Original Article

Bibliometric and visualized analysis of reporting and data systems from 2000 to 2022: research situation, global trends, and hotspots

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Background: The reporting and data system (RADS) has been researched across the world since it was first developed. This study used bibliometrics to analyze the research trends and current status of this field over the past almost 23 years and explored possible future research hotspots.
Methods: We searched the Web of Science (WOS) literature on RADSs from January 1, 2000, to November 1, 2022, and evaluated the findings visually with VOSviewer (1.6.18), CiteSpace (6.1.3), and the "bibliometrix" package in R version 4.2.1.
Results: We included 6,239 publications from 88 countries and regions. The number of published has shown an overall growth trend, especially since 2016. The United States was the country with the highest number of publications and citations. The top 10 most productive institutions in RADS research were mainly from South Korea and the United States. Kim EK was the most published author, and Turkbey B had the most cited publication. *European Radiology* had the most publications on the subject, while *Radiology* was the most influential journal. *Magnetic resonance imaging*, *carcinoma*, *ultrasound*, *RADS*, *mammography*, *breast neoplasms*, and *diagnosis* were the most common keywords. Artificial intelligence (AI) appears to be an emerging hotspot in the research of RADS.
Conclusions: This study provides an overview of the development status of research into RADSs over the past 23 years. Research into RADSs has included various systems of the body, with the most studied being the breast, prostate, liver, and thyroid. In terms of auxiliary diagnosis, there is an increasing amount of research into the application of AI in RADSs, which along with the interpretability of AI, will be a hotspot of research in the following years.

Keywords: Bibliometrics; visualized analysis; reporting and data system (RADS); Web of Science (WOS); VOSviewer

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Introduction

The reporting and data system (RADS) is an imaging-based rating system proposed by the American College of Radiology (ACR) in 1992 (1). RADSs include imaging examinations, mainly X-rays, routine ultrasound, computed tomography (CT), and magnetic resonance imaging (MRI). Recent studies and guidelines indicate that contrast-enhanced ultrasound (CEUS) and artificial intelligence (AI) can help in RADS classification, improve the specificity of diagnosis, and reduce unnecessary biopsies (2-4).

RADSs were first applied in breast disease and then gradually for those of the prostate, liver, thyroid, lung, bladder, colon, and ovaries (1-8). Numerous studies have been conducted on RADSs, and data on the subject are constantly being updated, with both the opportunities and challenges of RADSs being noted (9-11). The RADS aims to standardize the data collection, reporting, interpretation, and imaging inspection processes for at-risk patients. This can serve to reduce the overdiagnosis and overtreatment patients (12) and help to coordinate radiologists, pathologists, and clinicians.

Bibliometric analysis is a mathematical and statistical tool for examining the quantitative fluctuations, distributions, and changing trends in the published literature (13). For assessing the outcomes of research, it offers objective scientific indicators. The research and review of RADSs has discussed this structured system in a highly systematic and comprehensive fashion (14-17). However, no research has been conducted to examine the development trends and research hotspots of RADSs from the perspective of bibliometrics. Bibliometrics can characterize patterns in publications in a given field through a search in databases for variables such as the number of publications, author names, institutions, publication years, citations, journal names, and subject categories. Consequently, we used bibliometrics analysis to objectively describe the current situation and research directions in the RADS field and predict emerging research hotspots (13).

Methods

Data sources and search strategies

Bibliometrics analysis was performed based on the Science Citation Index Expanded (SCIE) and Social Sciences Citations Index (SSCI) of the Web of Science (WOS), which is considered the best database for conducting bibliometrics analysis.

The publication dates were from January 1, 2000, to November 1, 2022. The search term strategy was as follows: TS = ("Imaging-Reporting and Data System$" OR "imaging and Reporting Data System$" OR "Imaging Reporting Data System$" OR "Reporting and Data System$" OR "*I-RADS" OR "*IRADS" OR "Pulmonary embolism-RADS" OR "Lung-RADS" OR "brain tumo$r-RADS" OR "*O-RADS" OR "ACR-RADS" OR "CAD-RADS" OR "BT-RADS" OR "C-RADS" OR "MET-RADS" OR "ILF-RADS"). Of the various publication types, only original articles and reviews published in the English language were included. Of the retrieved literature, 760 non-articles or non-reviews and 151 non-English language publications were excluded. All records from the articles, including title, keywords, abstract, publication journal name, year of publication, authors' names, country of publication, and affiliation were exported and stored in TXT format (including the full text and cited references) for further analyses. To avoid the impact of WOS database updates, all data searches and data downloads were performed on November 1, 2022.

