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Review article

Artificial intelligence and atrial fibrillation: A bibliometric analysis from 2013 to 2023

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A R T I C L E I N F O

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A B S T R A C T

Background: In the study of atrial fibrillation (AF), a prevalent cardiac arrhythmia, the utilization of artificial intelligence (AI) in diagnostic and therapeutic strategies holds the potential to address existing limitations. This research employs bibliometrics to objectively investigate research hotspots, development trends, and existing issues in the application of AI within the AF field, aiming to provide targeted recommendations for relevant researchers.
Methods: Relevant publications on the application of AI in AF field were retrieved from the Web of Science Core Collection (WoSCC) database from 2013 to 2023. The bibliometric analysis was conducted by the R (4.2.2) "bibliometrix" package and VOSviewer(1.6.19).
Results: Analysis of 912 publications reveals that the field of AI in AF is currently experiencing rapid development. The United States, China, and the United Kingdom have made outstanding contributions to this field. Acharya UR is a notable contributor and pioneer in the area. The following topics have been elucidated: AI's application in managing the risk of AF complications is a hot mature topic; AI-electrocardiograph for AF diagnosis and AI-assisted catheter ablation surgery are the emerging and booming topics; smart wearables for real-time AF monitoring and AI for individualized AF medication are niche and well-developed topics.
Conclusion: This study offers comprehensive analysis of the origin, current status, and future trends of AI applications in AF, aiming to advance the development of the field.

1. Introduction

Atrial Fibrillation (AF) stands as the most prevalent form of cardiac arrhythmia globally, with its incidence escalating at an alarming pace [1], sharply elevates the susceptibility to stroke, heart failure, and mortality [2,3]. Therefore, the early and precise prediction, screening, and intervention hold significant clinical value. However, hitherto, certain challenges persist in promptly identifying, diagnosing, and treating AF. For instance, paroxysmal occurs intermittently, posing challenges for routine electrocardiograms (ECG) to capture. Equally, the employment of equipment for dynamic ECG proves cumbersome and inconvenient for patients [4]. The personalization and accuracy of anticoagulant therapy for AF patients remain inadequate, with the short-term conundrum between bleeding and thrombosis persisting. Furthermore, poor patient medication adherence further complicates matters [5]. Additionally, the heightened risk of recurrence post-catheter ablation substantially undermines its long-term efficacy and constrains its

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clinical utility [6]. Confronted with a burgeoning burden of AF disease, the shortcomings of traditional diagnostic and therapeutic paradigms become increasingly conspicuous.

Artificial Intelligence (AI) is swiftly progressing and revolutionizing conventional diagnostic and treatment modalities. Over recent years, AI has rapidly permeated the domain of cardiovascular medicine. At the 2020 European Society of Cardiology Congress, AI emerged as a frontrunner in cardiovascular development, catalyzing advancements in cardiovascular disease diagnosis, prevention, and treatment [7]. The past decade has witnessed a rapid evolution in AI application research pertaining to AF, warranting a scientific and comprehensive review of this realm.

The concept of bibliometrics was first introduced by Alan Pritchard in 1969. This approach quantitatively describes the publication trends, countries, institutions, authors, journals, keywords, and other scientific information within a research field from multiple dimensions and perspectives. It helps identify research hotspots and significant issues in a specific area, predicts future development trends, and overcomes the limitations of traditional review papers in terms of comprehensiveness and objectivity [8]. In recent years, bibliometrics has been widely applied in various fields. Research in the field of environmental ecology by Yixia Chen et al. explored the application of new technologies like ozone or membrane filtration in removing drug compounds from wastewater [9]. In the field of economics, Meihui Zhong et al. analyzed the impact of policy interventions on the economy during the COVID-19 pandemic and highlighted the development direction for the post-pandemic era [10]. Furthermore, the field of medicine has seen increasing attention towards research on AI and its applications in studying arrhythmia. Huang Junlin et al. found that among all types of arrhythmias, AF was most closely related to AI [11]. Gronthy UU et al. identified that machine learning (ML), ECG, and AF were prominent topics in arrhythmia detection [12]. However, it should be noted that while the aforementioned researchers established a close relationship between AI and AF, they did not delve into the specific applications of AI in managing AF, resulting in insufficient research depth.

This study represents the first bibliometric analysis in the field of AI applications for AF, integrating and summarizing publications from the Web of Science Core Collection (WoSCC) database from 2013 to 2023. The objective is to gain a comprehensive understanding of the current research status and existing challenges in this field, predict future development directions, and provide valuable references for clinicians and researchers.

2. Materials and methods

2.1. Data source and search strategy

The data was downloaded from the WoSCC database, widely recognized as one of the most comprehensive, systematic, and authoritative databases for visualizing scientific literature in the world [13]. To ensure comprehensive and accurate inclusion of research in this field, the search parameters were set as follows: Topic=("artificial intelligence" OR "machine learning" OR "data learning" OR "deep learning" OR "intelligent learning" OR "supervised learning" OR "unsupervised learning" OR "reinforcement learning" OR "neural network*" OR "Bayes* network" OR "feature* learning" OR "feature* selection" OR "support vector machine" OR "random forest" OR "semantic segmentation" OR "image* segmentation" OR "k-nearest neighbor") AND ("Atrial Fibrillation*" OR "Auricular Fibrillation*"); Time span: (2013–2023); Document type: (articles and review articles); Citation index: (SCI-Expanded). No language restrictions were applied. All records retrieved (including title, author, keywords, source, abstracts, and references) were exported in plain text format. The search was completed on Oct 18, 2023, to avoid inconsistent results due to database updates.

2.2. Data extraction and analysis

The downloaded literature was imported into EndNote X9 literature management software. Two authors (JB and CJ) screened the literature by reading the title, abstract, and keywords. In case of disagreements, third author (HY) was consulted for arbitration. The specific inclusion and exclusion criteria were as follows. Inclusion criteria: research articles specifically targeting the application of AI in AF. Exclusion criteria: conference/meeting abstracts, unpublished articles/reviews, repeated/retracted publications, editorial, letters, note and book chapters. The filtered literature data was imported into Microsoft Excel Office (2019), R (4.2.2), and VOSviewer (1.6.19) for visual analysis. Microsoft Excel Office was used to analyze annual publication and citation trends. Biblioshiny was co-developed by Massimo Aria from the University of Naples and Corrado Cuccumullo from the University of Campania in Italy [14]. Using the R "bibliometrix" software package, Biblioshiny was applied to analyze and visualize national publications and collaborations, core publishing journals, author publication schedules, trend themes, and topic maps of keywords in the field (detailed R code and procedures are available in the Supplementary material). Biblioshiny effectively visualizes time and trends to analyze and predict development trends in a specific field; however, its performance in presenting co-occurrence networks is average. VOSviewer excels in visualizing co-occurrence networks in scientific knowledge, providing a clearer display of relationships and nodes, thereby complementing Biblioshiny [14]. This study utilized VOSviewer to visually analyze the co-occurrence networks of institutions, journals, authors, and clustering keywords, represented as nodes in the co-occurrence network. The size of nodes indicates their frequency of occurrence, while the connections between nodes are represented as link lines. Nodes with similar features are grouped into clusters with the same color, and the influence or centrality is represented by link strength [15].

In addition to commonly used bibliometric indicators such as total publication (TP) and total citation (TC), the H-index was employed to evaluate researchers' scientific output and impact. The H-index is defined as the number of h articles published by a researcher that have been cited at least h times [16]. The proportion of Multiple Country Publications (MCP) was used to measure the level of international collaboration [17], total link strength (TLS) was used to evaluate the connections between institutions, and Impact Factor (IF) and Journal Citation Reports (JCR) categories were utilized to assess the quality of publications.

