 2024; **30**: 1461-1470.
[67] Holmstrom L, Chugh H, Nakamura K, Bhanji Z, Seifer M, Uy-Evanado A, et al. An ECG-based artificial intelligence model for assessment of sudden cardiac death risk. *Commun Med (Lond)* 2024; **4**: 17.
[68] Lee E, Ito S, Miranda WR, Lopez-Jimenez F, Kane GC, Asirvatham SJ, et al. Artificial intelligence-enabled ECG for left ventricular diastolic function and filling pressure. *NPJ Digit Med* 2024; **7**: 4.
[69] Bleijendaal H, Ramos LA, Lopes RR, Verstraelen TE, Baalman SWE, Oudkerk Pool MD, et al. Computer versus cardiologist: Is a machine learning algorithm able to outperform an expert in diagnosing a phospholamban p.Arg14del mutation on the electrocardiogram? *Heart rhythm : the official journal of the Heart Rhythm Society* 2021; **18**: 79-87.
[70] Chen L, Fu G, Jiang C. Deep learning-derived 12-lead electrocardiogram-based genotype prediction for hypertrophic cardiomyopathy: a pilot study. *Ann Med* 2023; **55**: 2235564.
[71] Călburean PA, Pannone L, Monaco C, Rocca DD, Sorgente A, Almorad A, et al. Predicting and Recognizing Drug-Induced Type I Brugada Pattern Using ECG-Based Deep Learning. *Journal of the American Heart Association* 2024; **13**: e033148.
[72] Jiang R, Cheung CC, Garcia-Montero M, Davies B, Cao J, Redfearn D, et al. Deep Learning-Augmented ECG Analysis for Screening and Genotype Prediction of Congenital Long QT Syndrome. *JAMA Cardiol* 2024; **9**: 377-384.
[73] Holmstrom L, Bednarski B, Chugh H, Aziz H, Pham HN, Sargsyan A, et al. Artificial Intelligence Model Predicts Sudden Cardiac Arrest Manifesting With Pulseless Electric Activity Versus Ventricular Fibrillation. *Circulation Arrhythmia and electrophysiology* 2024; **17**: e012338.
[74] Al-Zaiti SS, Martin-Gill C, Zègre-Hemsey JK, Bouzid Z, Faramand Z, Alrawashdeh MO, et al. Machine learning for ECG diagnosis and risk stratification of occlusion myocardial infarction. *Nat Med* 2023; **29**: 1804-1813.

[75] Barker J, Li X, Kotb A, Mavilakandy A, Antoun I, Thaitirarot C, et al. Artificial intelligence for ventricular arrhythmia capability using ambulatory electrocardiograms. *Eur Heart J Digit Health* 2024; **5**: 384-388.
[76] Shiraishi Y, Goto S, Niimi N, Katsumata Y, Goda A, Takei M, et al. Improved prediction of sudden cardiac death in patients with heart failure through digital processing of electrocardiography. *Europace : European pacing, arrhythmias, and cardiac electrophysiology : journal of the working groups on cardiac pacing, arrhythmias, and cardiac cellular electrophysiology of the European Society of Cardiology* 2023; **25**: 922-930.
[77] Sammani A, van de Leur RR, Henkens M, Meine M, Loh P, Hassink RJ, et al. Life-threatening ventricular arrhythmia prediction in patients with dilated cardiomyopathy using explainable electrocardiogram-based deep neural networks. *Europace : European pacing, arrhythmias, and cardiac electrophysiology : journal of the working groups on cardiac pacing, arrhythmias, and cardiac cellular electrophysiology of the European Society of Cardiology* 2022; **24**: 1645-1654.
[78] Kolk MZH, Ruipérez-Campillo S, Alvarez-Florez L, Deb B, Bekkers EJ, Allaart CP, et al. Dynamic prediction of malignant ventricular arrhythmias using neural networks in patients with an implantable cardioverter-defibrillator. *EBioMedicine* 2024; **99**: 104937.
[79] Cha YM, Attia IZ, Metzger C, Lopez-Jimenez F, Tan NY, Cruz J, et al. Machine learning for prediction of ventricular arrhythmia episodes from intracardiac electrograms of automatic implantable cardioverter-defibrillators. *Heart rhythm : the official journal of the Heart Rhythm Society* 2024.
