Breast Cancer Research

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Decoding breast cancer imaging trends: the role of AI and radiomics through bibliometric insights

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Abstract

Background Radiomics and AI have been widely used in breast cancer imaging, but a comprehensive systematic analysis is lacking. Therefore, this study aims to conduct a bibliometrics analysis in this field to discuss its research status and frontier hotspots and provide a reference for subsequent research.

Methods Publications related to AI, radiomics, and breast cancer imaging were searched in the Web of Science Core Collection. CiteSpace plotted the relevant co-occurrence network according to authors and keywords. VOSviewer and Pajek were used to draw relevant co-occurrence maps according to country and institution. In addition, R was used to conduct bibliometric analysis of relevant authors, countries/regions, journals, keywords, and annual publications and citations based on the collected information.

Results A total of 2,701 Web of Science Core Collection publications were retrieved, including 2,486 articles (92.04%) and 215 reviews (7.96%). The number of publications increased rapidly after 2018. The United States of America ($n = 17{,}762$) leads in citations, while China ($n = 902$) leads in the number of publications. Sun Yat-sen University ($n = 75$) had the largest number of publications. Bin Zheng ($n = 28$) was the most published author. Nico Karssemeijer ($n = 72.1429$) was the author with the highest average citations. "Frontiers in Oncology" was the journal with the most publications, and "Radiology" had the highest IF. The keywords with the most frequent occurrence were "breast cancer", "deep learning", and "classification". The topic trends in recent years were "explainable AI", "neoadjuvant chemotherapy", and "lymphovascular invasion".

Conclusion The application of radiomics and AI in breast cancer imaging has received extensive attention. Future research hotspots may mainly focus on the progress of explainable AI in the technical field and the prediction of lymphovascular invasion and neoadjuvant chemotherapy efficacy in clinical application.

Keywords Breast neoplasms, Radiomics, Artificial intelligence, Medical imaging

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Background

According to the Global Cancer Statistics 2022 report, the incidence (11.6%) and mortality (6.9%) of breast cancer rank first among malignant tumors in women worldwide [1]. Detection and diagnosis of early lesions can reduce the mortality of breast cancer [2, 3]. Generally, pathological biopsy of breast tissue is the gold standard for the diagnosis of breast cancer. However, this examination is invasive [4]. Therefore, non-invasive medical imaging has been gradually applied in the screening and diagnosing breast cancer and plays an increasingly important role [5, 6]. However, due to the heterogeneity of tumors and reliance on subjective factors, the sensitivity and specificity of medical imaging are still insufficient [7].

The emergence of radiomics and artificial intelligence (AI) has improved the accuracy of detection, classification, and diagnosis of breast lesions, which is conducive to the implementation of precision medicine for breast cancer [5, 8]. Radiomics can extract multiple quantitative features from single or multiple medical imaging modalities to enhance the detective and predictive potential of medical imaging and improve cancer diagnosis and prognosis [9]. However, radiomics still needs to improve regarding high generalization and reproducibility during model development [10, 11]. Therefore, radiomics is usually combined with AI and uses deep learning to overcome its limitations and improve model performance [12, 13]. The applications of radiomics and AI in breast cancer imaging are emerging, so it is necessary to analyze this field systematically. It is beneficial to reveal research hotspots and inform future research efforts.

Bibliometrics is a method that uses statistical techniques to quantitatively analyze many publications and their metadata in a specific field [14]. Compared with other reviews, bibliometrics with vivid charts can show this field's research status and development trend more intuitively by visualizing different authors, institutions, countries, journals, and keywords [15]. While relevant studies regarding bibliometric analysis for breast cancer exist, they do not investigate the application of AI and radiomics [16, 17]. Therefore, this study aims to comprehensively analyze the prospects and challenges of AI and radiomics in breast cancer imaging and provide a reference for future related research.

Materials and methods

Data source and search strategy

We searched on the Web of Science Core Collection (WoSCC), Science Citation Index Expanded (SCI-E), using its advanced search module, searching by the combination of "breast cancer", "medical imaging", "AI", and "radiomics". The search strategy is detailed in the supplementary materials. The search was dated up to August 10, 2024. The publication type was article or review, and the study language was English. All data was extracted from WoSCC on August 10, 2024; no ethics statement or approval was required.

Data processing

To ensure the quality of the included publications, two researchers independently screened the retrieved publication according to the title, abstract, and keywords. They excluded publications that were not related to the topic. When the two researchers disagreed, a third researcher was used to facilitate an agreement. The final exported data included the title, keywords, author, institution, address, abstract, and publication time of each publication. A detailed study flow chart is provided in Fig. 1.