3. Results

3.1. Publication outputs and citation trend

Through literature screening, 912 publications were included in the bibliometric analysis, comprising 806 articles and 106 reviews. Fig. 1 illustrates the annual publication volume and the average citation frequency of research in this field. The annual publication volume reflects the development trend of this discipline, which is currently experiencing rapid growth. We divided the history of research into three phases: (1) Initial stage (2013–2014): This period saw fewer than ten papers published annually. (2) Steady upward phase (2015–2017): During this phase, the number of publications increased slowly but steadily each year, indicating a growing interest in the field. (3) Early rapid development (2018–2019): The number of publications more than doubled compared to 2017 and remained stable. (4) Rapid growth phase (2020–2023): The annual publication volume increased rapidly from 128 papers to a peak of around 227 papers, with this growth expected to continue. The average citation frequency represents the average number of citations accrued by publications released within a given year. In 2019, this metric peaked at 12.77, indicating the presence of highly impactful papers in the field that year.

3.2. Analysis of countries/Regions

Seventy countries have published papers on the application of AI in the field of AF. Table 1 displays the top ten countries regarding publication volume and citation frequency. The top three countries with the highest number of publications are China (TP = 268), the United States (TP = 175), and the United Kingdom (TP = 62). The countries with the highest citation frequency are the United States (TC = 5925), China (TC = 3138), and the United Kingdom (TC = 1120). Fig. 2A illustrates a map of international cooperation, with countries having more than five collaborative papers connected by lines. The thickness of each line indicates the frequency of collaboration between two countries. The United States, China, and the United Kingdom have exhibited extensive cooperation, with the most frequent collaborations being between the United States and the United Kingdom (33), the United Kingdom and China (27), and China and the United Kingdom (23), highlighting the central position in the research field. The MCP index was used to evaluate national cooperation. Among the top 10 countries ranked by publication volume, the United Kingdom, Italy, and France show a notably high MCP proportion (≥50 %) as presented in Fig. 2B. For the remaining countries, it is imperative to enhance international collaboration, leverage mutual strengths, and thus foster more robust development in this field.

3.3. Analysis of institutions

A total of 1584 institutions participated in the research on AI and AF. Table 2 displays the top 10 institutions ranked by publication volume. The Mayo Clinic in the United States emerged as the most productive institution (TP = 35), followed by King's College London (TP = 22) and Imperial College London (TP = 21) from the United Kingdom. In terms of citation frequency, the University of California, San Francisco (TC = 1623), Stanford University (TC = 1591), Ngee Ann Polytechnic (TC = 1280), and Mayo Clinic (TC = 1243) were the top four institutions, each with citation frequencies exceeding 1000 times. A co-occurrence network graph (Fig. 3A) was generated using VOSviewer to analyze institutions with a publication volume of 8 or more. The network consisted of 34 nodes organized into 6 distinct clusters. King's College London (TLS = 31), Imperial College London (TLS = 29), and Ngee Ann Polytechnic (TLS = 20) led the research in this field. Fig. 3B depicts the timeline of institutional publications, where the color gradient indicates the

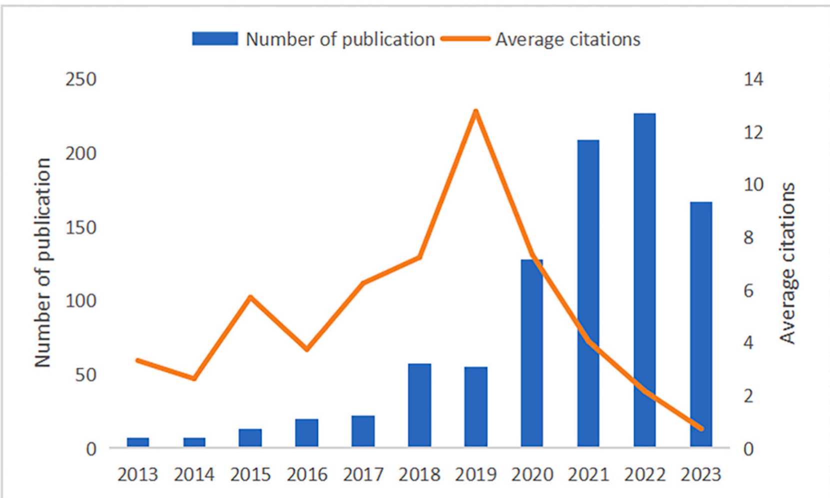

Fig. 1. The trend of publications and citations from 2023 to 2023.

Table 1
Top 10 contributing countries related to AI and AF.

Country	TP	Rank	Country	TC
CHINA	268	1	USA	5925
USA	175	2	CHINA	3138
UNITED KINGDOM	62	3	UNITED KINGDOM	1120
KOREA	55	4	JAPAN	609
INDIA	38	5	KOREA	456
SPAIN	26	6	CANADA	416
ITALY	23	7	DENMARK	353
GERMANY	22	8	NEW ZEALAND	338
FRANCE	19	9	GERMANY	324
JAPAN	17	10	BRAZIL	303

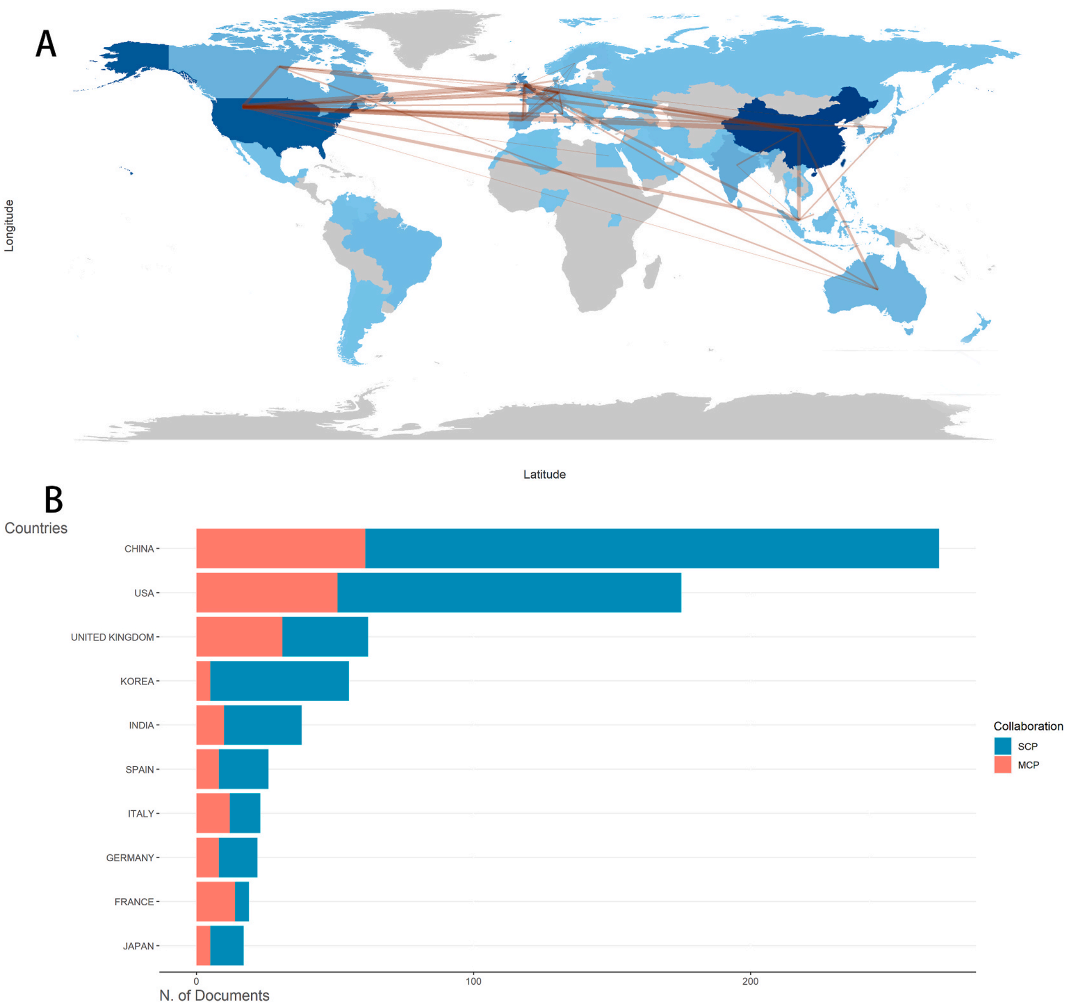

Fig. 2. Distribution map of countries. **A** The Country collaboration map. **B** The proportion of MCP in the top ten countries ranked by publication output. MCP: Multiple Country Publications; SCP: Single Country Publications.

publication chronology. Institutions that published earlier tend to be represented in shades of blue, while those publishing later are depicted in shades of yellow. Ngee Ann Polytechnic in Singapore and Harbin Institute of Technology in China were identified as early pioneers in the exploration of AI applications in AF. Over time, Southeast University and Liverpool Heart have progressively engaged in this research domain, underscoring the evolving landscape of contributions from various academic entities.