Visualization analysis

Bibliometrics analyses were performed using three tools: VOSviewer (v. 1.6.18), CiteSpace (v. 6.1.3), and the "bibliometrix" package in R (v. 4.2.1; The R Foundation for Statistical Computing). VOSviewer was used to analyze the coauthorship, co-occurrence, and citations and to establish a co-authorship network visualization map, all-keywords network visualization map, keywords overlay visualization map, and reference cocitation visualization map. Cluster analysis was also performed for countries and regions, institutions, authors, and keywords. A cluster is a group of items that are included in a map and have a similar theme. Additionally, a descriptive analysis was also conducted, which included the number of publications per year, countries and regions, journals, highly cited papers, institutions, and authors. CiteSpace was used to analyze the strongest citation bursts of references and keywords. The "bibliometrix" R package was used to draw a world map that represented the volume of publications by country and region.

Results

Number of global publications

A total of 6,239 articles and reviews related to RADSs

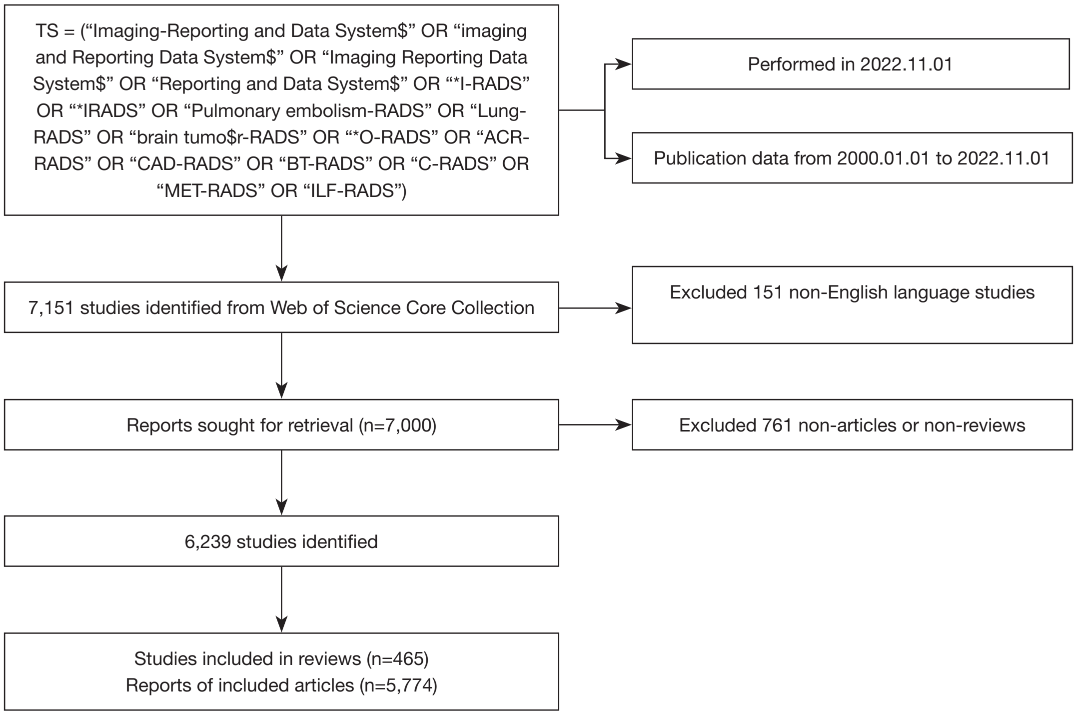

Figure 1 The data collection and retrieval strategy.

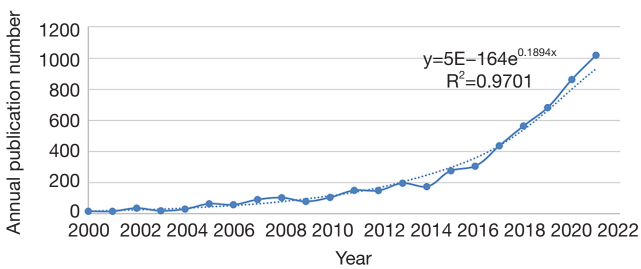

Figure 2 A line chart of the number of annual articles on reporting and data systems by year. The curve fits the overall yearly growth trend in publication number.

published between 2000 and 2022 were retrieved from the WOS according to the data collection and retrieval strategy (*Figure 1*). *Figure 2* depicts the results of the annual publications on RADSs. Because the statistical data were incomplete and some were not available online as of November 1, 2022, the publications that were published in that year were removed. The number of publications increased from 17 in 2000 to 1081 in 2021, with number of publications increasing each year. The polynomial-fitting curve (*Figure 2*) indicated the trend in the volume of papers published. Over the past 21 years, an increasing number of papers have been published, representing an overall growth trend (correlation coefficient R^2=0.9701). The number of publications exceeded 100 in 2010 and 300 in 2016. Overall, these findings indicate that research on RADSs has advanced rapidly, particularly since 2016.

Contributions and coauthorship of countries and regions

A total of 88 countries and regions contributed to the field of RADS, as shown by the geographic distribution of global publications in *Figure 3A*. *Table 1* lists the top 10 most productive countries in this field; the United States ranked first with 2015 publications, about twice as many as China, which had 1,083. Publications from the United States also had the highest citation number (60,523 citations), followed by Germany (15,711 citations). The citations from German publications only accounted for about one-quarter of those from the United States. Regarding the average number of citations, articles published in France (53 citations) and England (51 citations) were cited more than 50 times on average, demonstrating the high caliber of French and English publications. Furthermore, the average publication year of China was 2019.51, which was the latest average publication year among the top 10 contributing countries.

