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Research article

Research hotspots and trends of artificial intelligence in rheumatoid arthritis: A bibliometric and visualized study

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Abstract: Artificial intelligence (AI) applications on rheumatoid arthritis (RA) are becoming increasingly popular. In this bibliometric study, we aimed to analyze the characteristics of publications relevant to the research of AI in RA, thereby developing a thorough overview of this research topic. Web of Science was used to retrieve publications on the application of AI in RA from 2003 to 2022. Bibliometric analysis and visualization were performed using Microsoft Excel (2019), R software (4.2.2) and VOSviewer (1.6.18). The overall distribution of yearly outputs, leading countries, top institutions and authors, active journals, co-cited references and keywords were analyzed. A total of 859 relevant articles were identified in the Web of Science with an increasing trend. USA and China were the leading countries in this field, accounting for 71.59% of publications in total. Harvard University was the most influential institution. Arthritis Research & Therapy was the most active journal. Primary topics in this field focused on estimating the risk of developing RA, diagnosing RA using sensor, clinical, imaging and omics data, identifying the phenotype of RA patients using electronic health records, predicting treatment response, tracking the progression of the disease and predicting prognosis and developing new drugs. Machine learning and deep learning algorithms were the recent research hotspots and trends in this field. AI has potential applications in various fields of RA, including the risk assessment, screening, early diagnosis, monitoring, prognosis determination, achieving optimal therapeutic outcomes and new drug development for RA patients. Incorporating machine learning and deep learning algorithms into real-world clinical practice will be a future research hotspot and trend for AI in RA. Extensive collaboration to improve model maturity and robustness will be a critical step in the advancement of AI in healthcare.

Keywords: artificial intelligence; rheumatoid arthritis; hotspots; research; trends

1. Introduction

The ability of a computer system to carry out operations that would typically need human intelligence is known as AI [1]. Technology has recently advanced more quickly than ever, enabling capabilities that were unimaginable in the past [2]. Today's technology allows machines to accomplish things not just as well as people, but frequently even better. The application of AI is widespread in science, and it is also employed in healthcare [3]. Currently, there are potential applications involving AI in almost all areas of healthcare, including the diagnosis of diseases, medical image processing, drug development and estimation and prediction in public health [4–6]. The continuous development of stochastic technologies has led to significant improvements in AI, most notably the introduction of machine learning and deep learning.

RA is the world's second most common autoimmune illness, with the incidence of RA approaching 20 million cases as early as 2019 [7]. As with other immune disorders [8,9], if RA is not identified early and treated in a timely manner, it can lead to degenerative joint abnormalities that begin in the small joints of the extremities and progress to the larger joints [10]. However, current well-established diagnostic criteria for RA are lacking, making diagnoses derived from clinical symptom observations challenging for the identification of early RA [10]. Corticosteroids and nonsteroidal anti-inflammatory medicines are used as first-line treatments for RA, followed by disease-modifying anti-rheumatic pharmaceuticals [11]. Experiments and, more specifically, data analysis have resulted in the medicine we know today. It is therefore important to utilize the vast amount of data available in the most effective way, both for the diagnosis and treatment of RA [12]. By merging machine-like speed and human-like comprehension, AI aids in the achievement of this objective. AI systems might make use of almost any accessible data, including demographic information, electronic health records, omics data, clinical traits, medical pictures and data from wearable technology and sensors [12]. The findings drawn from these inputs may offer us helpful insights into a variety of disease-related topics, including its pathophysiology and epidemiological characteristics. In addition, AI algorithms are able to customize treatment plans for each patient based on their unique biological characteristics and disease state, therefore taking advantage of precision medicine [13].

Bibliometrics, a quantitative research technique for examining the academic qualities of literature, aids in locating research hotspots and trends in a specific area and forecasting its future prospects [14]. Bibliometric methods have been applied to the field of RA research. For the basic research field, the research hotspots and trends of macrophages [15,16], neutrophils [17], mesenchymal stem cells [18], fibroblasts [19] and gut microbiota [20] in RA have been identified by applying bibliometric methods. For the clinical therapeutic area, research hotspots and trends in pharmacologic [21], nonpharmacologic [22] and herbal therapies [23] in RA management were also identified by applying the bibliometric method. In addition, recent bibliometrics have reported cutting-edge hotspots and emerging research trends in RA-associated diseases, including osteoporosis [24] and interstitial lung disease [25]. Therefore, there is no doubt that the application of bibliometrics has contributed to the field of RA research.