Data analysis and visualization

R (version 4.4.1), CiteSpace (version 6.3.R3 Advanced), VOSviewer (version 1.6.20), and Pajek (version 5.19) were used to carry out data processing and visualization analysis. The chart of annual publications, citations and the contribution of the author, countries/regions, journals in this field were analyzed by ggplot2. The bibliometrix (R package) draws graphs related to institutions, references, and keyword trend topics to explore the evolution trend of research hotspots [18]. CiteSpace was used to draw the keyword co-occurrence map, timeline map, and keyword citation burst map to analyze the research content and hotspots and draw the collaborative network of authors to show the author's cooperation [19]. In addition, VOSviewer and Pajek were used to map the relationship network between institutions and countries to visually display the cooperative relationship in the field [20, 21].

Results

Annual publications and citations

Figure 2A shows the evolution trend of the number of publications and citations of AI and radiomics in breast cancer imaging from 2008 to August 2024. A total of 2,701 publications from WoSCC were retrieved, including 2,486 articles (92.04%) and 215 reviews (7.96%). From 2008 to 2023, the number of publications and citations has increased annually. The growth trend increased more rapidly since 2018.

Distribution of publications

In terms of publications (Fig. 2B), Bin Zheng ($n = 28$) is the author with the most publications, followed by Hui Li ($n = 26$) and Pinker, Katja ($n = 24$). Table 1 shows the number of publications of the top 25 institutions. Sun Yat-sen University ranks first with 75 related publications, followed by Fudan University ($n = 74$). Figure 2C shows that China has published 902 publications, ranking first, followed by the United States of America (USA)

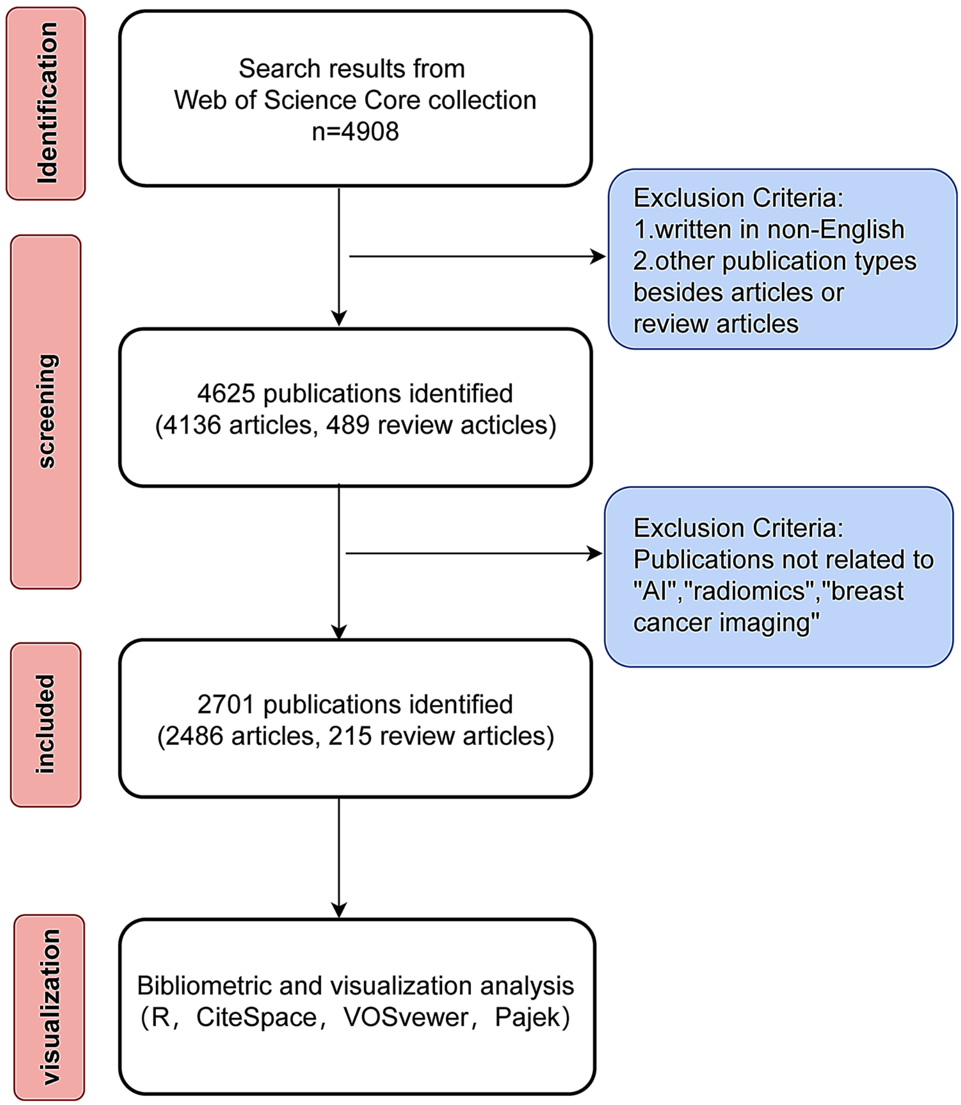

Fig. 1 Flowchart of the search strategy in the study

(360 publications), and India (251 publications). Detailed data on the top 40 countries/regions for publication volume can be found in Table S1.