[80] Kolk MZH, Ruipérez-Campillo S, Deb B, Bekkers EJ, Allaart CP, Rogers AJ, et al. Optimizing patient selection for primary prevention implantable cardioverter-defibrillator implantation: utilizing multimodal machine learning to assess risk of implantable cardioverter-defibrillator non-benefit. *Europace : European pacing, arrhythmias, and cardiac electrophysiology : journal of the working groups on cardiac pacing, arrhythmias, and cardiac cellular electrophysiology of the European Society of Cardiology* 2023; **25**.
[81] Corianò M, Lanera C, De Michieli L, Perazzolo Marra M, Iliceto S, Gregori D, et al. Deep learning-based prediction of major arrhythmic events in dilated cardiomyopathy: A proof of concept study. *PloS one* 2024; **19**: e0297793.
[82] Sau A, Ahmed A, Chen JY, Pastika L, Wright I, Li X, et al. Machine learning-derived cycle length variability metrics predict spontaneously terminating ventricular tachycardia in implantable cardioverter defibrillator recipients. *European Heart Journal - Digital Health* 2023; **5**: 50-59.
[83] Ginder C, Li J, Halperin JL, Akar JG, Martin DT, Chattopadhyay I, et al. Predicting Malignant Ventricular Arrhythmias Using Real-Time Remote Monitoring. *J Am Coll Cardiol* 2023; **81**: 949-961.
[84] Lee YJ, Cho KJ, Kwon O, Park H, Lee Y, Kwon JM, et al. A multicentre validation study of the deep learning-based early warning score for predicting in-hospital cardiac arrest in patients admitted to general wards. *Resuscitation* 2021; **163**: 78-85.
[85] Balaban G, Halliday BP, Hammersley D, Rinaldi CA, Prasad SK, Bishop MJ, et al. Left ventricular shape predicts arrhythmic risk in fibrotic dilated cardiomyopathy. *Europace : European pacing, arrhythmias, and cardiac electrophysiology : journal of the working groups on cardiac pacing, arrhythmias, and cardiac cellular electrophysiology of the European Society of Cardiology* 2022; **24**: 1137-1147.
[86] Zaidi HA, Jones RE, Hammersley DJ, Hatipoglu S, Balaban G, Mach L, et al. Machine learning analysis of complex late gadolinium enhancement patterns to improve risk prediction of major arrhythmic events. *Front Cardiovasc Med* 2023; **10**: 1082778.
[87] Popescu DM, Shade JK, Lai C, Aronis KN, Ouyang D, Moorthy MV, et al. Arrhythmic sudden death survival prediction using deep learning analysis of scarring in the heart. *Nat Cardiovasc Res* 2022; **1**: 334-343.

[88] Krebs J, Mansi T, Delingette H, Lou B, Lima JAC, Tao S, et al. CinE caRdiac magneTic resonAnce to predIct veNTricular arrhYthmia (CERTAINTY). *Sci Rep* 2021; **11**: 22683.
[89] Radhakrishnan A, Friedman SF, Khurshid S, Ng K, Batra P, Lubitz SA, et al. Cross-modal autoencoder framework learns holistic representations of cardiovascular state. *Nat Commun* 2023; **14**: 2436.
[90] Kolk MZH, Ruipérez-Campillo S, Allaart CP, Wilde AAM, Knops RE, Narayan SM, et al. Multimodal explainable artificial intelligence identifies patients with non-ischaemic cardiomyopathy at risk of lethal ventricular arrhythmias. *Sci Rep* 2024; **14**: 14889.
[91] Arevalo HJ, Vadakkumpadan F, Guallar E, Jebb A, Malamas P, Wu KC, et al. Arrhythmia risk stratification of patients after myocardial infarction using personalized heart models. *Nat Commun* 2016; **7**: 11437.
[92] O'Hara RP, Prakosa A, Binka E, Lacy A, Trayanova NA. Arrhythmia in hypertrophic cardiomyopathy: Risk prediction using contrast enhanced MRI, T1 mapping, and personalized virtual heart technology. *J Electrocardiol* 2022; **74**: 122-127.
[93] Corral-Acero J, Margara F, Marciniak M, Rodero C, Loncaric F, Feng Y, et al. The 'Digital Twin' to enable the vision of precision cardiology. *European heart journal* 2020; **41**: 4556-4564.
[94] Shade JK, Prakosa A, Popescu DM, Yu R, Okada DR, Chrispin J, et al. Predicting risk of sudden cardiac death in patients with cardiac sarcoidosis using multimodality imaging and personalized heart modeling in a multivariable classifier. *Sci Adv* 2021; **7**.