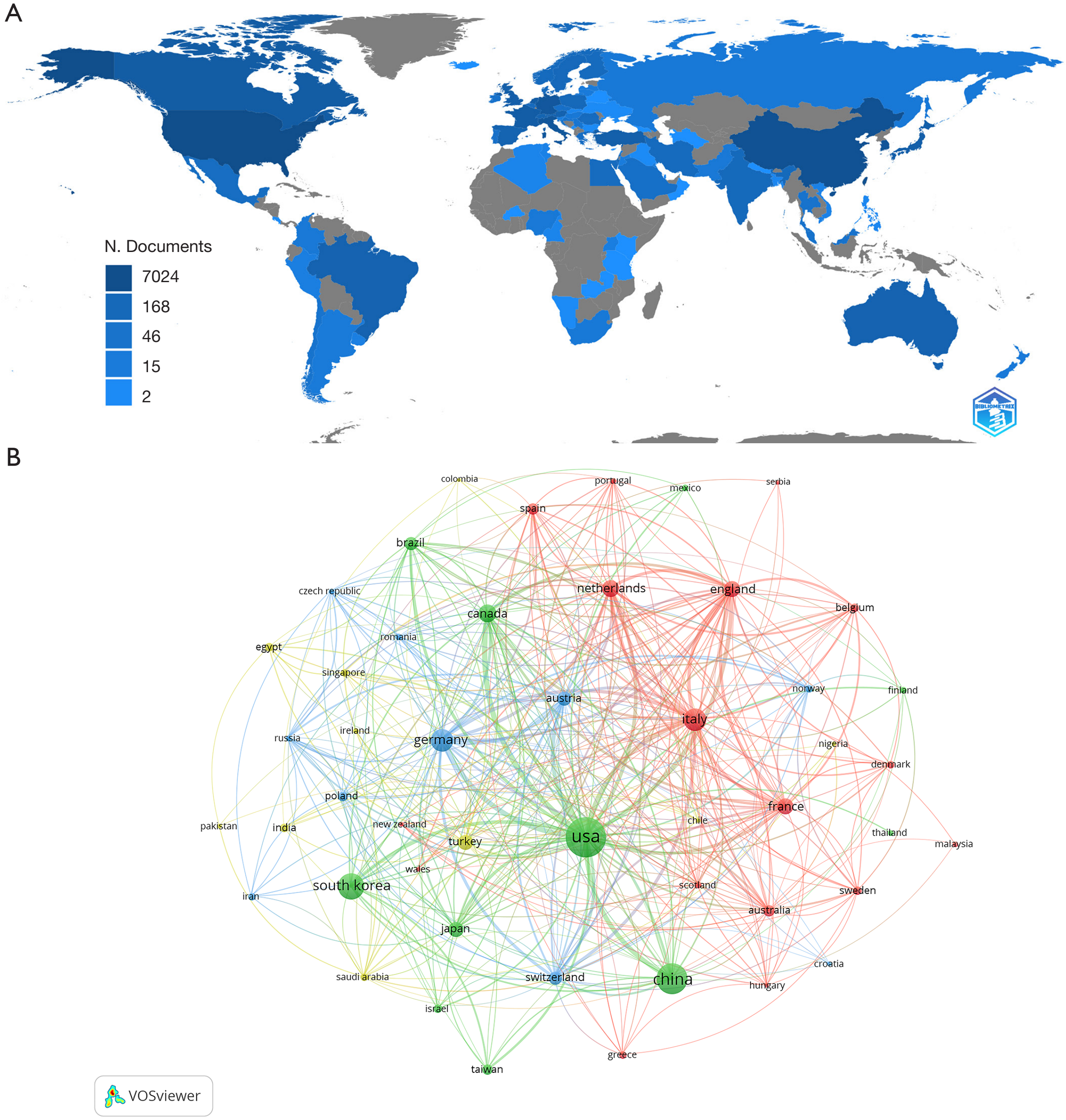

Figure 3 The country or region distribution of reporting and data system research. (A) Geographical distribution of publications on reporting and data systems. (B) The coauthorship network of countries and regions.

Before 2018, research on RADSs in China was almost in the single digits in terms of articles published and at most no more than double digits, but the average number of published papers in the 2019–2021 period was about 200, representing a leap in growth.