Distribution of citations

In terms of citations, Nico Karssemeijer ($n = 72.1429$) is the author with the highest average citations, followed by Maryellen L.Giger ($n = 70.2174$), Maciej A. Mazurowski ($n = 66.1111$) (Fig. 2B). As shown in Fig. 2D, the USA ranked first with 17,762 citations, followed by China ($n = 16{,}634$). Detailed data on the top 40 countries/regions for citations is shown in Table S2. Table 2 shows the top 15 most cited publications. As Table 2 shows, the study found that the publication "International Evaluation of an AI System for Breast Cancer Screening" by Scott Mayer McKinney in 2020 received the highest number of citations (1,354 times). This was followed by Thijs Kooi's publication in 2016, "Large Scale Deep Learning for Computer-Aided Detection of Mammographic Images" which was cited 657 times.

Distribution of Cooperation

Figure 3A shows the collaboration of authors. For example, Heng Ma, Ning Mao, and Hanzhu Xie cooperated closely with each other. In Fig. 3B, this study observes institutions' collaboration by clusters. For example, Sun Yat-sen University and Guangzhou University of Chinese Medicine cooperate closely. Fudan University and Shandong University also cooperate closely. According to the cooperation network of countries/regions shown in Fig. 3C, most publications are concentrated in Asian, North American, and European countries. The country with the highest proportion of single-country publications (SCP) is India ($n = 88.4\%$), followed by China with

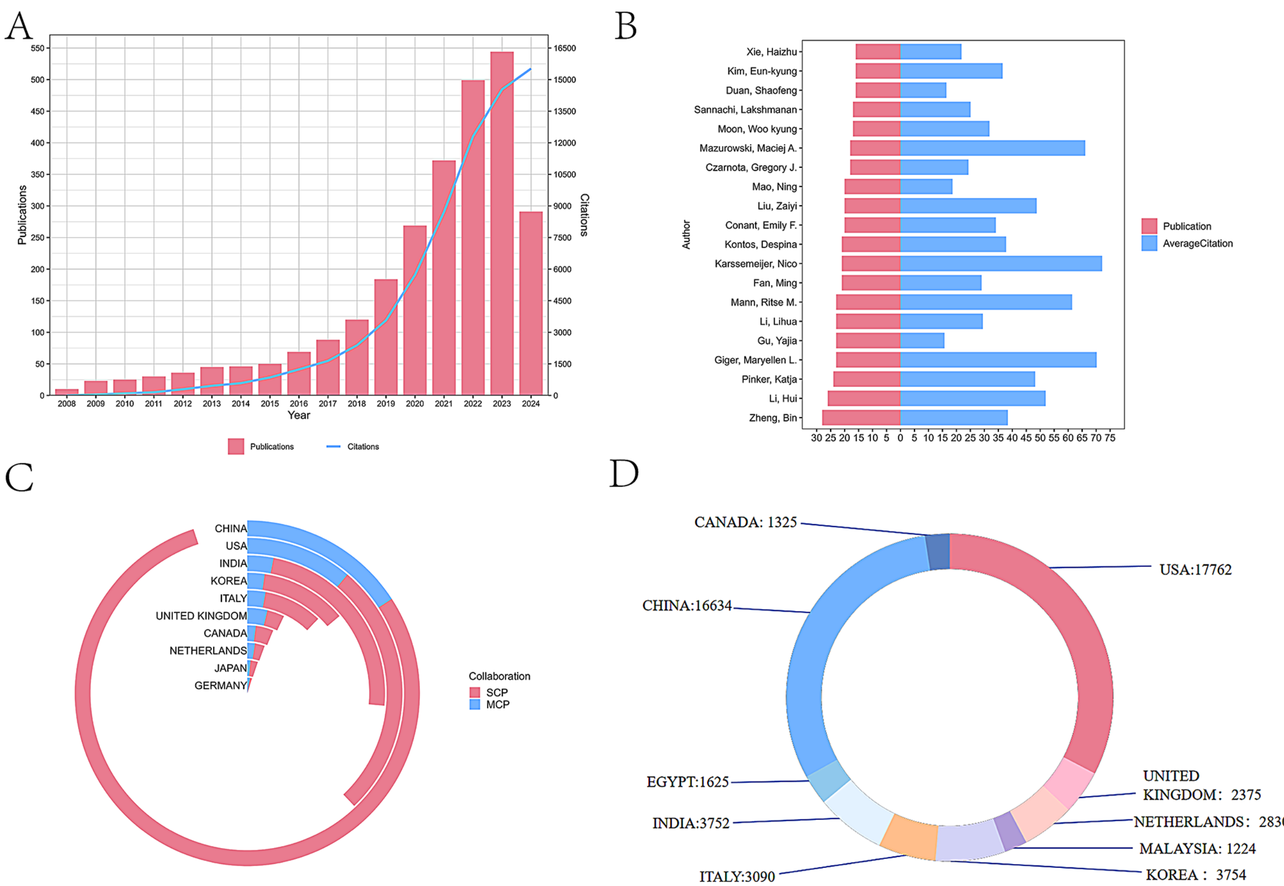

Fig. 2 Publications and citations contribution graph. (**A**) Chart of the trend of publications and citations from 2008 to August 2024. The line shows trends in citations, and the bar shows trends in publications. (**B**) Map of publications and average number of citations by authors in the top 20 publications. (**C**) Chart of corresponding author's countries/regions, categorized by single country publication (SCP) and multiple country publication (MCP). (**D**) Map of the top 10 countries/regions for citations