Publications on the use of AI in RA have grown in recent years. The increasing number of publications brings challenges along with the promotion of the discipline, as it is difficult to avoid the laborious task of combing through publications while exploring the hotspots and frontiers of research [26]. To the best of our knowledge, no bibliometric study has been performed on an in-depth analyses of research trends in RA-related AI, which has somewhat limited the progress of research in this area. Therefore, to better understand the development and future trends in the field of RA-related AI research, it is important to identify a shift in the research paradigm. For this aim, we introduced bibliometric methods in the present study. Through a bibliometric approach, we aim to map the literature, identify key publications and trends and analyze patterns of collaboration and knowledge dissemination in RA-related AI research areas. Furthermore, the current bibliometric study was carried out to highlight the contributions of leading nations, authorities and notable scholars, as well as to provide a thorough assessment of hotspots and trends in the application of AI in RA.

2. Materials and methods

2.1. Search strategy

The most frequently used database for bibliometric analysis, Web of Science Core Collection, has a huge selection of journal categories. When compared to other databases, the Web of Science Core Collection is regarded as the finest alternative for bibliometric study because it is the most detailed, transparent and extensive [27–29]. We conducted a systematic search of Web of Science on 5 August, 2023 using the strategy as follows: TS = (rheumatoid arthritis OR RA OR arthritis) AND TS = (artificial intelligence OR computational intelligence OR AI OR computer reasoning OR machine learning OR knowledge representation OR knowledge acquisition OR computer vision system). Studies met the following inclusion criteria: (i) Articles were the only type of publications allowed; (ii) articles published from January 1, 2003, to December 31, 2022; (iii) language was limited to English.

2.2. Data acquisition

For further investigation, we downloaded the txt or BibTex formats of complete records and references of the acquired articles. Characteristics of the publication in detailed were recorded from Web of Science, including source, country, institution, author, title, abstract, keywords, number of citations, cited literature, H index and 2022 IF of the top 10 most productive journals. Data extraction was carried out by two independent researchers.

2.3. Bibliometric analysis

Bibliometric analysis was performed using Microsoft Excel 2019, R software (3.5.6) and VOSviewer (1.6.18). In our analysis, the bibliometric analysis's publication count and citation count were summarized using Microsoft Excel. An R package called Bibliometrix has a number of functions for conducting quantitative scientometric research. To determine the annual cumulative occurrences of the top keywords/terms and to create a three-field plot of the Keywords Plus analysis, Bibliometrix was used to calculate the frequency of international cooperation. With the same hue denoting better correlation between nodes, the distance-based bibliometric tool VOSviewer groups a collection of closely connected nodes into clusters. A co-citation network was created using VOSviewer to examine the references in the publications, and a co-occurrence network was created to show the relationships between the keyworks. Furthermore, the international cooperation between nations was represented using a bibliometric tool available online (https://bibliometric.com/).

3. Results

3.1. Annual growth trend

There have been 859 articles (Figure 1) published during the past 20 years discussing the use of AI in RA. Generally speaking, the number of publications increased, from 2 in 2003 to 217 in 2022 (Figure 2A). The number of articles published over the previous five years peaked in 2018 with 71.59% (615/859) of the total articles published. The exponentially fitted curve, with an R^2 value of 0.861, showed that study in this field will be expanded (Figure 2B). The quantity of yearly publications aids in revealing the general direction of connected research.

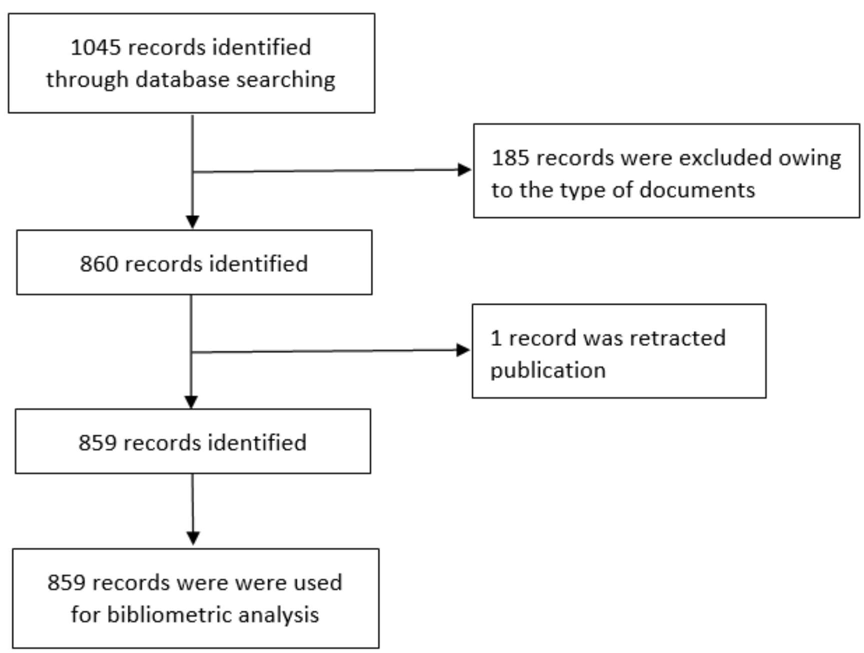

Figure 1. Flow diagram of the literature selection process.