Table 2
The top 10 contributing institutions related to AI and AF.

Rank	Institution	Country	TP	TC	TLS
1	Mayo Clinic	USA	35	1243	14
2	King's College London	United Kingdom	22	383	31
3	Imperial College London	United Kingdom	21	443	29
4	Stanford University	USA	20	1591	19
5	Ngee Ann Polytechnic	Singapore	20	1280	20
6	Shanghai Jiao Tong University	China	20	340	17
7	Fudan University	China	19	249	17
8	University of California, San Francisco	USA	15	1623	7
9	Zhejiang University	China	14	243	6
10	Columbia university	USA	13	386	11

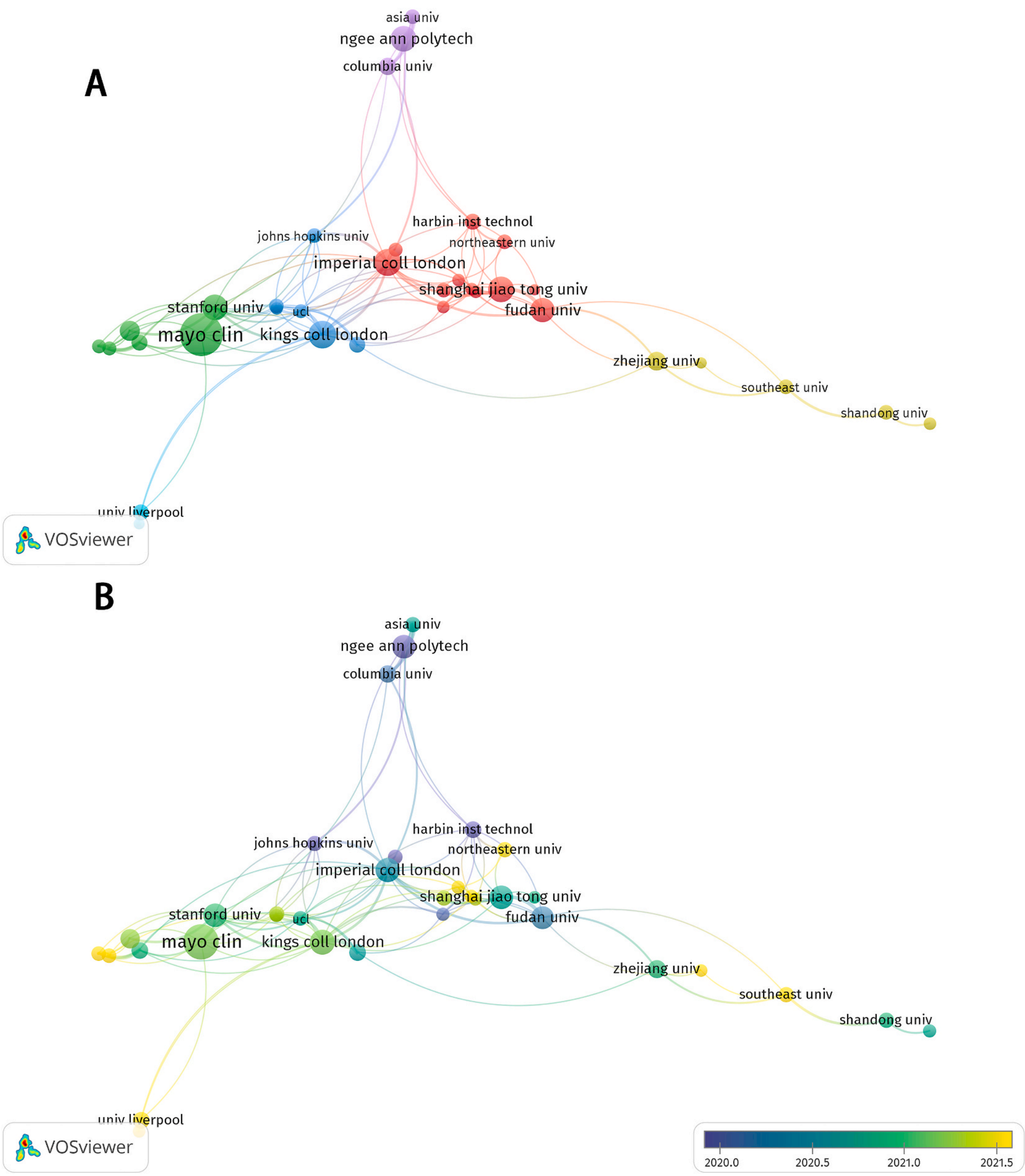

Fig. 3. Distribution map of institutions. **A** Network map of institution collaboration analysis. **B** Overlay visualization of the institution according to the time course.

3.4. Journal analysis

A total of 311 journals contributed to the research outputs, with the top 10 journals, accounting for approximately 30 % of the total publication volume, publishing 269 papers (Table 3). Among these top journals, the preeminent one is Frontiers in Cardiovascular Medicine, dedicated to cardiovascular research. Following closely is Frontiers in Physiology, focusing primarily on physiology, and Biomedical Signal Processing and Control, ranking third, which delves into engineering, computer science, and nuclear medicine. Bradford's Law computation identified these top 10 journals as core journals in the field, as depicted in Fig. 4A. Additionally, the co-occurrence network analysis of academic journals revealed 39 journals with a minimum of five papers published, which were clustered into three distinct groups, totaling 342 links, as shown in Fig. 4B. The red cluster predominantly includes journals revolving around cardiovascular medicine, the green cluster focuses on computer science and engineering technology research, and the blue cluster encompasses the interdisciplinary field of computer science and medicine.

3.5. Analysis of authors

A total of 4753 authors have contributed to the research findings. An evaluation was conducted to identify the most influential authors within the field in the past decade based on the publication output, local citations (LCS), and H-index (Table 4). Noseworthy, PA, from Mayo Clinic in the United States, leads in publication volume having published 25 papers with a primary focus on cardiovascular disease. Acharya UR, a researcher at the University of Southern Queensland in Australia, tops the list for local citation frequency and H-index, and holds the second in publication volume. His research is centered in the in the interdisciplinary field of computer science and medicine. Fig. 5A illustrates the author's research output situation over a period of time. Acharya UR has been dedicated to multidisciplinary computer science and medicine research since 2013 with ongoing contributions up to 2021 that position the researcher as a frontrunner in AI and AF research. In the past five years, a group of authors, including Noseworthy PA, Friedman PA, Attia ZI, and Lip GYH, have consistently published impactful literature, gradually solidifying their roles as key figures in this research area. Notably, a pattern of close collaboration exists among highly productive authors, as illustrated in Fig. 5B, with Noseworthy PA, Friedman PA, and Attia ZI forming strong collaborative ties.