83.4%. In contrast, European countries demonstrate a higher proportion of multi-country publications (MCP), with Germany having the highest MCP ratio of 56.5% and the United Kingdom following closely with 53.7% (Fig. 2C).

Analysis of journals

Figure 4A shows the impact factor (IF), local citations, and the number of publications of the top 15 journals in the number of publications in this field. Among them, "Frontiers in Oncology" has published 140 related publications, ranking first, followed by "European Radiology" ($n = 84$). "Radiology" has the highest IF (IF = 12.1), followed by "Computers in Biology and Medicine"(IF = 7). Figure 4B shows the trend of the number of publications of the top ten journals over time. Since 2020, the number of "Frontiers in Oncology" publications has increased rapidly.

Analysis of keywords and hotspots

This study analyzed keyword co-occurrence and visualized the results (Fig. 5A). Breast cancer (1,310 times) was the keyword with the highest frequency, followed by deep learning (551 times) and classification (517 times). In Fig. 5B, a total of seven clusters were identified, each representing a specific research direction. Those clusters represented radiomics, neoadjuvant chemotherapy (NAC), machine learning, breast cancer, axillary lymph node, texture analysis, and deep learning. In recent years, radiomics, NAC, and deep learning have continuously progressed in the timeline view (Fig. 5B). Figure 5C illustrates the trend in topics from 2008 to August 2024, highlighting the time range and frequency of the author's keywords. In the past two years, the focus has shifted to lymphovascular invasion (LVI), NAC, explainable AI, and attention mechanism. Meanwhile, Fig. 5D presents the top 50 keywords with the strongest citation bursts. In the past year, terms such as AI, pathological complete response, lymph node metastasis, NAC, and attention mechanism have shown significant increases in citation intensity.

Table 1 The publications and citations of the top 25 most published institutions

Rank	Institution	Publications	Total Citations	Average Citations
1	Sun Yat-sen University	75	1,974	26.32
2	Fudan University	74	1,765	23.8514
3	Southern Medical University	57	1,394	24.4561
4	Chinese Academy of Sciences	56	2,595	46.3393
5	Memorial Sloan Kettering Cancer Center	50	2,252	45.04
6	China Medical University	47	1,025	21.8085
7	Radboud University	45	2,833	62.9556
8	Shanghai Jiao Tong University	40	496	12.4
9	Yonsei University	38	1,134	29.8421
10	Nanjing Medical University	36	407	11.3056
11	Medical University of Vienna	35	1,640	46.8571
12	Qingdao University	35	436	12.4571
13	The University of Chicago	35	1,919	54.8286
14	University of Pennsylvania	31	1,123	36.2258
15	Zhejiang University	30	774	25.8
16	GE HealthCare	29	539	18.5862
17	Guangdong Academy of Medical Sciences	28	1,347	48.1071
18	Huazhong University of Science and Technology	28	770	27.5
19	University of Pittsburgh	28	1,439	51.3929
20	Harbin Medical University	27	408	15.1111
21	South China University of Technology	27	536	19.8519
22	Hangzhou Dianzi University	26	699	26.8846
23	Northeastern University	26	728	28
24	Shandong University	25	857	34.28
25	The University of Oklahoma	25	953	38.12

Discussion

A bibliometric study of AI and radiomics in breast cancer imaging was conducted in this study, including 2,701 publications as of August 10, 2024. The number of publications and citations has increased annually from 2008 to 2023. The hotspot and frontier of AI and radiomics in breast cancer imaging can be divided into two levels. Deep learning and explainable AI are at the technical level, while LVI and NAC are at the clinical application level.

Nico Karssemeijer, Maryellen L.Giger, and Maciej A. Mazurowski are the top three authors with average citations. This indicates that they greatly influence the field, and their publications can provide important insights for follow-up research. "Radiology" is the journal with the highest IF. It reflects its academic status and influence in the field. It is worth looking forward to more publications in such an excellent journal in the future.

The majority of the top 10 countries in publication volume are Western nations, which can be attributed to several factors. In these countries, higher rates of protein-truncating variants in breast cancer risk genes, such as those seen in white women, contribute to an increased incidence of cancer due to more frequent early detection through screening [22]. Additionally, the strong economic infrastructure in developed countries supports greater investment in research, fostering more advanced progress in the field. Notably, while both China and the USA show comparable citation counts, China's substantially higher publication volume leads to a lower average citation per paper than the USA. This suggests a need for greater influence and impact in Chinese research and highlights the challenge of balancing quantity with quality. Although the number of publications from China has surged in recent years, the citation growth may take several more years to catch up [23].