VOSviewer was used for coauthorship analysis of the countries or regions to characterize the international cooperation in this field. The coauthorship network of countries or regions is shown in *Figure 3B*. Of the 88 contributing countries or regions, 48 had more than 10 documents occurrences, and these countries or regions were divided into four clusters and coded into four colors: red, green, blue, and yellow (*Figure 3B*). The largest cluster (in red), consists of 17 countries or regions and is centered

Table 1 Top 10 most productive countries or regions in reporting and data system research

Rank	Country	Publications, n	Citations, n	Average citations	Average publication year
1	USA	2,015	60,523	30	2016.57
2	China	1,083	9,459	8	2019.51
3	South Korea	734	13,560	18	2017.12
4	Italy	525	11,555	22	2018.2
5	Germany	515	15,711	30	2016.74
6	Canada	308	12,331	40	2017.62
7	Netherlands	260	12,243	47	2017.39
8	England	223	11,590	51	2018.1
9	France	216	11,517	53	2016.81
10	Turkey	199	2,176	10	2017.92

Table 2 The top 10 most productive institutions in reporting and data system research

Rank	Institution	Country	Publications, n	Citations, n	Average citations
1	Yonsei University	Korea	194	4,248	21
2	University of California, San Francisco	United States	164	6,540	39
3	Seoul National University	Korea	139	3,117	22
4	Memorial Sloan Kettering Cancer Center	United States	131	4,532	34
5	Sungkyunkwan University	Korea	121	1,113	9
6	Sun Yat-sen University	China	116	1,169	10
7	Medical University of Vienna	Austria	111	2,202	19
8	University of Ulsan	Korea	111	2,030	18
9	Duke University	United States	110	4,935	44
10	University of Washington	United States	99	5,104	51

on Italy, the Netherlands, and England. The green cluster includes 11 countries or regions, the blue cluster 10, and the yellow cluster 10. The United States had the most significant number of cooperating partners (n=44), followed by Italy (n=40), England (n=39), and Germany (n=36).

Distribution and coauthorship of institutions

Our analysis indicated that 5,277 different institutions have contributed to the RADS research field. The top 10 most productive institutions are listed in the organization output chart (*Table 2*): Yonsei University produced the most publications (n=194), followed by the University of California, San Francisco (n=164) and Seoul National University (n=139). The only institution in the top 10 to obtain an average of more than 50 citations was the University of Washington (n=51). A total of 100 institutions had an organizational coauthorship network with more than 24 documents occurrences; they were divided into 5 clusters and coded in different colored dots (*Figure 4*). VOSviewer was applied to conduct a coauthorship analysis of these 100 productive institutions. In *Figure 4*, each node represents an institution, the size of the node represents the number of publications, a link represents collaboration, and the distance and the thickness of the link between nodes represent the relative strength of the relation. The red cluster consisting of 34 institutions centered on Memorial Sloan Kettering Cancer Center, Duke University, and

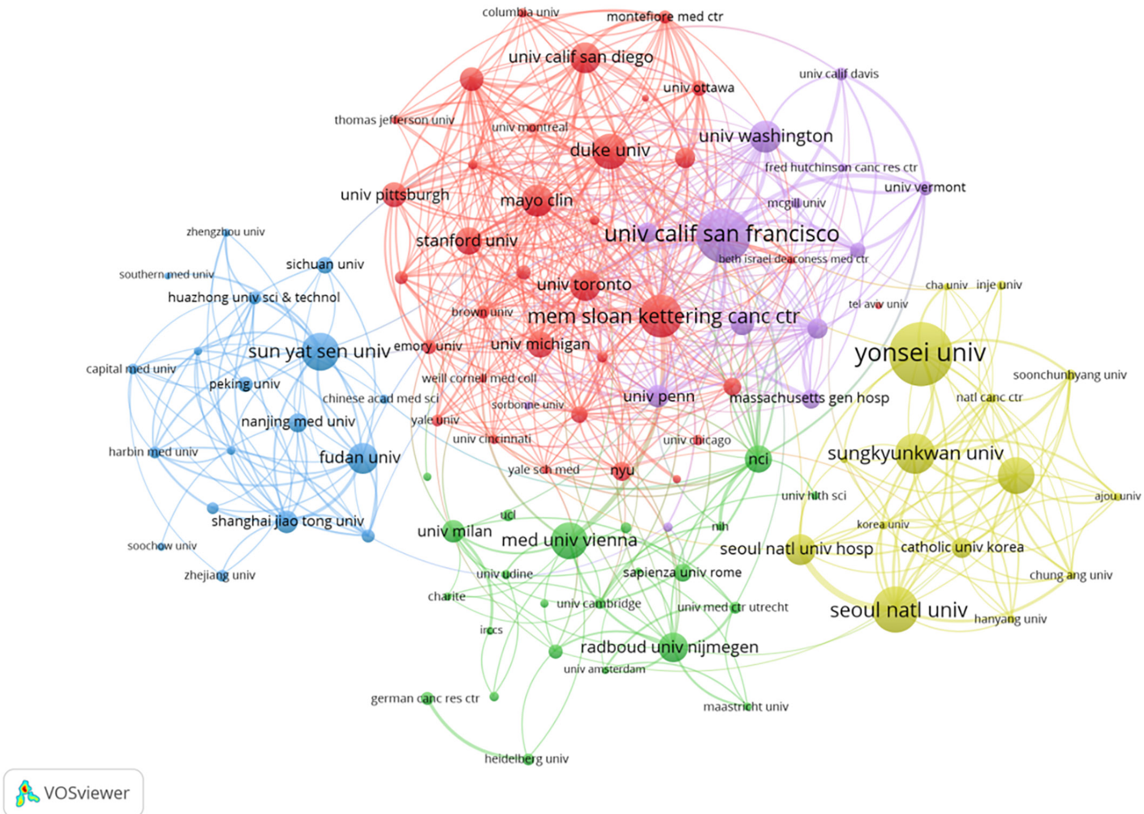

Figure 4 The coauthorship network of institutions.