3.6. Analysis of significant publications

A comprehensive analysis of the top 10 most frequently cited literature was conducted to enhance our understanding of the significant advancements in this area (Table 5). Among these highly cited works, the article titled "Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network", published in NATURE MEDICINE in 2019, stood out with the highest number of citations. This was closely followed by an article published in LANCET in the same year, titled "An AI-enabled ECG algorithm for the identification of patients with AF during sinus rhythm: a retrospective analysis of outcome prediction." In the selection of top-cited literature, with the exception of one review article, the remaining eight papers primarily focus on the utilization of AI-electrocardiogram (AI-ECG) or smart wristbands for AF diagnosis and detection, while on study was dedicated to the risk prediction of complications associated with AF

3.7. Keywords analysis

Keyword analysis is a crucial method for identifying central themes in a research domain and monitoring the progression of scientific advancements. Synonyms were integrated for better consistency, such as replacing "ecg" with "electrocardiogram." In a comprehensive analysis of 912 research articles, 3012 keywords were extracted. Fig. 6A visualizes keyword density using VOSviewer, with colors shifting towards yellow to indicate higher occurrence frequencies. As shown in Table 6, the most frequently occurring keywords are "atrial fibrillation," "electrocardiogram," "machine learning," "classification," "deep learning," and "stroke." Next, we conducted a co-occurrence analysis of keywords, resulting in the generation of 3 clusters. As shown in Fig. 6B, Cluster 1 (green): AI for managing AF complication risk, involving a total of 114 keywords. Representative keywords include "atrial fibrillation," "machine learning," "stroke," and "risk". Cluster 2 (red): AI-ECG for AF diagnosis, involving a total of 116 keywords. Representative keywords

Table 3
The top 10 journals related to AI and AF.

Rank	Journal	TP	TC	JCR	IF $_{2022}$
1	Frontiers in Cardiovascular Medicine	37	107	Q2	3.6
2	Frontiers in Physiology	34	260	Q2	4
3	Biomedical Signal Processing and Control	32	709	Q2	5.1
4	Sensors	31	373	Q2	3.9
5	Computers in Biology and Medicine	29	1146	Q1	7.7
6	Physiological Measurement	27	618	Q2	3.2
7	Ieee Access	26	330	Q2	3,9
8	Ieee Journal of Biomedical and Health Informatics	24	512	Q1	7.7
9	Computer Methods and Programs in Biomedicine	22	420	Q1	6.1
10	Scientific Reports	22	176	Q2	4.6

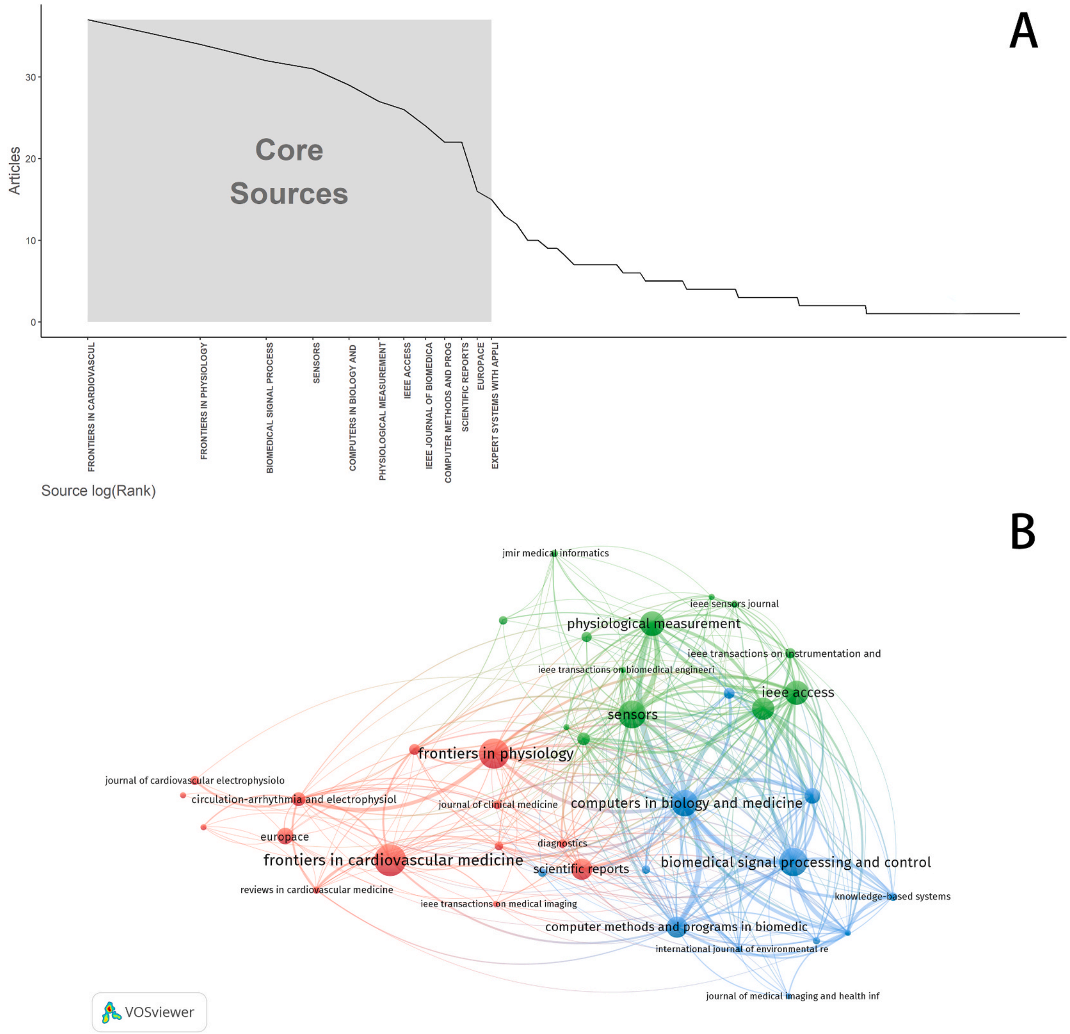

Fig. 4. Distribution map of journals. **A** Core sources by Bradford's Law. **B** The occurrence of contributing journals.

Table 4
The most influential authors in the field of AI and AF.

Rank	Author	TP	Author	LCS	Author	H-index
1	Noseworthy PA	25	Acharya UR	321	Acharya UR	16
2	Acharya UR	20	Fujita H	209	Noseworthy PA	10
3	Friedman PA	17	Noseworthy PA	195	Attia ZI	9
4	Attia ZI	15	Friedman PA	185	Friedman PA	9
5	Lip GYH	12	Attia ZI	182	Yao XX	8
6	Chen J	10	Tison GH	166	Chen J	7
7	Li Y	10	Wang KQ	160	Lip GYH	7
8	Peters NS	10	Turakhia MP	149	Wang KQ	7
9	Yao XX	10	Yao XX	147	Chon KH	6
10	Liu CY	9	Zhang HG	147	Liu Y	6

include "electrocardiogram," "classification," "deep learning," "diagnosis," and "convolutional neural network." Cluster 3 (blue): AI and catheter ablation surgery, involving a total of 60 keywords. Representative keywords include "catheter ablation," "recurrence," "mechanisms," and "pulmonary vein isolation."