From the perspective of collaboration, compared with China and India, European countries generally have higher rates of MCP and prefer international cooperation. This may be attributed to the physical proximity of neighboring countries and municipal transportation infrastructure that supports collaboration. It makes communication between them convenient. In addition, data-sharing policies between European countries have fostered closer collaboration across Europe [24]. The study also found that publications with high IF are often published collaboratively by different institutions and countries/regions [25–27]. Collaboration between institutions and countries/regions can collect large amounts of imaging data in this field and stimulate the collision of thinking. However, especially in transnational cooperation, researchers need to overcome data-sharing policy constraints to improve model generalization while maintaining local applicability.

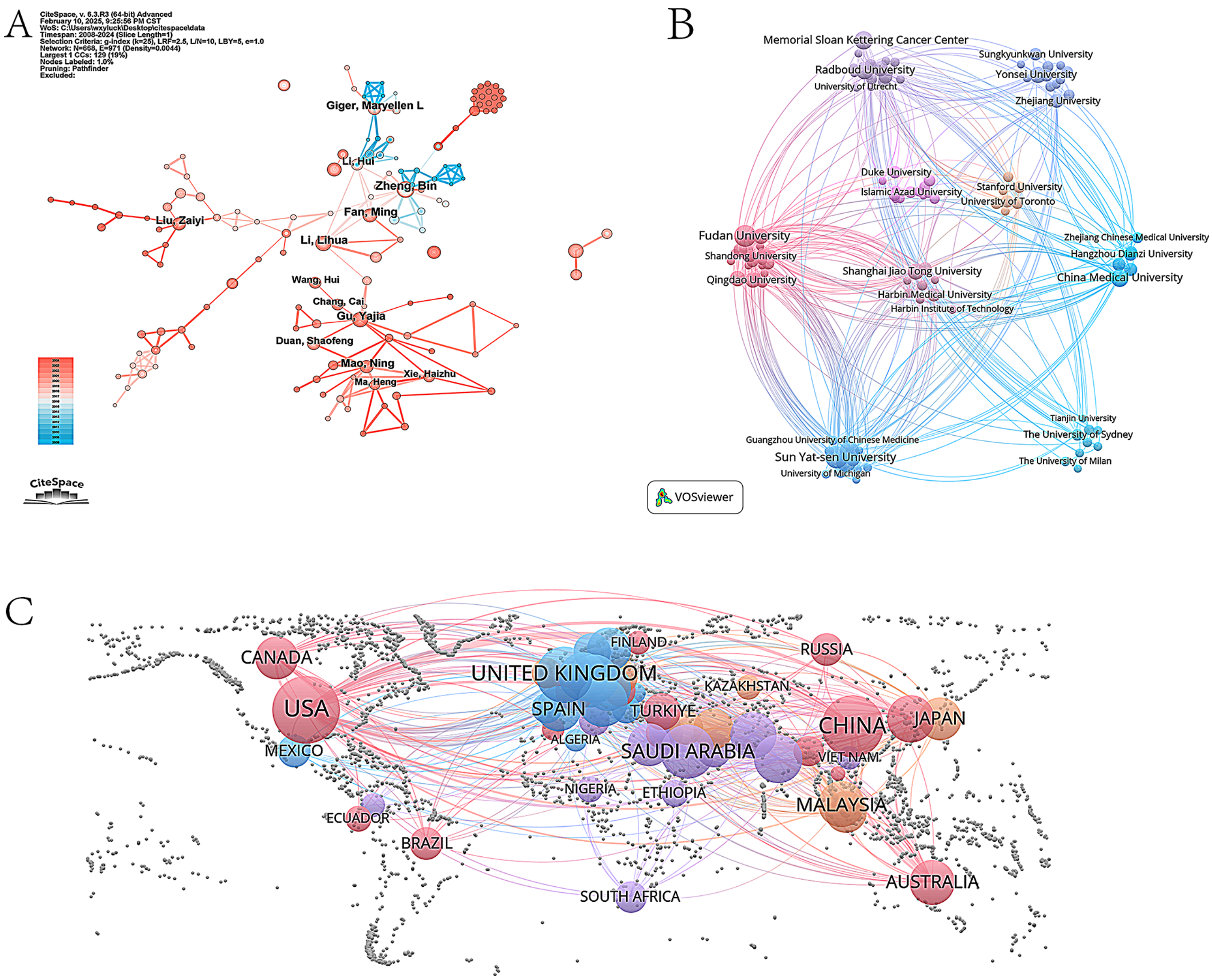

Fig. 3 Collaborative network of authors, institutions, and countries/regions. (**A**) A collaborative network of authors. Each node represents each author, the size of the nodes reflects the number of publications, and the lines connecting the nodes indicate the collaboration between the authors. (**B**) A collaborative network of institutions. (**C**) Network of countries/regions' co-authorship analysis