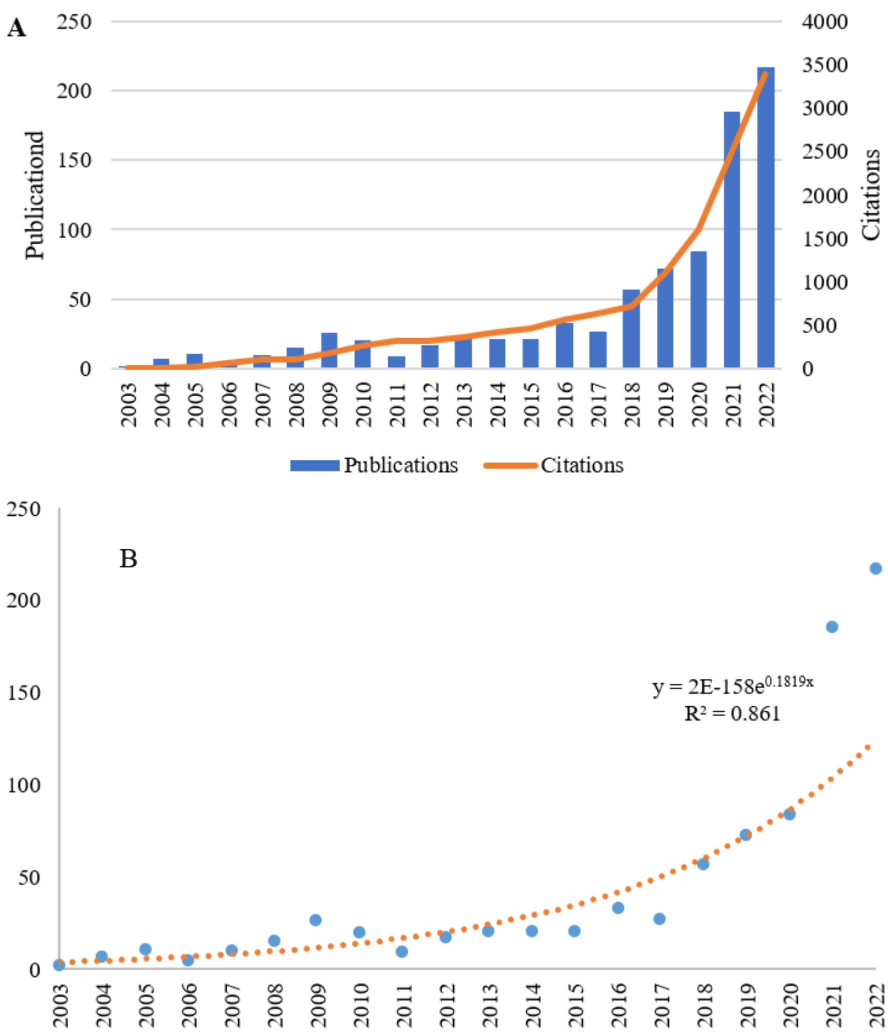

Figure 2. (A) Times cited and publications over time. (B) Curve fitting of the of the annual growth trend of publications.

3.2. Analysis of countries

The top ten most productive countries are listed in Table 1. With 240 articles, the USA came out on top in terms of output. China came in second with 197 publications, and England came in third with 85 publications. The USA had the most citations overall, whereas England had the most average citations per publication. There is extensive international scientific collaboration, with USA and China collaborating the most frequently, followed by England, Germany, France, Canada and Korea (Figure 3).

Table 1. The top 10 productive countries/regions.

Ranking	Country/Region	Publications	% of (859)	Total citations	Average citations	H-index
1	USA	240	27.94	5356	22.32	39
2	China	197	22.93	2766	14.04	29
3	England	85	9.90	2428	28.56	25
4	Germany	64	7.45	1189	18.58	20
5	Canada	63	7.33	1314	20.86	20
6	France	43	5.00	704	16.37	14
7	Indian	43	5.00	749	17.42	15
8	Spain	43	5.00	830	19.30	13
9	Italy	42	4.89	970	23.10	17
10	Korea	42	4.89	344	8.19	11