[95] Shade JK, Ali RL, Basile D, Popescu D, Akhtar T, Marine JE, et al. Preprocedure Application of Machine Learning and Mechanistic Simulations Predicts Likelihood of Paroxysmal Atrial Fibrillation Recurrence Following Pulmonary Vein Isolation. *Circ Arrhythm Electrophysiol* 2020; **13**: e008213.
[96] Scquizzato T, Landoni G, Consolo F, Scandroglio AM. Google’s loss of pulse detection: Unwitnessed cardiac arrest ‘witnessed’ by a smartwatch. *Resuscitation* 2024; **202**.
[97] Sau A, Ibrahim S, Kramer DB, Waks JW, Qureshi N, Koa-Wing M, et al. Artificial intelligence–enabled electrocardiogram to distinguish atrioventricular re-entrant tachycardia from atrioventricular nodal re-entrant tachycardia. *Cardiovascular Digital Health Journal* 2023; **4**: 60-67.
[98] Honarbakhsh S, Schilling RJ, Providencia R, Dhillon G, Bajomo O, Keating E, et al. Ablation guided by STAR-mapping in addition to pulmonary vein isolation is superior to pulmonary vein isolation alone or in combination with CFAE/linear ablation for persistent AF. *Journal of cardiovascular electrophysiology* 2021; **32**: 200-209.
[99] Boyle PM, Zghaib T, Zahid S, Ali RL, Deng D, Franceschi WH, et al. Computationally guided personalized targeted ablation of persistent atrial fibrillation. *Nat Biomed Eng* 2019; **3**: 870-879.
[100] Liao S, Ragot D, Nayyar S, Suszko A, Zhang Z, Wang B, et al. Deep Learning Classification of Unipolar Electrograms in Human Atrial Fibrillation: Application in Focal Source Mapping. *Front Physiol* 2021; **12**: 704122.
[101] Seitz J, Durdez TM, Albenque JP, Pisapia A, Gitenay E, Durand C, et al. Artificial intelligence software standardizes electrogram-based ablation outcome for persistent atrial fibrillation. *J Cardiovasc Electrophysiol* 2022; **33**: 2250-2260.
[102] Manongi N, Kim J, Goldbarg S. Dispersion electrogram detection with an artificial intelligence software in redo paroxysmal atrial fibrillation ablation. *HeartRhythm Case Rep* 2023; **9**: 948-953.
[103] Bahlke F, Englert F, Popa M, Bourier F, Reents T, Lennerz C, et al. First clinical data on artificial intelligence-guided catheter ablation in long-standing persistent atrial fibrillation. *Journal of cardiovascular electrophysiology* 2024; **35**: 406-414.
[104] Sakata K, Bradley RP, Prakosa A, Yamamoto CAP, Ali SY, Loeffler S, et al. Assessing the arrhythmogenic propensity of fibrotic substrate using digital twins to inform a mechanisms-based atrial fibrillation ablation strategy. *Nat Cardiovasc Res* 2024; **3**: 857-868.

[105] Roney CH, Sim I, Yu J, Beach M, Mehta A, Alonso Solis-Lemus J, et al. Predicting Atrial Fibrillation Recurrence by Combining Population Data and Virtual Cohorts of Patient-Specific Left Atrial Models. *Circulation Arrhythmia and electrophysiology* 2022; **15**: e010253.
[106] Tang S, Razeghi O, Kapoor R, Alhusseini MI, Fazal M, Rogers AJ, et al. Machine Learning-Enabled Multimodal Fusion of Intra-Atrial and Body Surface Signals in Prediction of Atrial Fibrillation Ablation Outcomes. *Circulation Arrhythmia and electrophysiology* 2022; **15**: e010850.
[107] Razeghi O, Kapoor R, Alhusseini MI, Fazal M, Tang S, Roney CH, et al. Atrial fibrillation ablation outcome prediction with a machine learning fusion framework incorporating cardiac computed tomography. *Journal of cardiovascular electrophysiology* 2023; **34**: 1164-1174.
[108] Liu CM, Chang SL, Chen HH, Chen WS, Lin YJ, Lo LW, et al. The Clinical Application of the Deep Learning Technique for Predicting Trigger Origins in Patients With Paroxysmal Atrial Fibrillation With Catheter Ablation. *Circ Arrhythm Electrophysiol* 2020; **13**: e008518.