Table 2 List of the top 15 most cited publications

Author	Journal	IF(2023)	Publication Year	Total Citations	Citations per year	DOI
MCKINNEY SM	Nature	50.5	2020	1,354	225.67	https://doi.org/10.1038/s41586-019-1799-6
KOOI T	Medical Image Analysis	10.7	2017	657	73	https://doi.org/10.1016/j.media.2016.07.007
CHENG HD	Pattern Recognition	7.5	2010	503	31.44	https://doi.org/10.1016/j.patcog.2009.05.012
SHEN L	Scientific Reports	3.8	2019	458	65.43	https://doi.org/10.1038/s41598-019-48995-4
BRAMAN NM	Breast Cancer Research	6.1	2017	447	49.67	https://doi.org/10.1186/s13058-017-0846-1
RIBLI D	Scientific Reports	3.8	2018	414	51.75	https://doi.org/10.1038/s41598-018-22437-z
LEE RS	Scientific Data	5.8	2017	406	45.11	https://doi.org/10.1038/sdata.2017.177
YALA A	Radiology	12.1	2019	379	54.14	https://doi.org/10.1148/radiol.2019182716
AGGARWAL R	NPJ Digital Medicine	12.4	2021	369	73.8	https://doi.org/10.1038/s41746-021-00438-z
ZHENG XY	Nature Communications	14.7	2020	367	61.17	https://doi.org/10.1038/s41467-020-15027-z
WU N	IEEE Transactions on Medical Imaging	8.9	2020	366	61	https://doi.org/10.1109/TMI.2019.2945514
LI H	Radiology	12.1	2016	361	36.1	https://doi.org/10.1148/radiol.2016152110
RODRIGUEZ-RUIZ A	Radiology	12.1	2019	342	48.86	https://doi.org/10.1148/radiol.2018181371
RODRIGUEZ-RUIZ A	Journal of the National Cancer Institute	10	2019	336	48	https://doi.org/10.1093/JNCI/DJY222
LIU ZY	Clinical Cancer Research	10.4	2019	312	44.57	https://doi.org/10.1158/1078-0432.CCR-18-3190

Through keyword analysis, this study found that research in this field has mainly focused on radiomics at the technical level since Lambin proposed radiomics [28] (Fig. 5C). Moreover, there has been continuous progress in radiomics from a timeline view. However, these models need higher reproducibility and generalization [10, 11]. Deep learning was widely applied in this field, which can improve these limitations [12, 13] (Fig. 5C). Deep learning has many applications as a hotspot in AI. Applications include lesion detection, image segmentation, reconstruction, breast cancer classification, diagnosis, prognosis and distant metastasis prediction [29, 30]. However, the "black-box" nature of deep learning leads to a lack of interpretability [31].

In recent years, explainable AI has been increasingly applied to breast cancer imaging (Fig. 5C), overcoming the opacity of AI's "black-box" and enhancing its interpretability and credibility [32]. In radiology, explainable AI currently provides visual explanations, textual descriptions, example-based explanations, or combinations of these to explain the algorithmic decision basis [33]. The attention mechanism plays a pivotal role by enabling neural networks to focus on the most critical parts of the input, offering visual interpretations that further advance explainable AI [34]. However, faced with the uncertainty of explainable AI, standardized methods are still needed to assess its accuracy and comprehensiveness [35]. Looking ahead, researchers can work toward unifying these standards, striking a balance between interpretability and accuracy, and advancing explainable AI into the realm of trustworthy AI.

Classification has been a hotspot at the clinical application level in the early stage (Fig. 5A and D). It has a high frequency of occurrence ($n = 517$) and citation burst intensity ($n = 17.03$). Recent advancements in classification primarily focus on developing clinical prediction models, particularly for predicting responses to NAC and LVI status in breast cancer patients over the past two years (Fig. 5C). NAC is one of the primary therapies for breast cancer, which can reduce the clinical stage of tumors, increase drug sensitivity, and improve the success rate of surgery [36]. Accurate prediction of NAC response is critical for optimizing therapeutic strategies, such as tailoring chemotherapy regimens or determining