We have compared the keyword co-occurrence network generated by VOSviewer (Fig. 6B), the trend topic map, and thematic map produced by Biblioshiny (Fig. 7A and B) to gain a more intuitive and comprehensive insight into the research hotspots in this field. Fig. 7A presents a trend topic map illustrating each year's most significant research topics. The size of the circles corresponds to the frequency of corresponding keywords, while the blue line represents the periods in which keywords appear frequently. Prominent

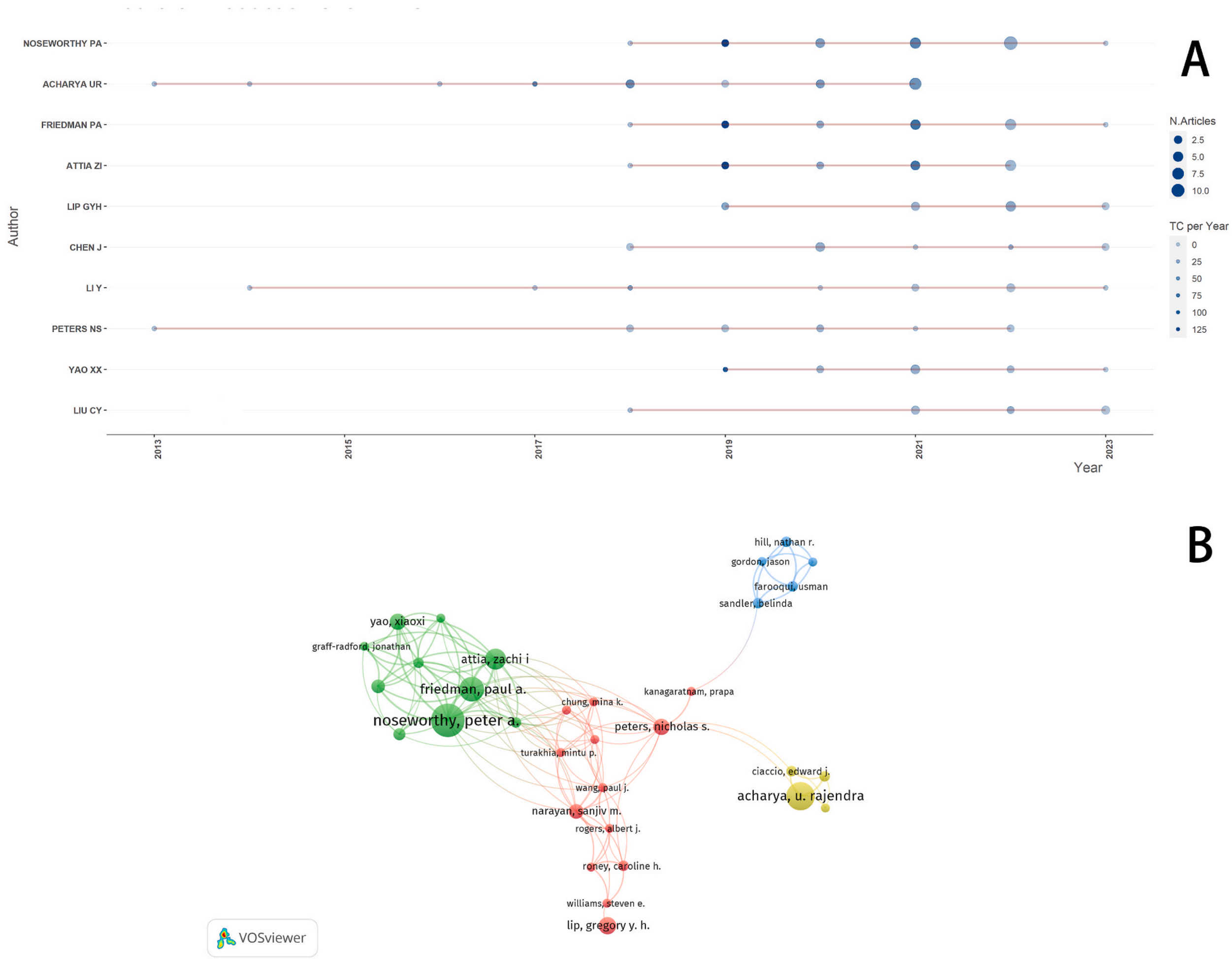

Fig. 5. Distribution map of authors. **A** Author's production over time. **B** Cooperation map of authors.

Table 5
Top 10 highest citation publications in the field of AI and AF.

Paper	Year	Journal	TC	First author	Content
Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network.	2019	NATURE MEDICINE	1157	Hannun, AY	diagnosis/ detection
An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction.	2019	LANCET	497	Attia, ZI	diagnosis/ detection
Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network.	2017	INFORMATION SCIENCES	424	Acharya, UR	diagnosis/ detection
Epidemiology of Atrial Fibrillation in the 21st Century Novel Methods and New Insights.	2020	CIRCULATION RESEARCH	372	Kornej, J	review
Interpretable classifiers using rules and Bayesian analysis: Building a better stroke prediction model.	2015	ANNALS OF APPLIED STATISTICS	301	Letham, B	Complication prediction
Passive Detection of Atrial Fibrillation Using a Commercially Available Smartwatch.	2018	JAMA CARDIOLOGY	258	Tison, GH	diagnosis/ detection
Automatic diagnosis of the 12-lead ECG using a deep neural Network.	2020	NATURE COMMUNICATIONS	249	Ribeiro, AH	diagnosis/ detection
Deep Convolutional Neural Networks and Learning ECG Features for Screening Paroxysmal Atrial Fibrillation Patients.	2018	IEEE TRANSACTIONS ON SYSTEMS MAN CYBERNETICS-SYSTEMS	243	Pourbabaee, B	diagnosis/ detection
A deep learning approach for real-time detection of atrial Fibrillation.	2019	EXPERT SYSTEMS WITH APPLICATIONS	200	Andersen, RS	diagnosis/ detection
Detecting atrial fibrillation by deep convolutional neural Networks.	2018	COMPUTERS IN BIOLOGY AND MEDICINE	193	Xia, Y	diagnosis/ detection