[109] Missel R, Gyawali PK, Murkute JV, Li Z, Zhou S, AbdelWahab A, et al. A hybrid machine learning approach to localizing the origin of ventricular tachycardia using 12-lead electrocardiograms. *Comput Biol Med* 2020; **126**: 104013.
[110] Prakosa A, Arevalo HJ, Deng D, Boyle PM, Nikolov PP, Ashikaga H, et al. Personalized virtual-heart technology for guiding the ablation of infarct-related ventricular tachycardia. *Nat Biomed Eng* 2018; **2**: 732-740.
[111] John LA, John, II, Tedford RJ, Gregoski MJ, Gold MR, Field ME, et al. Substrate Imaging Before Catheter Ablation of Ventricular Tachycardia: Risk Prediction for Acute Hemodynamic Decompensation. *JACC Clin Electrophysiol* 2023; **9**: 1684-1693.
[112] Takigawa M, Duchateau J, Sacher F, Martin R, Vlachos K, Kitamura T, et al. Are wall thickness channels defined by computed tomography predictive of isthmuses of postinfarction ventricular tachycardia? *Heart Rhythm* 2019; **16**: 1661-1668.
[113] Ciaccio EJ, Cedilnik N, Hsia HH, Biviano AB, Garan H, Yarmohammadi H. Wavefront curvature analysis derived from preprocedural imaging can identify the critical isthmus in patients with postinfarcted ventricular tachycardia. *Heart Rhythm* 2024.
[114] Soto-Iglesias D, Penela D, Jauregui B, Acosta J, Fernandez-Armenta J, Linhart M, et al. Cardiac Magnetic Resonance-Guided Ventricular Tachycardia Substrate Ablation. *JACC Clin Electrophysiol* 2020; **6**: 436-447.
[115] Teres C, Soto-Iglesias D, Penela D, Jauregui B, Ordonez A, Chauca A, et al. Personalized paroxysmal atrial fibrillation ablation by tailoring ablation index to the left atrial wall thickness: the 'Ablate by-LAW' single-centre study-a pilot study. *Europace* 2022; **24**: 390-399.
[116] Dokuchaev A, Chumarnaya T, Bazhutina A, Khamzin S, Lebedeva V, Lyubimtseva T, et al. Combination of personalized computational modeling and machine learning for optimization of left ventricular pacing site in cardiac resynchronization therapy. *Front Physiol* 2023; **14**: 1162520.
[117] Rostock T, Benz AP, Spittler R. Artificial intelligence-guided mapping of persistent atrial fibrillation: Complementary to or better than the electrophysiologist? *J Cardiovasc Electrophysiol* 2024; **35**: 415-417.
[118] Fox SR, Toomu A, Gu K, Kang J, Sung K, Han FT, et al. Impact of artificial intelligence arrhythmia mapping on time to first ablation, procedure duration, and fluoroscopy use. *J Cardiovasc Electrophysiol* 2024.
[119] Baek YS, Lee SC, Choi W, Kim DH. A new deep learning algorithm of 12-lead electrocardiogram for identifying atrial fibrillation during sinus rhythm. *Sci Rep* 2021; **11**: 12818.
[120] Jo YY, Cho Y, Lee SY, Kwon JM, Kim KH, Jeon KH, et al. Explainable artificial intelligence to detect atrial fibrillation using electrocardiogram. *International journal of cardiology* 2021; **328**: 104-110.

[121] Michel P, Ngo N, Pons JF, Delliaux S, Giorgi R. A filter approach for feature selection in classification: application to automatic atrial fibrillation detection in electrocardiogram recordings. *BMC Med Inform Decis Mak* 2021; **21**: 130.
[122] Bahrami Rad A, Galloway C, Treiman D, Xue J, Li Q, Sameni R, et al. Atrial fibrillation detection in outpatient electrocardiogram monitoring: An algorithmic crowdsourcing approach. *PloS one* 2021; **16**: e0259916.
[123] Raghunath S, Pfeifer JM, Kelsey CR, Nemani A, Ruhl JA, Hartzel DN, et al. An ECG-based machine learning model for predicting new-onset atrial fibrillation is superior to age and clinical features in identifying patients at high stroke risk. *J Electrocardiol* 2023; **76**: 61-65.