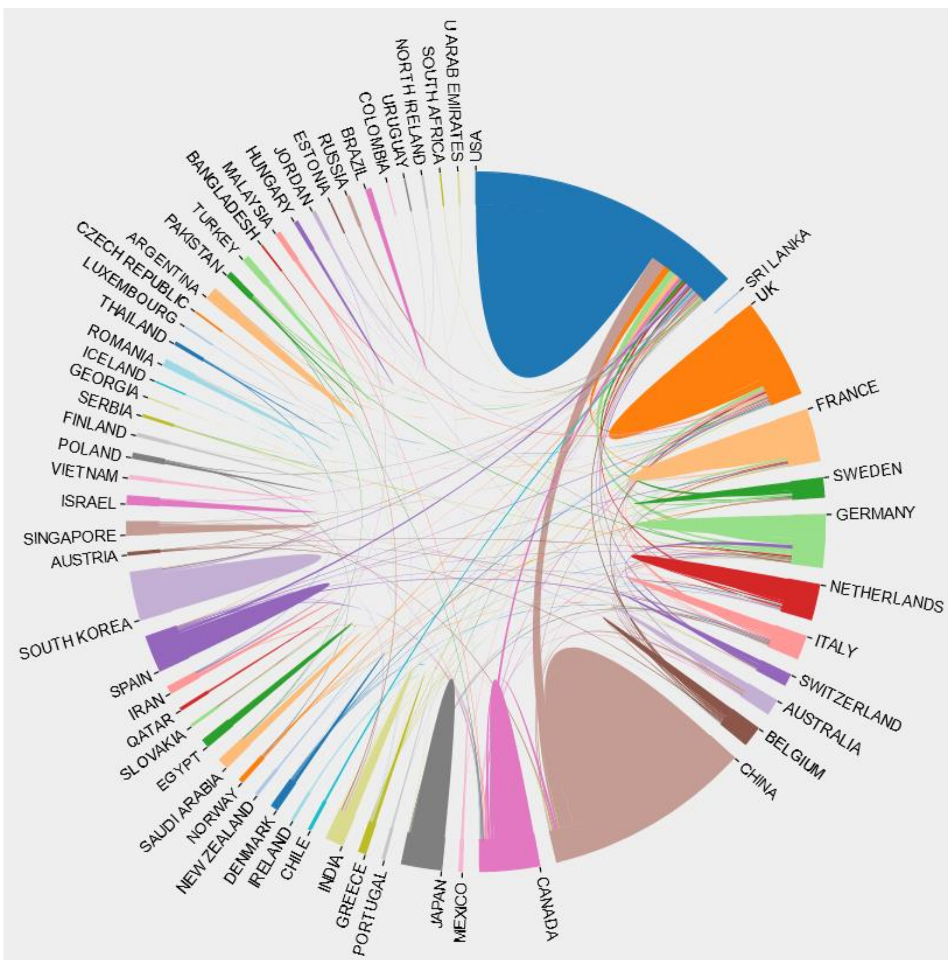

Figure 3. International collaboration between countries.

In addition, considering the potential impact that economic factors may have on the development of RA-related AI research fields, we obtained gross national income data of 2022 from the World Bank (https://wdi.worldbank.org/table/WV.1) for the top ten most productive countries and conducted a Spearman correlation analysis between gross national income and the number of publications. The surprising results (Figure 4) suggested that the gross national income of the top ten most productive countries showed a positive correlation with the number of publications ($P < 0.05$).

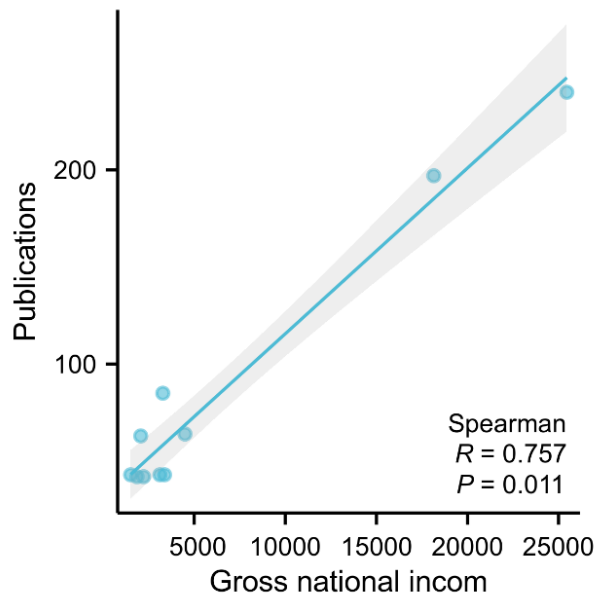

Figure 4. Correlation between gross national income ($ billions) and number of publications in the top 10 productive countries.

3.3. Analysis of institutions

The top ten producing institutions are listed in Table 2. With 39 articles, Harvard University came out on top in terms of output, the University of California System in second with 25 publications and Brigham & Women's Hospital came in third with 24 publications. The most articles were cited overall by Harvard University, and the most citations per publication were made by University of Toronto. Extensive research cooperation exists between different institutions, with cooperation between Women's Hospital, Harvard Medical School and tBoston Childres Hospital being the most frequent, followed by cooperation between University of Toronto and University of Calgary (Figure 5).