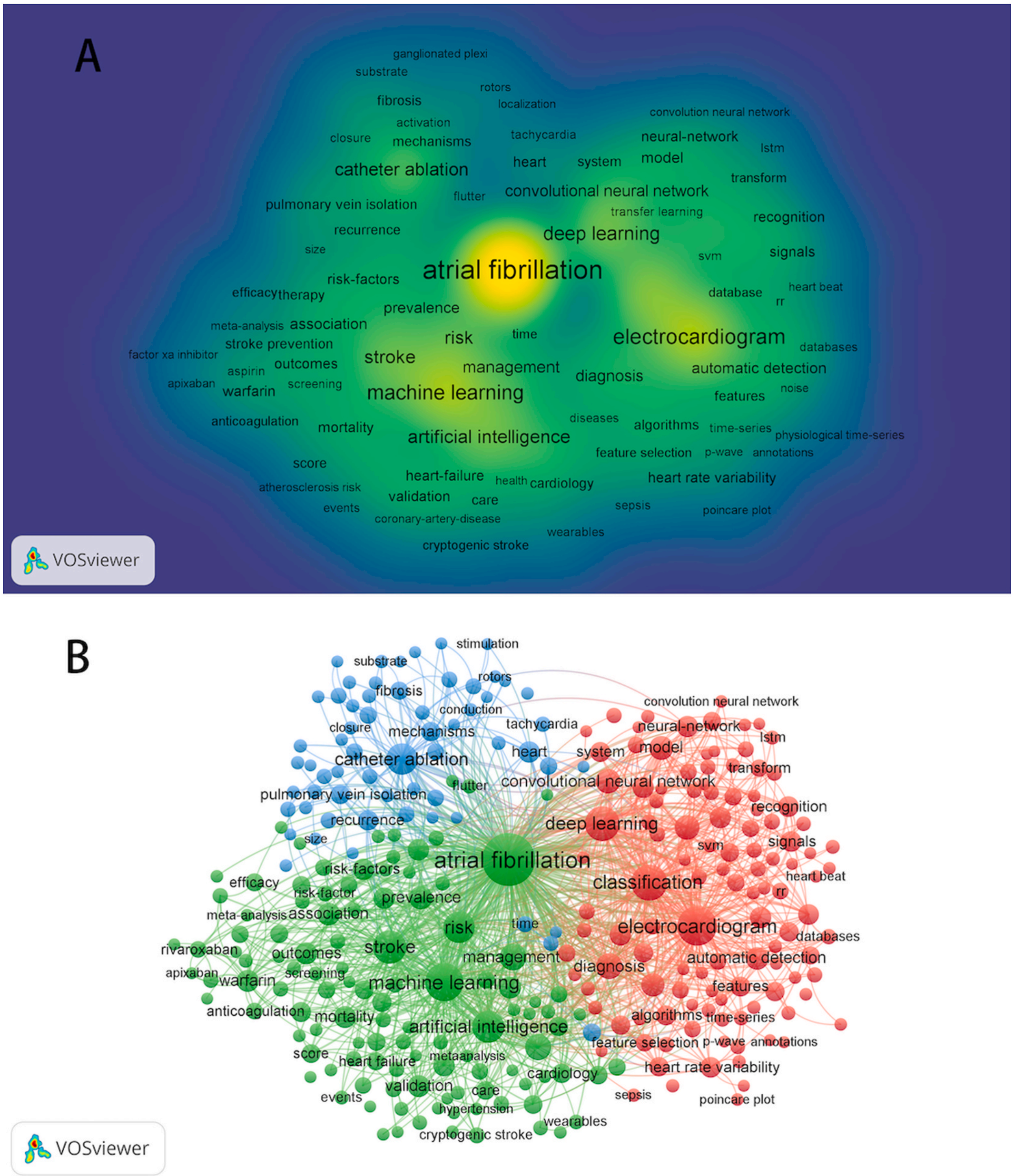

Fig. 6. Visualization of keywords. **A** The density visualization of keywords. **B** The cluster map of keywords.

keywords in the past three years encompass AF, classification, and risk for 2021; prediction, association, and impact for 2022; and cardiac surgery, convolutional neural network (CNN), and apixaban for 2023. Thematic maps enable an in-depth examination of thematic evolution patterns, providing insights into future research trajectories. The horizontal axis represents the centrality of the theme, indicating its core position and connection with other themes, while the vertical axis denotes its maturity level. The thematic map is divided into four quadrants: The first quadrant represents the core themes with high maturity, the second quadrant consists of highly specialized niche topics that are increasingly gaining popularity, the third quadrant encompasses specific emerging or declining themes, and the fourth quadrant signifies fundamental themes that hold significant importance in the field but not fully explored. Each bubble in the map represents a cluster, with the bubble size proportional to the frequency of main keywords in the cluster.

By combining the keyword clustering (Fig. 6B) and the trend topic (Fig. 7A), an in-depth analysis of the thematic map (Fig. 7B) was conducted. The results reveal two themes in quadrant one and quadrant four, corresponding to clusters 1 and 2, respectively. These themes highlight the research on AI in stroke risk control for AF patients and application of AI-ECG in AF classification and diagnosis, holding central positions in this field and representing the industry's cutting edge and focal point. Research on integrating AI and wearable devices for real-time AF monitoring is located in the second quadrant, demonstrating strong specialization and niche appeal

Table 6
The top 30 keywords in the field of AI and AF.

Rank	Keywords	Occurrences	Rank	Keywords	Occurrences
1	atrial fibrillation	605	16	algorithm	40
2	electrocardiogram	226	17	prevalence	39
3	machine learning	209	18	automatic detection	38
4	classification	171	19	association	36
5	deep learning	146	20	outcomes	34
6	stroke	128	21	validation	34
7	artificial intelligence	119	22	mortality	33
8	catheter ablation	107	23	warfarin	33
9	risk	106	24	impact	32
10	management	64	25	neural-network	32
11	diagnosis	58	26	wavelet transform	32
12	prediction	57	27	epidemiology	31
13	arrhythmia	51	28	heart-failure	31
14	convolutional neural network	51	29	rhythm	31
15	model	44	30	arrhythmia detection	29

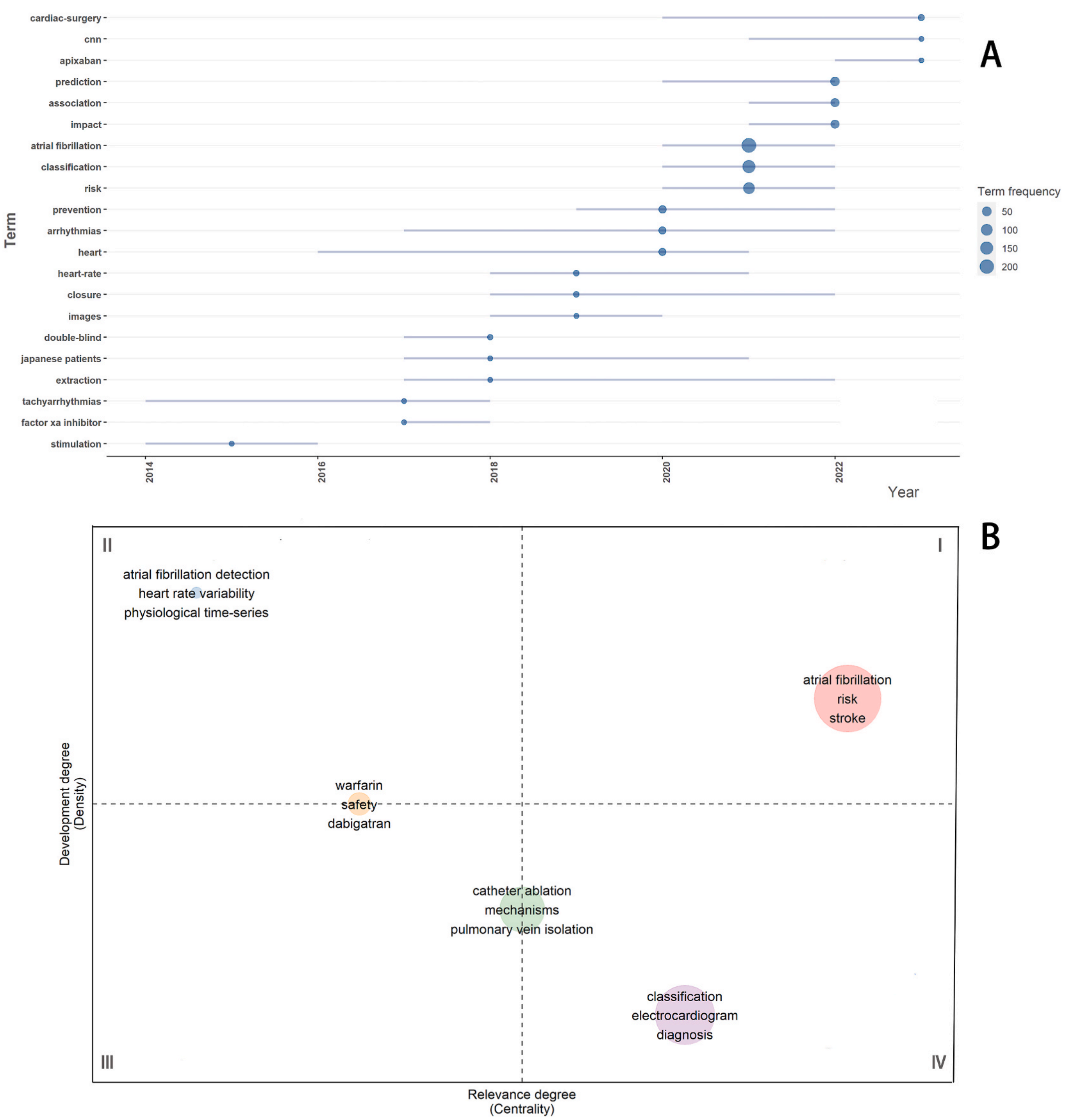

Fig. 7. Theme analysis map. **A** Trend topic map. **B** Thematic map.

with growing attention in recent years. Additionally, the utilization of AI in research on the safety of anticoagulant drug use and cardiac surgery is positioned at the quadrant intersection, indicating the maturity and centrality of these two themes are gradually increasing.