the University of California, San Diego, was the largest cluster. The second-largest cluster was the green cluster, consisting of 23 institutions, followed by the blue cluster (18 institutions), the yellow cluster (15 institutions), and the purple cluster (14 institutions). The relationship between University of California, San Francisco, and other institutions was the strongest, followed by that of University of California, San Diego, the University of Colorado, and Duke University.

Distribution of authors and coauthorship

A total of 26,995 authors published papers on RADS from 2000 to 2022. The top 10 most productive authors are listed in *Table 3*. Kim EK was the most productive, with 81 publications, followed by Yoon JH (62 publications) and Moon WK (57 publications). Despite having only the eighth-highest number of publications, Turkbey B had the most citations (n=2,661), demonstrating the high-quality of this author's work. The top 10 most productive authors were almost entirely from the United States and South Korea.

The coauthorship network, including 100 authors who published over 17 articles, was divided into 11 clusters and coded by different colors, as shown in *Figure 5*. The red cluster is the largest, with 16 authors centered around Sirlin CB, Fowler KJ, and Panebianco V. In addition to the red cluster, there are 4 clusters with more than 10 authors: the green cluster (13 authors), blue cluster (11 authors), and the yellow cluster (11 authors). The top three authors with the most publications were Kim EK (publications =81), Yoon JH (publications =62), and Moon WK (publications =57).

Contribution analysis of the top 10 journals

The publications on RADS were published across 729 journals. The top 10 journals with the most publications are shown in *Table 4* along with their impact factors (IFs) for 2021. Nearly one-third of the papers were published in the top 10 journals (30.5%). These journals' IFs varied, with *Radiology* having the highest at 29.1. In terms of Journal

Table 3 The top 10 most productive authors in reporting and data system research

Rank	Author	Country	Publications, n	Citations, n	Average citations
1	Kim, Eun-Kyung	South Korea	81	2,457	30
2	Yoon, Jung Hyun	South Korea	62	1,789	28
3	Moon, Woo Kyung	South Korea	57	2,174	38
4	Helbich, Thomas H	Austria	55	2,302	41
5	Sirlin, Claude B.	USA	55	1,564	28
6	Moon, Hee Jung	USA	52	1,590	30
7	Kim, Min Jung	South Korea	50	1,050	21
8	Turkbey, Baris	USA	48	2,661	55
9	Chang, Jung Min	South Korea	46	1,565	34
10	Fowler, Kathryn J.	USA	46	1,578	34