Table 2. The top 10 productive affiliations.

Ranking	Affiliation	Country	Publications	Total citations	Average citations	H-index
1	Harvard University	USA	39	993	25.46	15
2	University of California System	USA	25	584	23.36	13
3	Brigham & Women's Hospital	USA	24	529	22.04	11
4	Udice French Research Universities	France	22	394	17.91	11
5	Harvard Medical School	USA	21	521	24.81	10
6	University of London	England	20	871	43.55	12
7	Institut National de la Sante et de la Recherche Medicale	France	18	319	17.72	10
8	University of Toronto	Candad	15	674	44.93	11
9	Egyptian Knowledge Bank	Egypt	14	214	15.29	7
10	Mayo Clinic	USA	14	245	17.50	7

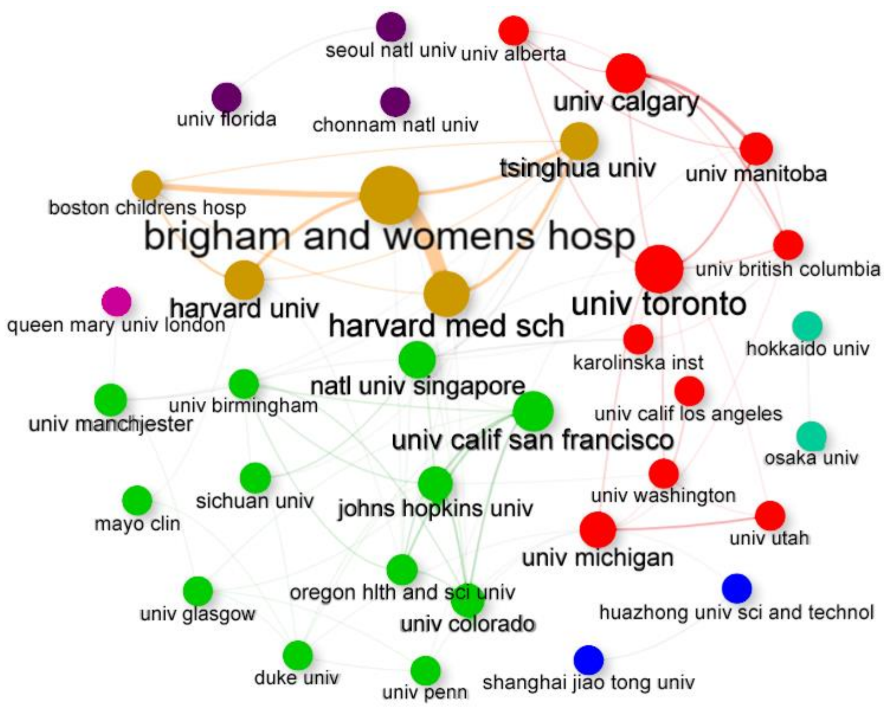

Figure 5. Collaboration between institutions.

3.4. Analysis of journals

The top ten most prolific journals are listed in Table 3. With 21 publications, Arthritis Research & Therapy and Frontiers in Immunology led the pack in terms of output, followed by Scientific Reports, PLoS One and Rheumatology. The journal with the most overall, average and impact factors was Annals of the Rheumatic Diseases. Furthermore, the top five most productive journals have seen a significant increase in the number of annual publications over the last five years (Figure 6).

Table 3. The top 10 most active journals.

Ranking	Journal	Publications	Total citations	Average citations	2022 IF
1	Arthritis Research & Therapy	21	343	16.33	4.9
2	Frontiers in Immunology	21	187	8.90	7.3
3	Scientific Reports	14	173	12.36	4.6
4	PLoS One	13	211	16.23	3.7
5	Rheumatology	13	317	24.38	5.5
6	Arthritis Rheumatology	12	547	45.58	13.3
7	Annals of the Rheumatic Diseases	11	696	63.27	27.4
8	Arthritis Care Research	10	160	16.00	4.7
9	Frontiers in Medicine	10	51	5.10	3.9
10	Journal of Rheumatology	10	346	34.6	3.9