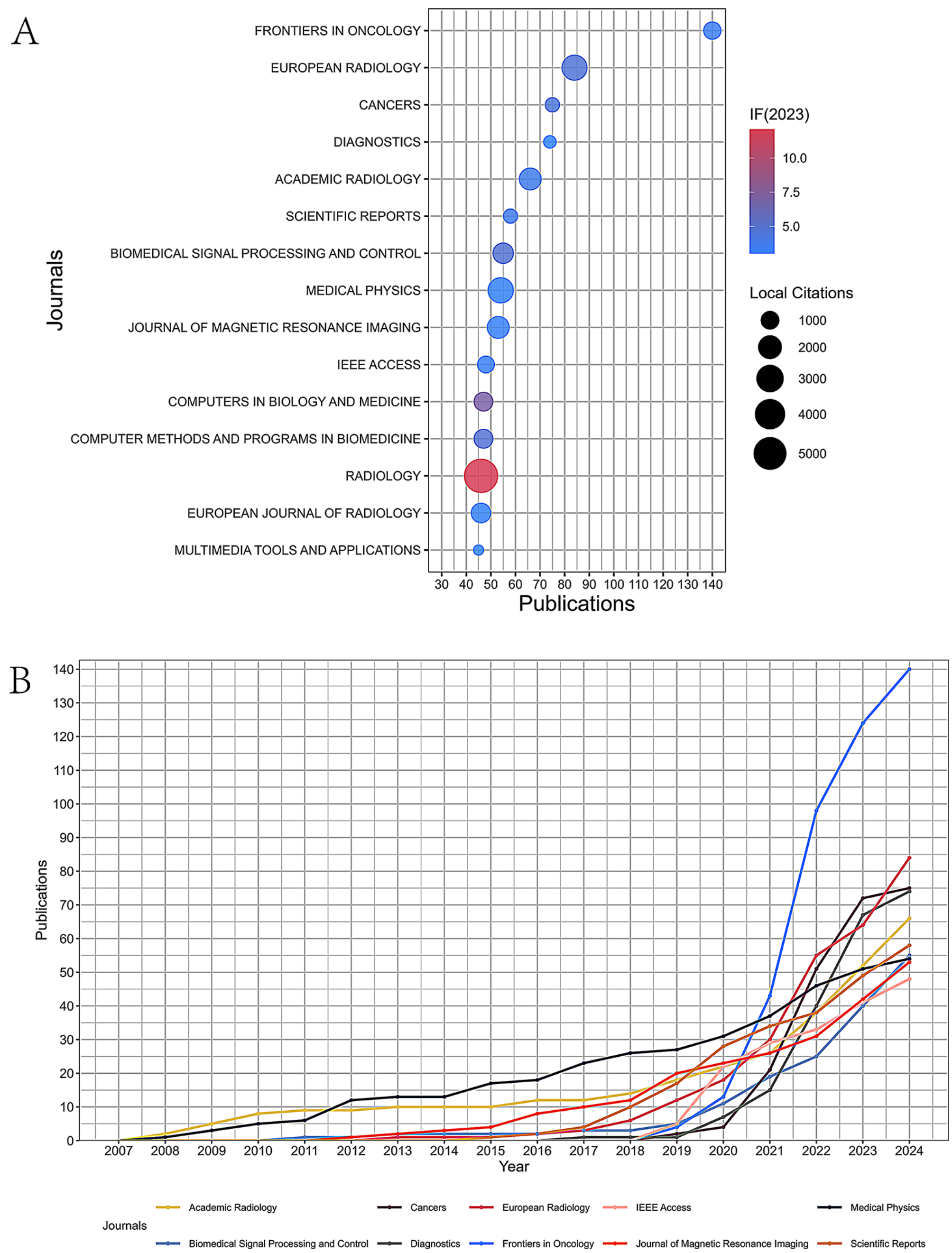

Fig. 4 Visualization of journals. (**A**) The bubble map of the top 15 journals in the number of publications. The Y-axis shows the types of journals, and the X-axis shows the number of publications. The bubble size represents the local citations, and the color represents the IF. IF is the data from 2023. Local citations is the number of citations in the included dataset. (**B**) Map of top 10 journals' production over time