4. Discussion

4.1. General information

We conducted a bibliometric analysis of 912 relevant studies from the WoSCC database, covering the period from 2013 to 2023, focusing on the application of AI in AF field. Over the past decade, there has been a consistent rise in the volume of publications within this domain globally. As of 2023, 167 articles have already been published, and while this figure does not represent the complete output for the year, research productivity is anticipated to further escalate. The average annual citation frequency reached its peak in 2019. The literature analysis revealed that the two most highly cited papers [18,19] published in the same year were both related to the application of AI-ECG in AF diagnosis, highlighting their significant reference value. The United States, China, and the United Kingdom have made outstanding contributions in this field, leading in terms of publication volume and citation frequency (Table 1), with 90 % of the top 10 institutions in publication volume being from these three countries (Table 2). Although China has published 93 more articles than the United States, it has received 2787 fewer citations, indicating a need to shift its focus from quantity to quality in research and improve the rate of producing high-quality articles.

For the author contributions, Acharya UR from the University of Southern Queensland in Australia stands out, leading in citation frequency and H-index. His outstanding contributions to the application of AI in AF highlight the importance of nurturing interdisciplinary talents who possess a robust foundation in both computer science and medicine, underscoring the necessity of enhancing cross-disciplinary collaboration. The impact of the journals in which research is published is critical for the dissemination of findings. However, the proportion of publications in high-impact journals within the field of AI applications for AF remains relatively low. This may be attributed to the field's inherently interdisciplinary nature and its relatively nascent stage of development. To foster further advancement in this domain, it is imperative to establish more high-quality, interdisciplinary journals that can effectively bridge the gap between computer science and medical research.

4.2. Overview of AI algorithms

The core technology within AI is ML, which is further categorized into supervised learning, unsupervised learning, and reinforcement learning based on distinguishable characteristics of models and algorithms. Supervised learning is a method where a computer learns and identifies objective patterns from a dataset containing labeled outputs or results, using annotated data for training. Supervised machine learning algorithms include logistic regression, support vector machines, decision trees, naive Bayes, and random forest algorithms [20,21]. Unsupervised learning is the process of learning and discovering underlying patterns from unlabeled datasets, classifying data through clustering and similarity principles. Commonly used algorithms include K-means clustering, hierarchical clustering, principal component analysis, and factor analysis [22]. Reinforcement learning enhances the accuracy of decision-making algorithms by maximizing the reward function. While reinforcement learning models are mostly applied in gaming, the use in medicine is relatively rare [23]. Deep learning (DL), as a branch of ML, simulates the cognitive mechanisms of the human brain to analyze and learn from data. It constructs neural networks to interpret multimodal information such as images, sounds, and text, including CNN, deep neural network (DNN), artificial neural network, long short-term memory, and other algorithms. CNN is widely applied in medical image processing, such as AI-ECG [24]. Different ML algorithms vary in their applicability for addressing various clinical problems.

4.3. Theme analysis

Our findings identified one hot mature topic, two emerging and booming topics, and two niche and well-developed topics. The subsequent discussion section will delve into the current research status and future development directions of these three themes.

4.4. Hot mature topic

AI for managing AF complication risks. As a common risk factor for cardioembolic stroke, AF currently falls short in stroke risk prediction when stroke risk using the CHA2DS2-VASc score [25,26]. Therefore, it is crucial to develop new methods for accurate and effective stroke risk prediction in patients with AF. Seonwoo Jung et al. analyzed data from 754,949 patients with paroxysmal AF provided by the Korean National Health Insurance Service database, utilizing logistic regression analysis to identify 48 features associated with ischemic stroke occurrence [27]. They subsequently constructed a DNN model for predicting ischemic stroke in AF patients. Validation of this DNN model demonstrated superior performance compared to the CHA2DS2-VASc score, as evidenced by the Receiver Operating Characteristics Curve (AUROC): (0.727 ± 0.003 VS 0.651 ± 0.007). Similarly, Hui Li et al. addressed the typical characteristics of small vessel ischemia and hypoxia associated with ischemic stroke and AF by collecting retinal images at wavelengths of 548 nm, 605 nm, and 810 nm [28]. They trained a DNN model to predict ischemic stroke risk in AF patients based on these images. Their findings revealed that the prediction accuracy of DNN trained with either single or multi-spectral composite images exceeded 78 %. Notably, the DNN trained with 605 nm spectral images exhibited more stable performance in detecting ischemic stroke, with the area under the curve (AUC) for the multi-spectral composite model reaching 0.954, surpassing the single-spectral model. Despite significant advances in acute stroke management over recent years, early neurological deterioration (END) continues to present devastating clinical outcomes. The incidence of END remains relatively high, and its prediction is challenging due to the complexity and heterogeneity [29,30]. Kim et al. developed a prediction model for END in stroke-related AF using various ML algorithms, including support vector machines and light gradient boosting machines (LightGBM). LightGBM showed the best predictive performance among these algorithms, with an AUROC value of 0.772 [31]. Future applications of this model in clinical practice can aid in predicting END in patients with AF-related stroke, facilitating early intervention and reducing harm.

4.5. Emerging and booming theme

(1) *AI-ECG for AF Diagnosis.* As one of the most frequently employed diagnostic tools, ECG faces several challenges in practical utilization. Firstly, subjective discrepancies in ECG interpretation among clinicians may compromise the diagnostic precision. Secondly, conventional ECGs capture abnormalities only during arrhythmia episodes, making them less effective for diagnosing transient arrhythmias like AF. AI technology can enhance diagnostic efficiency by simulating sinus rhythm ECG during AF-free periods to identify high-risk individuals. The two most highly cited articles (Table 5) demonstrated the effectiveness of AI-ECG in diagnosing AF. The HANNUN team developed an AI-ECG system utilizing advanced DNN technology, which accurately diagnoses a comprehensive range of 12 cardiac arrhythmias, including AF, atrial flutter, and atrioventricular block, with an average AUC value of 0.97 [18]. This system outperformed cardiac experts in terms of average positive predictive value and sensitivity. Meanwhile, the ATTIA team created an AI-ECG model using CNN to predict AF by identifying ECG features during sinus rhythm in patients with paroxysmal AF [19]. This model achieved an AUC value of 0.87, with sensitivity and specificity both approaching 80 %. Applying this model in clinical practice may reduce the miss rate paroxysmal AF patients. In the future, combining AI-ECG with conventional diagnostic indicators, such as myocardial enzymes, coagulation, and inflammation, could provide a comprehensive assessment and diagnosis for AF patients, further enhancing diagnostic efficiency.

(2) *AI and catheter ablation surgery.* Radiofrequency catheter ablation is a crucial treatment modality for AF. Its success largely depends on the precise segmentation of the left atrium (LA). While three-dimensional magnetic resonance imaging (MRI) effectively depicts cardiac structures, accurately segmenting the LA from MRI images remains challenging due to complex anatomical structures and variations in image quality [32]. To address this, Chen et al. developed a deep convolutional neural network model using cardiac CT images from 97 patients, facilitating automated segmentation and three-dimensional reconstruction of the LA [33]. Their model achieved a remarkable 99.0 % accuracy in identifying LA structures within CT images, with a sensitivity of 99.3 % and specificity of 98.7 %. Liu et al. combined CNN with Recurrent Neural Network to enhance the accuracy and efficiency of LA segmentation, supporting catheter ablation procedures for AF [32]. Meanwhile, personalized ablation strategies are essential to improving the success rates of radiofrequency ablation. Marica Muffoletto et al. employed a two-dimensional atrial tissue model to simulate typical AF ablation scenarios, training a DNN to classify and predict the optimal CA patterns [34]. This model achieved an overall accuracy of 79 % in identifying the best CA strategy. Despite the effectiveness of catheter ablation, AF recurrence remains a significant concern, with rates reaching up to 75 % within seven years for persistent AF [35]. AI technologies can accurately predict AF recurrence after catheter ablation, enabling early interventions. Tang et al. developed a CNN-based multimodal fusion framework incorporating intracardiac electrogram, ECG signals, and clinical features to forecast AF recurrence one year after ablation, achieving an AUROC of 0.859 [36]. Additionally, Liu et al. created a predictive model for non-pulmonary vein (NPV) triggers, essential for recurrence prediction [37]. Their deep learning model demonstrated an accuracy of 82.4 %, sensitivity of 64.3 %, and specificity of 88.4 %, identifying patients at high risk for NPV triggers and facilitating early interventions to minimize the likelihood of AF recurrence after catheter ablation.