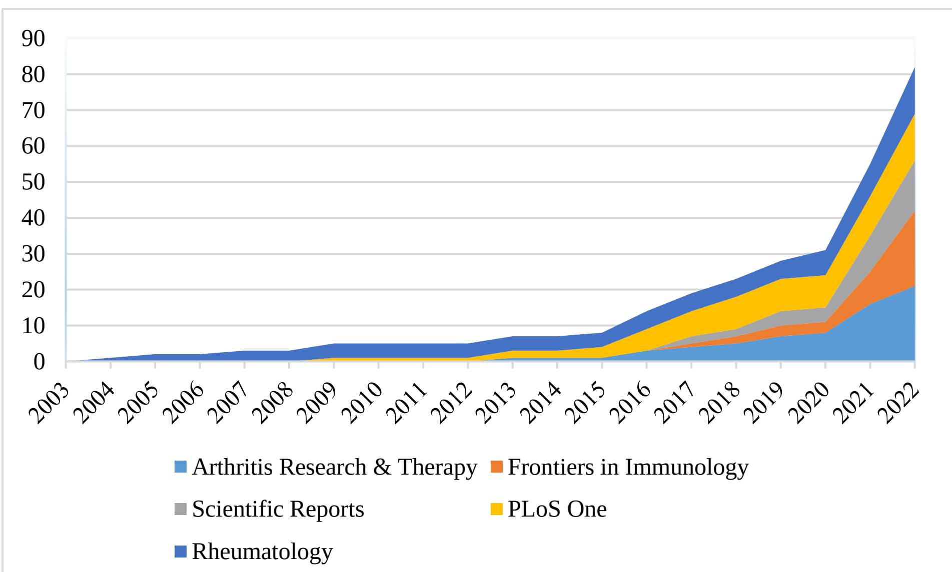

Figure 6. Publications of the top 5 most active journals over time.

3.5. Analysis of co-cited references

A total of 20,625 references were found to be co-cited. The 54 co-cited references discovered after lowering the threshold to 5 citations created a network of 3 clusters (Figure 7). The development and validation of AI models was the main focus of cluster 1 (in red), the application of AI models was the main focus of cluster 2 (in green) and the use of AI models in the field of healthcare was the main focus of cluster 3 (in blue).

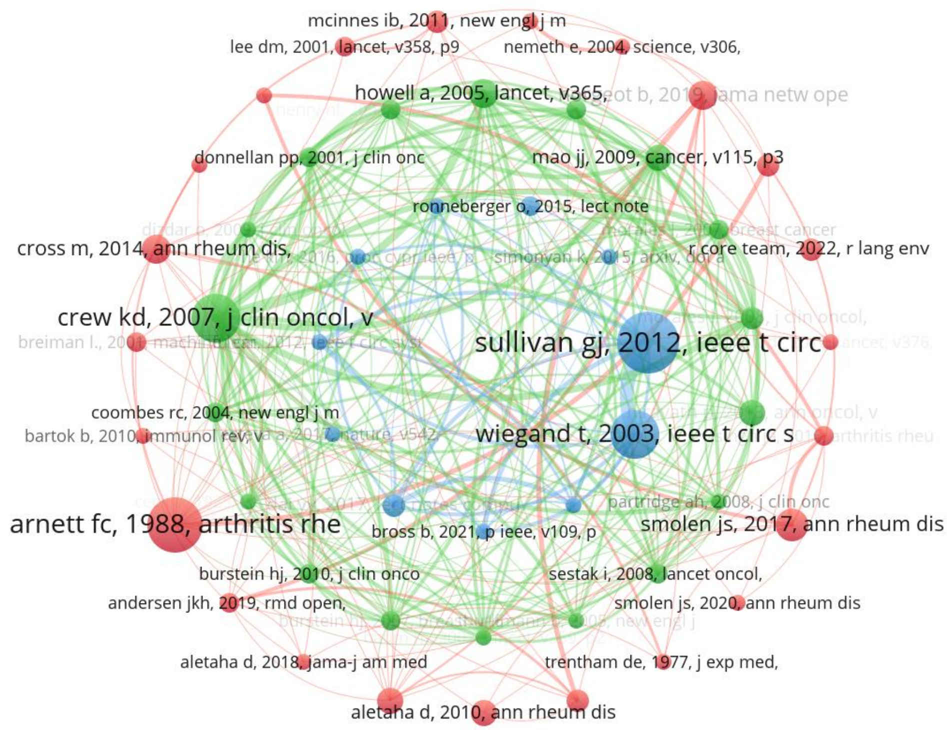

Figure 7. Network map of co-cited references.

3.6. Analysis of hotspots and trends

A total of 1976 keywords were obtained. The 97 co-occurrence keywords discovered after lowering the threshold to 5 clustered together in a network (Figure 8A). Cluster 1 (in red) primarily centered on the application of AI models in early clinical diagnosis and prognosis of RA, the application of on AI in drug development and precision therapy was the main focus of cluster 2 (in green), the common use of AI technologies in RA was the main focus of cluster 3 (in yellow), the role of AI assessment in the clinical management of RA was the main focus of cluster 4 (in blue) and the use of AI in identifying pathogenic risks of RA was the main focus of cluster 5 (in purple). It was worth noting that “deep learning” and “machine learning” were recent emerging hot topics (Figure 8B).