[124] Schwab K, Nguyen D, Ungab G, Feld G, Maisel AS, Than M, et al. Artificial intelligence MacHIne learning for the detection and treatment of atrial fibrillation guidelines in the emergency department setting (AIM HIGHER): Assessing a machine learning clinical decision support tool to detect and treat non-valvular atrial fibrillation in the emergency department. *J Am Coll Emerg Physicians Open* 2021; **2**: e12534.
[125] Sekelj S, Sandler B, Johnston E, Pollock KG, Hill NR, Gordon J, et al. Detecting undiagnosed atrial fibrillation in UK primary care: Validation of a machine learning prediction algorithm in a retrospective cohort study. *Eur J Prev Cardiol* 2021; **28**: 598-605.
[126] Taniguchi H, Takata T, Takechi M, Furukawa A, Iwasawa J, Kawamura A, et al. Explainable Artificial Intelligence Model for Diagnosis of Atrial Fibrillation Using Holter Electrocardiogram Waveforms. *Int Heart J* 2021; **62**: 534-539.
[127] Chen B, Javadi G, Hamilton A, Sibley S, Laird P, Abolmaesumi P, et al. Quantifying deep neural network uncertainty for atrial fibrillation detection with limited labels. *Sci Rep* 2022; **12**: 20140.
[128] Kaminski AE, Albus ML, Ball CT, White LJ, Sheele JM, Attia ZI, et al. Evaluating atrial fibrillation artificial intelligence for the ED: statistical and clinical implications. *Am J Emerg Med* 2022; **57**: 98-102.
[129] Mannhart D, Lischer M, Knecht S, du Fay de Lavallaz J, Strebel I, Serban T, et al. Clinical Validation of 5 Direct-to-Consumer Wearable Smart Devices to Detect Atrial Fibrillation: BASEL Wearable Study. *JACC Clin Electrophysiol* 2023; **9**: 232-242.
[130] Noseworthy PA, Attia ZI, Behnken EM, Giblon RE, Bews KA, Liu S, et al. Artificial intelligence-guided screening for atrial fibrillation using electrocardiogram during sinus rhythm: a prospective non-randomised interventional trial. *Lancet* 2022; **400**: 1206-1212.
[131] Pujadas ER, Raisi-Estabragh Z, Szabo L, Morcillo CI, Campello VM, Martin-Isla C, et al. Atrial fibrillation prediction by combining ECG markers and CMR radiomics. *Sci Rep* 2022; **12**: 18876.
[132] Schnabel RB, Witt H, Walker J, Ludwig M, Geelhoed B, Kossack N, et al. Machine learning-based identification of risk-factor signatures for undiagnosed atrial fibrillation in primary prevention and post-stroke in clinical practice. *Eur Heart J Qual Care Clin Outcomes* 2022; **9**: 16-23.
[133] Asadi M, Poursalim F, Loni M, Daneshtalab M, Sjödin M, Gharehbaghi A. Accurate detection of paroxysmal atrial fibrillation with certified-GAN and neural architecture search. *Sci Rep* 2023; **13**: 11378.
[134] Gadaleta M, Harrington P, Barnhill E, Hytopoulos E, Turakhia MP, Steinhubl SR, et al. Prediction of atrial fibrillation from at-home single-lead ECG signals without arrhythmias. *NPJ Digit Med* 2023; **6**: 229.
[135] Kim JY, Kim KG, Tae Y, Chang M, Park SJ, Park KM, et al. An Artificial Intelligence Algorithm With 24-h Holter Monitoring for the Identification of Occult Atrial Fibrillation During Sinus Rhythm. *Front Cardiovasc Med* 2022; **9**: 906780.
[136] Kim Y, Joo G, Jeon BK, Kim DH, Shin TY, Im H, et al. Clinical applicability of an artificial intelligence prediction algorithm for early prediction of non-persistent atrial fibrillation. *Front Cardiovasc Med* 2023; **10**: 1168054.
[137] Laghari AA, Sun Y, Alhussein M, Aurangzeb K, Anwar MS, Rashid M. Deep residual-dense network based on bidirectional recurrent neural network for atrial fibrillation detection. *Sci Rep* 2023; **13**: 15109.

[138] Sarkar S, Majumder S, Koehler JL, Landman SR. An ensemble of features based deep learning neural network for reduction of inappropriate atrial fibrillation detection in implantable cardiac monitors. *Heart Rhythm O2* 2023; **4**: 51-58.