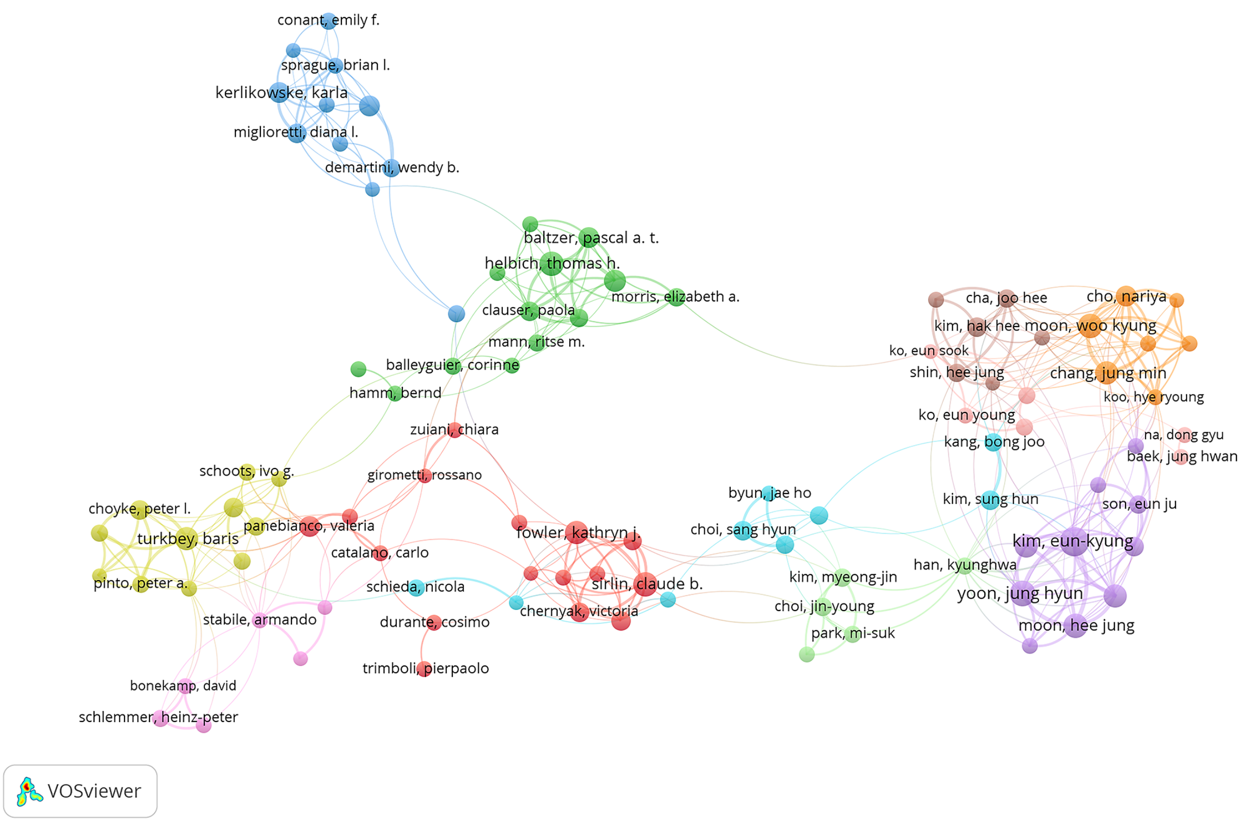

Figure 5 The coauthorship network of authors.

Citation Reports (JCR), most of the journals were classified into Q1 (60%) or Q2 (30%). Sixty percent of the journals came from the United States, with the remaining portion originating from Germany, Ireland, Sweden, and England.

Analysis of references

Among the 6,239 total publications, there were 122,850 citations. *Table 5* lists the top 10 most cited articles on RADS. The top two most referenced publications were

Table 4 Top 10 journals with the most publications on RADS

Rank	Journal	Country	Impact factor 2021	JCR-c	Publications, n	Citations, n	Average citations
1	*European Radiology*	Germany	7.034	Q1	371	10,967	29
2	*American Journal of Roentgenology*	USA	6.582	Q1	330	10,873	32
3	*Radiology*	USA	29.146	Q1	245	17,802	72
4	*European Journal of Radiology*	Ireland	7.034	Q1	237	4,394	18
5	*Abdominal Radiology*	USA	2.886	Q2	170	2,026	11
6	*Academic Radiology*	USA	5.482	Q1	132	2,585	19
7	*Journal of Magnetic Resonance Imaging*	USA	5.119	Q1	129	2,680	20
8	*Journal of Ultrasound in Medicine*	USA	2.754	Q2	99	1,433	14
9	*Acta Radiological*	Sweden	1.701	Q3	98	1,142	11
10	*British Journal of Radiology*	England	3.629	Q2	96	935	9

RADS, reporting and data system; JCR-c, Journal Citation Reports category.

cited 1,759 and 1,756 times, respectively, and both papers were *European Radiology* studies on prostate grading systems. Along with conventional X-rays, ultrasound, MRI for RADS, and breast elastography, half of the top 10 publications discuss the Breast Imaging Reporting and Data System (BI-RADS). The most recent publication with a high number of citations (681 citations) is titled "Prostate Imaging Reporting and Data System Version 2.1: 2019 Update of Prostate Imaging Reporting and Data System Version 2" and was published in *European Urology* in 2019. These findings indicate that the Prostate Imaging Reporting and Data System (PI-RADS) and BI-RADS are receiving considerable attention.

Figure 6 summarizes the top 25 references in terms of strongest citation bursts. The two most recent citation bursts were detected in 2020 and have endured until now; they are focused around MRI-targeted biopsies for diagnosing prostate cancer (18,19).

The co-occurrence of keywords

In addition to search terms, keywords of the 6,239 included publications were extracted from the titles, abstracts, and author keywords and analyzed with VOSviewer. The 100 keywords were grouped into five clusters (*Figure 7A*) based on their number of article co-occurrence. In addition to this, a word cloud analysis was conducted on the keywords (*Figure 7B*). There were 32 keywords in the first cluster (red dots), which included the terms *mammography*, *breast neoplasm*, *lesions in woman*, and *risk*. There were 31 keywords in the second cluster (green points), with the terms *magnetic resonance imaging*, *diagnosis*, *prostatic neoplasms biopsy*, and *accuracy* appearing often in this cluster. For the third cluster (blue points), there were 21 keywords, with the terms *carcinoma*, *ultrasound*, *management*, *benign*, and *thyroid nodule* appearing often in this cluster. There were nine keywords for the fourth cluster (yellow points), with the terms *RADS*, *computed tomography*, *data system*, *hepatocellular carcinoma*, and *CEUS* appearing often in this cluster. There were seven keywords in the fifth cluster (purple points), with the terms *classification*, *imaging*, *computer-aided diagnosis*, *deep learning*, *radiomics*, *artificial intelligence*, and *machine learning* having the highest frequency in this cluster. The most frequently occurring keywords were *MRI*, *carcinoma*, *ultrasound*, *RADS*, *mammography*, *breast neoplasms*, and *diagnosis*, suggesting that the diagnosis and RADs of cancer are highly associated with ultrasound, MRI, and mammography. RADs can be applied to the breast, prostate, thyroid, liver, and other organs, with the RADS for breast neoplasms being the earliest proposed and the most studied.