A

B

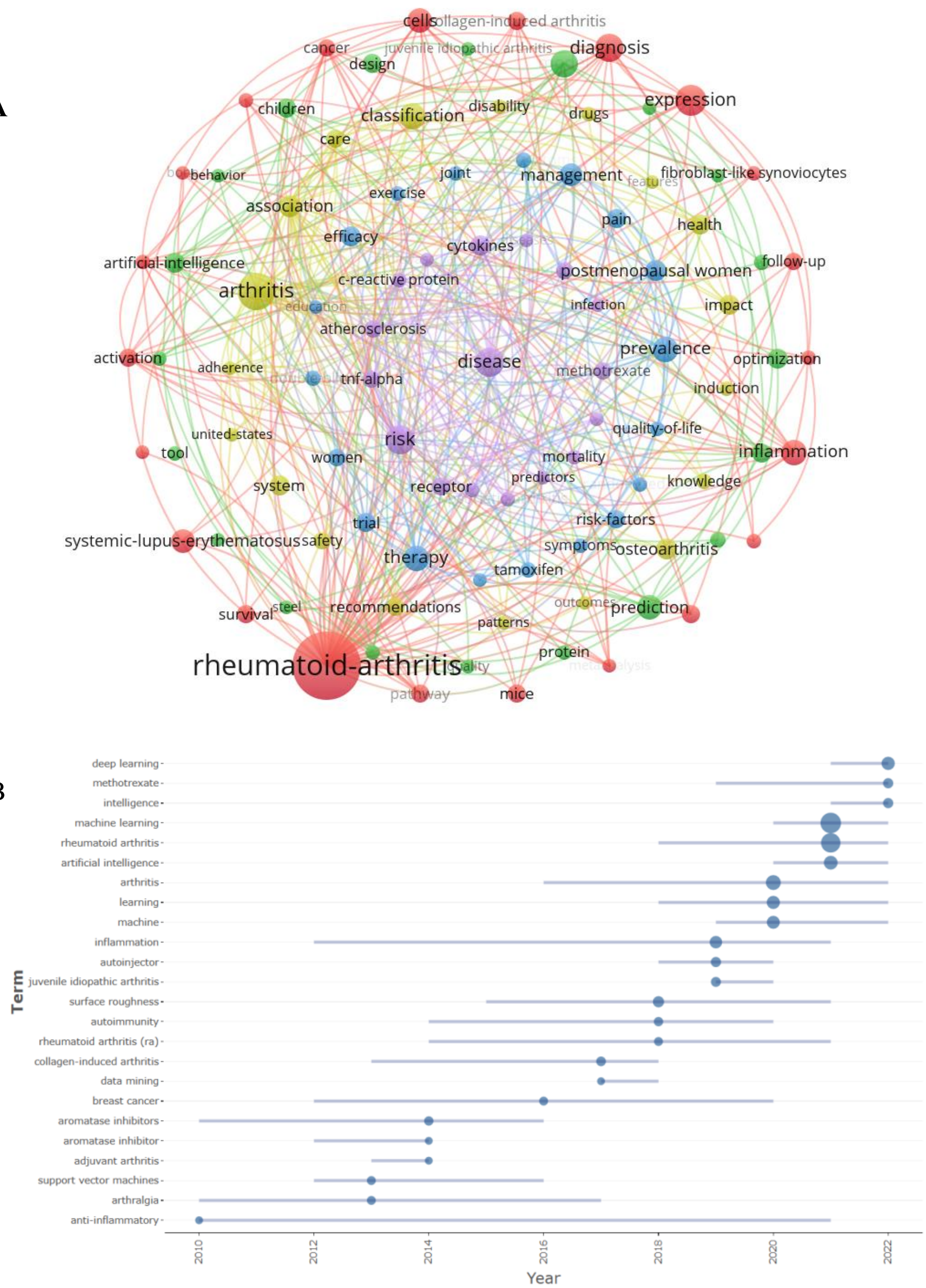

Figure 8. (A) Network map of keywords on AI in RA. (B) Trend of Topics over time.

4. Discussion

The application of AI in RA during the previous 20 years was examined in this bibliometric analysis study. Over the past two decades, especially after 2018, articles on this topic have shown an upward tendency. The increased understanding of the significance of AI in health and the corresponding rise in research funding in this field may be a driving factor behind the expansion of research [27]. The sharp rise in annual publications since the last five years can be attributed to advances in AI technology. Based on current trends, annual publications are anticipated to keep growing.