[139] Weidlich S, Mannhart D, Kennedy A, Doggart P, Serban T, Knecht S, et al. Reducing the burden of inconclusive smart device single-lead ECG tracings via a novel artificial intelligence algorithm. *Cardiovasc Digit Health J* 2024; **5**: 29-35.
[140] Choi J, Kim JY, Cho MS, Kim M, Kim J, Oh IY, et al. Artificial intelligence predicts undiagnosed atrial fibrillation in patients with embolic stroke of undetermined source using sinus rhythm electrocardiograms. *Heart rhythm : the official journal of the Heart Rhythm Society* 2024; **21**: 1647-1655.
[141] Kim J, Lee SJ, Ko B, Lee M, Lee YS, Lee KH. Identification of Atrial Fibrillation With Single-Lead Mobile ECG During Normal Sinus Rhythm Using Deep Learning. *J Korean Med Sci* 2024; **39**: e56.
[142] Mandala S, Rizal A, Adiwijaya, Nurmaini S, Suci Amini S, Almayda Sudarisman G, et al. An improved method to detect arrhythmia using ensemble learning-based model in multi lead electrocardiogram (ECG). *PloS one* 2024; **19**: e0297551.
[143] Wan X, Liu Y, Mei X, Ye J, Zeng C, Chen Y. A novel atrial fibrillation automatic detection algorithm based on ensemble learning and multi-feature discrimination. *Med Biol Eng Comput* 2024; **62**: 1809-1820.
[144] Christopoulos G, Attia ZI, Van Houten HK, Yao X, Carter RE, Lopez-Jimenez F, et al. Artificial intelligence-electrocardiography to detect atrial fibrillation: trend of probability before and after the first episode. *Eur Heart J Digit Health* 2022; **3**: 228-235.
[145] Duan J, Wang Q, Zhang B, Liu C, Li C, Wang L. Accurate detection of atrial fibrillation events with R-R intervals from ECG signals. *PloS one* 2022; **17**: e0271596.
[146] Dupulthys S, Dujardin K, Anné W, Pollet P, Vanhaverbeke M, McAuliffe D, et al. Single-lead electrocardiogram Artificial Intelligence model with risk factors detects atrial fibrillation during sinus rhythm. *Europace : European pacing, arrhythmias, and cardiac electrophysiology : journal of the working groups on cardiac pacing, arrhythmias, and cardiac cellular electrophysiology of the European Society of Cardiology* 2024; **26**.
[147] Goettling M, Hammer A, Malberg H, Schmidt M. xECGArch: a trustworthy deep learning architecture for interpretable ECG analysis considering short-term and long-term features. *Sci Rep* 2024; **14**: 13122.
[148] Wang Q, Li B, Chen K, Yu F, Su H, Hu K, et al. Machine learning-based risk prediction of malignant arrhythmia in hospitalized patients with heart failure. *ESC Heart Fail* 2021; **8**: 5363-5371.
[149] Smole T, Žunkovič B, Pičulin M, Kokalj E, Robnik-Šikonja M, Kukar M, et al. A machine learning-based risk stratification model for ventricular tachycardia and heart failure in hypertrophic cardiomyopathy. *Comput Biol Med* 2021; **135**: 104648.
[150] Lee H, Yang HL, Ryu HG, Jung CW, Cho YJ, Yoon SB, et al. Real-time machine learning model to predict in-hospital cardiac arrest using heart rate variability in ICU. *NPJ Digit Med* 2023; **6**: 215.
[151] Baalman SWE, Lopes RR, Ramos LA, Neefs J, Driessen AHG, van Boven WP, et al. Prediction of Atrial Fibrillation Recurrence after Thoracoscopic Surgical Ablation Using Machine Learning Techniques. *Diagnostics (Basel)* 2021; **11**.
[152] Krummen DE, Villongco CT, Ho G, Schricker AA, Field ME, Sung K, et al. Forward-Solution Noninvasive Computational Arrhythmia Mapping: The VMAP Study. *Circulation Arrhythmia and electrophysiology* 2022; **15**: e010857.
[153] Chauhan VS, Verma A, Nayyar S, Timmerman N, Tomlinson G, Porta-Sanchez A, et al. Focal source and trigger mapping in atrial fibrillation: Randomized controlled trial evaluating a novel adjunctive ablation strategy. *Heart rhythm : the official journal of the Heart Rhythm Society* 2020; **17**: 683-691.