The co-occurrence overlay visualization map of the top 100 keywords is shown in *Figure 7C*. The color of the frames represents the average publication year of the keywords. The frames were colored from blue to yellow with VOSviewer, with the color representing the average publication year from early to late. The recent emergent keywords included *artificial intelligence*, *radiomics*, *deep learning*, *machine learning*, *nomogram*, *CEUS*, *prostate biopsy*,

Table 5 Top 10 publications on RADS with the highest number of citations

Rank	Year	First author	Title	Journal	Citations
1	2012	Barentsz JO	ESUR prostate MR guidelines	*European Radiology*	1,759
2	2016	Weinreb JC	PI-RADS prostate imaging-reporting and data system: 2015 version 2	*European Radiology*	1,756
3	2006	McCormack VA	Breast density and parenchymal patterns as makers of breast cancer risk: a meta-analysis	*Cancer Epidemiology Biomarkers & Prevention*	1,396
4	2017	Tessler FN	ACR thyroid imaging, reporting and data system (TI-RADS): white paper of the ACR TI-RADS committee	*Journal of the American College of Radiology*	859
5	2004	Warner E	Surveillance of BRCA1 and BRCA2 mutation carriers with magnetic resonance imaging, ultrasound, mammography, and clinical breast examination	*Jama-Journal of the American Medical Association*	823
6	2000	Mandelson MT	Breast density as a predictor of mammographic detection: Comparison of interval- and screen-detected cancers	*Journal of the National Cancer Institute*	695
7	2019	Turkbey B	Prostate Imaging Reporting and Data System Version 2.1: 2019 Update of Prostate Imaging Reporting and Data System Version 2	*European Urology*	681
8	2011	Kwak JY	Thyroid imaging reporting and data system	*Radiology*	638
9	2012	Berg WA	Shear-wave Elastography Improves the Specificity of Breast US: The BE1 Multinational Study of 939 Masses	*Radiology*	572
10	2008	Tanter M	Quantitative assessment of breast lesion viscoelasticity: Initial clinical results using supersonic shear imaging	*Ultrasound in Medicine and Biology*	545

RADS, reporting and data system; ESUR, European Society of Urogenital Radiology; MR, magnetic resonance; PI-RADS, Prostate Imaging Reporting and Data System; ACR, American College of Radiology; TI-RADS, Thyroid Imaging Reporting and Data System; BRCA1, breast cancer gene 1; BRCA2, breast cancer gene 2; US, ultrasonography.

thyroid nodules, *hepatocellular carcinoma*, and *risk stratification*, indicating that these issues have recently garnered increased attention and may continue to be a focus of research in upcoming years.

Discussion

Bibliometrics and visual analysis can not only be used to analyze the development status of a field but also predict the future trends. Articles on RADS showed a growing trend from 2000 to 2021, particularly since 2016. This bibliometric analysis was performed to evaluate RADS in relation to contributing countries, institutions, authors, journals, highly-cited references, and research hotspots.

The mammography-based classification system, proposed by Remington *et al.* (1), was the earliest RADs proposed. Over the past 23 years, 6,239 articles on RADS have been published in 729 journals by 26,995 authors in 88 countries. The number of publications and associated citations from the United States (2,015 publications and 60,523 citations) are much higher than those from other countries, suggesting that the United States is leading contributing country in this field. Despite the fact that there are fewer articles and citations from England and France than from the United States, the average number of citations in these two nations is higher, indicating that the articles from these two countries of excellent quality and worth reading. The United States and South Korea ranked first and third in terms of the number of articles published, respectively, and the majority of the institutions and authors hailed from the United States or South Korea, which highlights how institutional researchers ultimately determine a nation's degree of research. In addition, we also conducted co-authorship analysis. Kim EK was the most published author, and Turkbey B had the most cited publications, suggesting that the former may be constantly exploring the field, while the latter has made outstanding contributions to the development of the field.