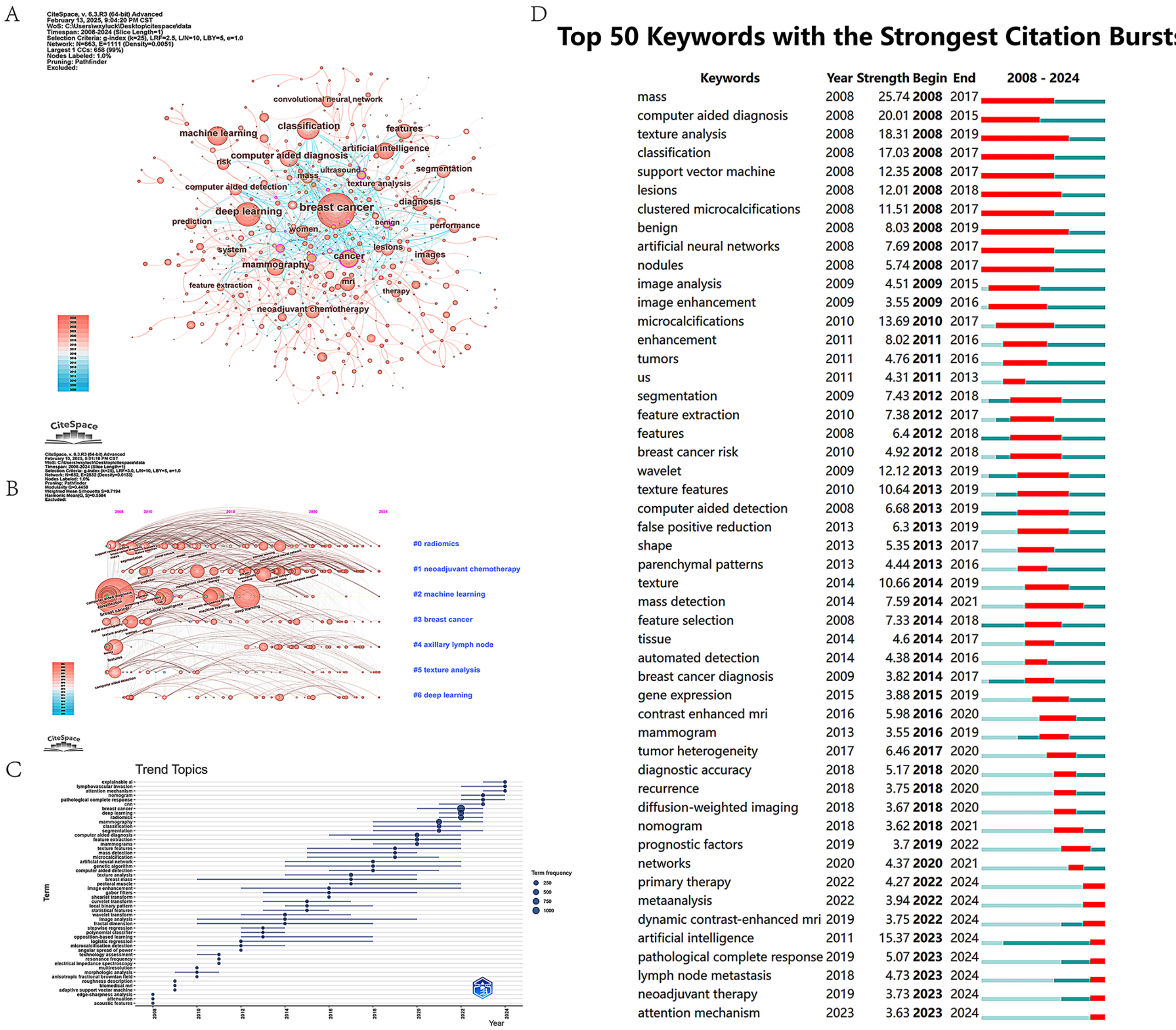

Fig. 5 Visual analysis of keywords and topics. (**A**) The Keyword co-occurrence network. The size of the nodes represents the frequency of keyword occurrences. The lines connecting the nodes reflect the connections between keywords. (**B**) Timeline view of keywords. (**C**) Trend topics of author's keywords from 2008 to August 2024. (**D**) The top 50 keywords with the strongest citation bursts. The timeline is depicted as a blue line, and the red segment is the burst time slot on the blue timeline

appropriate surgery strategy [37]. LVI status has also emerged as a predictive biomarker for the efficacy of NAC [38]. Moreover, accurately predicting LVI status can help forecast positive margins and locoregional recurrence in breast-conserving surgery, potentially reducing the need for unnecessary axillary lymph node dissection [39]. In recent years, several studies have utilized radiomics and deep learning techniques to develop predictive models for these outcomes [37–39]. However, their clinical utility remains limited by small sample sizes and retrospective study designs [37–39]. Future studies should incorporate prospective multicenter cohorts, and this direction may have good development prospects in the future.

Admittedly, this study has some limitations. First, we only screened the publications from WoSCC on August 10, 2024 and limited the publication type and research language. This may lead to the omission of current popular topics. Second, this study used different software for data analysis, which may have minor discrepancies. Finally, we performed data cleaning by merging keywords with minor semantic variations. We believe this preprocessing step enhances the quality and accuracy of the bibliometric analysis.

Conclusion

In conclusion, we performed a comprehensive bibliometric analysis of AI and radiomics applications in breast cancer imaging, systematically examining publications, authors, institutions, countries, journals, references, and keywords. The results show that this field is booming, and future research hotspots may mainly focus on explainable AI, LVI, and NAC. This study may offer a valuable reference point for researchers.

Abbreviations

AI	Artificial intelligence
WoSCC	Web of Science Core Collection
SCI-E	Science Citation Index Expanded
SCP	Single-country publication
MCP	Multi-country publication
USA	United States of America
IF	Impact factor
NAC	Neoadjuvant chemotherapy
LVI	Lymphovascular invasion

Supplementary Information

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Supplementary Material 1

Supplementary Material 2

Supplementary Material 3

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Author contributions

XW and YX: Investigation, Formal analysis, Data Curation, Visualization, Writing - Original Draft, Writing - Reviewing and Editing. XL: Investigation, Data Curation, Validation. KH: Formal analysis, Data Curation, Visualization. LW and CG: Conceptualization, Methodology, Resources, Investigation, Data Curation, Writing - Reviewing and Editing, Supervision, Project administration. All authors read and approved the final manuscript.

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Data availability

Data is provided within the manuscript or supplementary information files.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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