The majority of the relevant publications in our analysis were published in nations such as the USA, China, Germany and England. Bibliometric research in other disciplines, such as intensive care medicine [28], cancers [29] and neurology [30], have shown similar tendencies. The financial standing of a country has a significant impact on academic competence [31]. A further significant predictor of the results of medical research may be government spending on healthcare [32]. With USD 10,202 spent on healthcare per person, the USA outspends any other nation [33], which may help to explain why there are more publications there. Given the USA has made a significant contribution to this academic field and because the majority of partnerships on AI in RA research are similarly focused on the USA, there is a clear need for increased international collaboration with the USA.

The majority of the pertinent publications were published by affiliations from nations including the United States, China, Germany and France, which is consistent with the findings of the contributions of various nations. Furthermore, authors from economically developed nations like China, the United States and Canada contributed the majority of the pertinent papers. The fact that collaborative efforts comprised the majority of the pertinent articles in this sector suggests that interinstitutional collaboration is a key tactic for boosting the quantity and quality of publications.

Understanding current trends can be aided by looking at the characteristics of worldwide peer-reviewed journals [34,35]. The top 10 most active journals in this discipline are largely composed of publishers from the USA and Western Europe. Arthritis Research & Therapy is the most productive journal in this field of research. Not surprisingly, the journal also has the highest number of articles in other RA-related academic areas, as it is itself a special issue on the subject of RA. Contrarily, there are no publishers established in East Asia, despite the fact that China and Japan contributed significantly to AI-related RA research. This discovery emphasizes how crucial it is for Asia to produce significant international journals. The IF of journals is an important evaluative metric. No statistically significant correlations between the quantity of articles and IF, on the other hand, were discovered, suggesting that journals may employ various strategies to determine the significance of their study. Several articles are published in some journals, yet high-quality publications with lots of citations and high IF values are preferred by other journals.

The advancement of medicine benefits from the use of AI [36,37]. One of the primary approaches in bibliometric analysis is that hotspots describe a scientific topic in a particular study field over a specified time period [38]. AI has shown promise in a variety of areas of RA based on the author's keywords in the recognized categories. To estimate the risk of developing RA, diagnose RA using sensor, clinical, imaging and omics data, identify the phenotype of RA patients using electronic health records, predict treatment response, track the progression of the disease and predict prognosis and develop new drugs, AI models are commonly used [39–41]. An increasing corpus of research has been identified to support the idea that AI could revolutionize the methods for diagnosing, treating and screening patients with RA. It is critical to take into account the challenges that AI introduces in healthcare because any decision made in this setting could have disastrous implications.

AI-based algorithms are promising for revealing mechanisms of disease occurrence, early diagnosis of diseases and exploring mechanisms of drug action [42–44]. Applying AI models to health care is hindered by a number of technological issues. Small training datasets might cause overfitting of the model while developing supervised models. In light of this, a significant challenge is the requirement for vast quantities of data that are appropriately categorized. A solution to this problem is the development of sizable, excellent open databases. Furthermore, accuracy metrics given in academic articles might only reflect model performance in datasets from certain populations and may not offer results that can be extrapolated to other populations [45]. Various healthcare facilities may use different data collection techniques, coding and patient populations. The extensive clinical applicability of AI models is constrained by these variational factors [46]. Models created using multicenter or even globally shareable datasets would therefore have a wider range of clinical applications. In addition, algorithmic bias and the intent behind the development of AI algorithms should also be considered as potential challenges to the implementation of AI in healthcare [47,48]. Therefore, it is crucial to ensure adherence to guideline specifications for model development in AI research. The “Good Practice in Digital and Data-Driven Health Technologies” guidelines published by the UK’s National Health Service [49] and Checklist for Artificial Intelligence in Medical Imaging [50] are noteworthy examples.

Limitations should be acknowledged. First, the data were retrieved solely from the Web of Science Core Collection, which may have biased the results of this study. Second, limiting the keyword search for topic (TS) may be the major reason for the small size of the final set and may also result in missing a portion of relevant studies. Third, due to language preference, some keywords may not be included in the search formula and thus may also lead to compromised integrity of the search results.

5. Conclusions

AI has potential applications in various fields of RA, including the risk assessment, screening, early diagnosis, monitoring, prognosis determination, achieving optimal therapeutic outcomes and new drug development for RA patients. Incorporating machine learning and deep learning algorithms into real-world clinical practice will be a future research hotspot and trend for AI in RA. Extensive collaboration to improve model maturity and robustness will be a critical step in the advancement of AI in medicine.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Authors' contributions

Di Zhang and Bing Fan conceived the topic and drafted the manuscript. They are the co-first authors. Liu Lv, Da li, Huijun Yang and Ping Jiang collected the references and wrote the manuscript. The revision of the manuscript was completed by Fangmei Jin. All authors read, critically reviewed and approved the final manuscript.

Conflict of interest

The authors declare there is no conflict of interest.

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