4.6. Niche and well-developed theme

(1) *Smart wearables for real-time AF monitoring.* Research indicates that over one-third of AF patients are asymptomatic, discovering their condition only after experiencing severe diseases such as stroke or embolism. The asymptomatic AF is associated with a higher risk of cardiovascular disease and mortality compared to symptomatic AF [38]. Therefore, it is crucial to adopt simple and accurate real-time monitoring methods to improve AF detection rates in the general population. AI-powered wearable devices offer new opportunities for screening and diagnosing asymptomatic AF patients. There devices' portability allows for real-time, continuous, and dynamic capture of subjects' heart rate, rhythm, and other relevant data, making them suitable for large-scale population screening [39,40]. In the Apple Heart Study, 419,297 healthy individuals participated an 8-month prospective AF screening study using Apple Watches equipped with photoplethysmography (PPG) technology and a corresponding mobile app The final results revealed that the PPG-supported wearable devices had a positive predictive value of 84 % for detecting AF [41]. Similarly, the Huawei Heart Study screened 187,912 individuals utilizing PPG-supported Huawei smartwatches/wristbands, achieving a positive predictive value of 91.6 % [40]. Smart wearable devices provide technological possibilities for real-time AF monitoring. However, challenges remain, such as insufficient monitoring accuracy, inadequate data management standards, and high device usage costs [42]. Looking ahead, optimizing algorithms, improving data management standards, and exploring the inclusion of smart wearable devices in medical insurance could enhance monitoring accuracy, safeguard patient privacy, reduce usage costs, and promote the widespread application of wearable devices for early screening and real-time monitoring of AF.

(2) *AI and individualized medication for AF.* Dofetilide is a medication used to modulate AF rhythms, but its administration carries the risk of inducing arrhythmias. Hence, monitoring its plasma concentration is crucial during its clinical usage [43]. The QT interval is an essential indicator for assessing dofetilide plasma drug concentration, though it has limitations [44]. To address this, ATTIA et al. developed a DL algorithm to assess the relationship between morphological changes in the QTc interval on ECG and plasma concentrations of Dofetilide [45]. The results demonstrated a strong correlation ($r = 0.64$) between the DL-based linear model of QTc and Dofetilide plasma drug concentrations, outperforming methods relying solely on QT intervals for predicting plasma concentrations of Dofetilide. Anticoagulants are widely used for stroke prevention of stroke in AF patients. However, they face challenges in achieving the right balance: insufficient dosages fail to prevent thrombosis, while excessive dosages can cause bleeding complications. The balance increases the complexity of clinical applications. AI offers personalized solutions for anticoagulant therapy for AF patients. Heemoon Lee et al. developed a DNN-based model to predict the international normalized ratio of prothrombin time and created an individualized warfarin dosage-prothrombin time international normalized ratio (PT INR) table generator based on this predictive model [46]. Their results demonstrated that the neural network-based warfarin dosing algorithm outperformed expert doctors in predicting future PT INR values. Cheng Chen et al. utilized logistic regression, random forest, and eXtreme Gradient Boosting (XGBoost)-based ML methods to analyze the risk factors for bleeding and establish corresponding prediction models [47]. The XGBoost model exhibited the highest discriminative power and accuracy in predicting bleeding risk associated with rivaroxaban, benefiting individualized anticoagulation treatment in elderly patients. Poor compliance with anticoagulant medications is a common issue, affecting effectiveness of anticoagulation therapy. Although the introduction of new oral anticoagulants has somewhat improved medication adherence, the enhancement is not noteworthy [48]. LABOVITZ et al. combined smartphones and AI platforms to monitor patients' regular intake of anticoagulant medication [49]. The results showed a 100 % medication adherence in the intervention group, compared to only 50 % in the traditional methods group.

4.7. Current issues and future directions

The keyword analysis reveals that AI has been extensively utilized in monitoring, diagnosing, and treating of AF. However, several challenges persist, and future developments are anticipated based on these identified issues.

(1) The application of AI in managing risk factors and comorbidities associated with AF has not yet gained widespread attention. The 2010 European guidelines for AF management introduced the "upstream therapy" concept, which involved lifestyle modifications and medication to control risk factors such as hypertension, dyslipidemia, and inflammation [50]. This approach aimed to reduce cardiac burden, delay and reverse atrial remodeling, and prevent new-onset AF or its recurrence and progression. Although AI advancements have been made in managing hypertension, diabetes, and obesity, a comprehensive system incorporating these specific risk factors as comorbidities related to AF has not yet been established [51,52].
(2) AF is a complex disease requiring a comprehensive analysis of various test results, including ECG, imaging studies, and coagulation indicators, to develop personalized treatment plans. However, most existing AI models are trained using data from only one aspect, such as AI-ECG, limiting their comprehensiveness in clinical applications and potentially affecting their diagnostic and therapeutic capabilities.

Given these challenges, we have explored future development trends in AI applications for AF. Each AI algorithm possesses unique advantages and limitations; therefore, integrating different AI algorithms and leveraging their strengths is essential to enhance the effectiveness of AI in managing AF risk factors and associated comorbidities. Furthermore, incorporating multidimensional examination results, such as ECG, imaging studies, and laboratory tests, during the training of AI models will improve their diagnostic and therapeutic efficacy, ultimately achieving comprehensive precision management for AF.

5. Limitations

Firstly, this bibliometric analysis exclusively included publications from the WoSCC database, thus excluding publications from other databases such as PubMed and Embase, which might affect the comprehensiveness of the data analysis. Secondly, the study only covered articles published up to October 18, 2023, potentially overlooking recent research findings. Thirdly, despite the three authors' comprehensive review of existing literature to develop search strategies and their collaboration in screening literature related to AI and cardiovascular research, there was a possibility of subjective bias in the selection process. Future research should incorporate multiple databases for a more comprehensive analysis and ensure timely updates with the latest research results to promote better development in this field.

6. Conclusions

The results of the bibliometric analysis indicated that from 2013 to 2023, the number of research publications on the application of AI in AF had rapidly increased, showcasing broad prospects and rapid development in this field. Currently, AI's application in managing the risk of AF complications is a hot mature topic. AI-ECG for AF diagnosis and AI-assisted catheter ablation surgery are the emerging and booming topics. Smart wearables for Real-Time AF monitoring and AI for individualized AF medication are niche and well-developed topics. Future research should focus on the application of AI in controlling risk factors and managing AF complications.

Moreover, integrating multiple tests such as ECGs, imaging examinations, and coagulation indicators into AI model training is necessary to further improve the model's efficiency, aiming for comprehensive and accurate management of AF.

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Data availability statement

All data are reported in the manuscript, references and supplement file therein. For more information, please contact the corresponding author.

CRediT authorship contribution statement

Bochao Jia: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Jiafan Chen:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Yujie Luan:** Writing – original draft, Methodology, Data curation. **Huan Wang:** Methodology, Data curation. **Wei Yi:** Methodology, Data curation. **Yuanhui Hu:** Writing – review & editing, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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