The top 10 journals in terms of RADS publications are listed in *Table 4*. *European Radiology*, *the American Journal*

References	Year	Strength	Begin	End	2000 – 2022
American COLLEGE OF RADIOLOGY, 2003, BREAST IM REP DAT SY, V0, P0	2003	39.46	2005	2008	
Hong AS, 2005, AM J ROENTGENOL, V184, P1260, DOI 10.2214/ajr.184.4.01841260, DOI	2005	26.4	2006	2010	
Lazarus E, 2006, RADIOLOGY, V239, P385, DOI 10.1148/radiol.2392042127, DOI	2006	33.65	2007	2011	
Itoh A, 2006, RADIOLOGY, V239, P341, DOI 10.1148/radiol.2391041676, DOI	2006	22.83	2007	2011	
Saslow D, 2007, CA-CANCER J CLIN, V57, P75, DOI 10.3322/canjclin.57.2.75, DOI	2007	22.15	2008	2012	
Kuhl C, 2007, RADIOLOGY, V244, P356, DOI 10.1148/radiol.2442051620, DOI	2007	23.89	2009	2012	
Berg WA, 2008, JAMA-J AM MED ASSOC, V299, P2151, DOI 10.1001/jama.299.18.2151, DOI	2008	26.09	2010	2013	
Athanasiou A, 2010, RADIOLOGY, V256, P297, DOI 10.1148/radiol.10090385, DOI	2010	27.73	2011	2015	
Berg WA, 2012, RADIOLOGY, V262, P435, DOI 10.1148/radiol.11110640, DOI	2012	40.16	2012	2017	
Barentsz JO, 2012, EUR RADIOL, V22, P746, DOI 10.1007/s00330-011-2377-y, DOI	2012	100.24	2013	2017	
Dickinson L, 2011, EUR UROL, V59, P477, DOI 10.1016/j.eururo.2010.12.009, DOI	2011	27.81	2013	2016	
Berg WA, 2012, JAMA-J AM MED ASSOC, V307, P1394, DOI 10.1001/jama.2012.388, DOI	2012	25.72	2013	2017	
Hooley RJ, 2012, RADIOLOGY, V265, P59, DOI 10.1148/radiol.12120621, DOI	2012	23.06	2013	2016	
Skaane P, 2013, RADIOLOGY, V267, P47, DOI 10.1148/radiol.12121373, DOI	2013	27.61	2014	2017	
Schimmoller L, 2013, EUR RADIOL, V23, P3185, DOI 10.1007/s00330-013-2922-y, DOI	2013	23.88	2014	2017	
Morris EA, 2013, ACR BIRADS ATLAS BRE, V0, P0	2013	38.89	2015	2018	
Pokorny MR, 2014, EUR UROL, V66, P22, DOI 10.1016/j.eururo.2014.03.002, DOI	2014	30.78	2015	2019	
Heidenreich A, 2014, EUR UROL, V65, P124, DOI 10.1016/j.eururo.2013.09.046, DOI	2014	24.2	2015	2018	
Hamoen EHJ, 2015, EUR UROL, V67, P1112, DOI 10.1016/j.eururo.2014.10.033, DOI	2015	23.74	2015	2018	
Siddiqui MM, 2015, JAMA-J AM MED ASSOC, V313, P390, DOI 10.1001/jama.2014.17942, DOI	2015	39.65	2016	2019	
Muller BG, 2015, RADIOLOGY, V277, P741, DOI 10.1148/radiol.2015142818, DOI	2015	22.12	2016	2019	
Futterer JJ, 2015, EUR UROL, V68, P1045, DOI 10.1016/j.eururo.2015.01.013, DOI	2015	27.46	2017	2019	
Weinreb JC, 2016, EUR UROL, V69, P16, DOI 10.1016/j.eururo.2015.08.052, DOI	2016	25.1	2018	2019	
Rouviere O, 2019, LANCET ONCOL, V20, P100, DOI 10.1016/S1470-2045(18)30569-2, DOI	2019	25.68	2020	2022	
Kasivisvanathan V, 2018, NEW ENGL J MED, V378, P1767, DOI 10.1056/NEJMoa1801993, DOI	2018	24.84	2020	2022	

Figure 6 The top 25 references with the strongest citation bursts. Pale green represents the time period when the article was not cited, dark green represents the period when it had begun to be cited, and red represents when the burst citation appeared.

of Roentgenology, and *Radiology* have published numerous articles on RADS, each of which has been cited more than 10,000 times. *Radiology* had a significantly higher average number of citations (n=72) and IF (IF =29.146) than did the other journals, demonstrating its high level of authority in the RADS fields. The journals in this discipline should be prospective authors' primary focus, and literature from these journals should be considered when new research is performed. The top 10 articles on the RADS with the highest number of citations were high-quality papers that are worthwhile reading according to the analysis of references. Consulting the top 25 references in terms of strongest citation bursts can help us understand the current state of research in this field.

VOSviewer can be used to conduct keyword co-occurrence analysis. There were 10,220 keywords identified in this study, 100 of which have been used over 68 times. The top 100 most frequent keywords were divided into 5 clusters, each of which represents a specific area of research.

Red cluster: *BI-RADS*

BI-RADS is a reporting guideline for the early screening and interpretation of breast tumors, which can effectively improve the survival rate of patients with breast cancer and reduce the incidence of advanced breast cancer (20). Although mammography is an excellent screening approach for breast carcinoma, a portion of interval breast

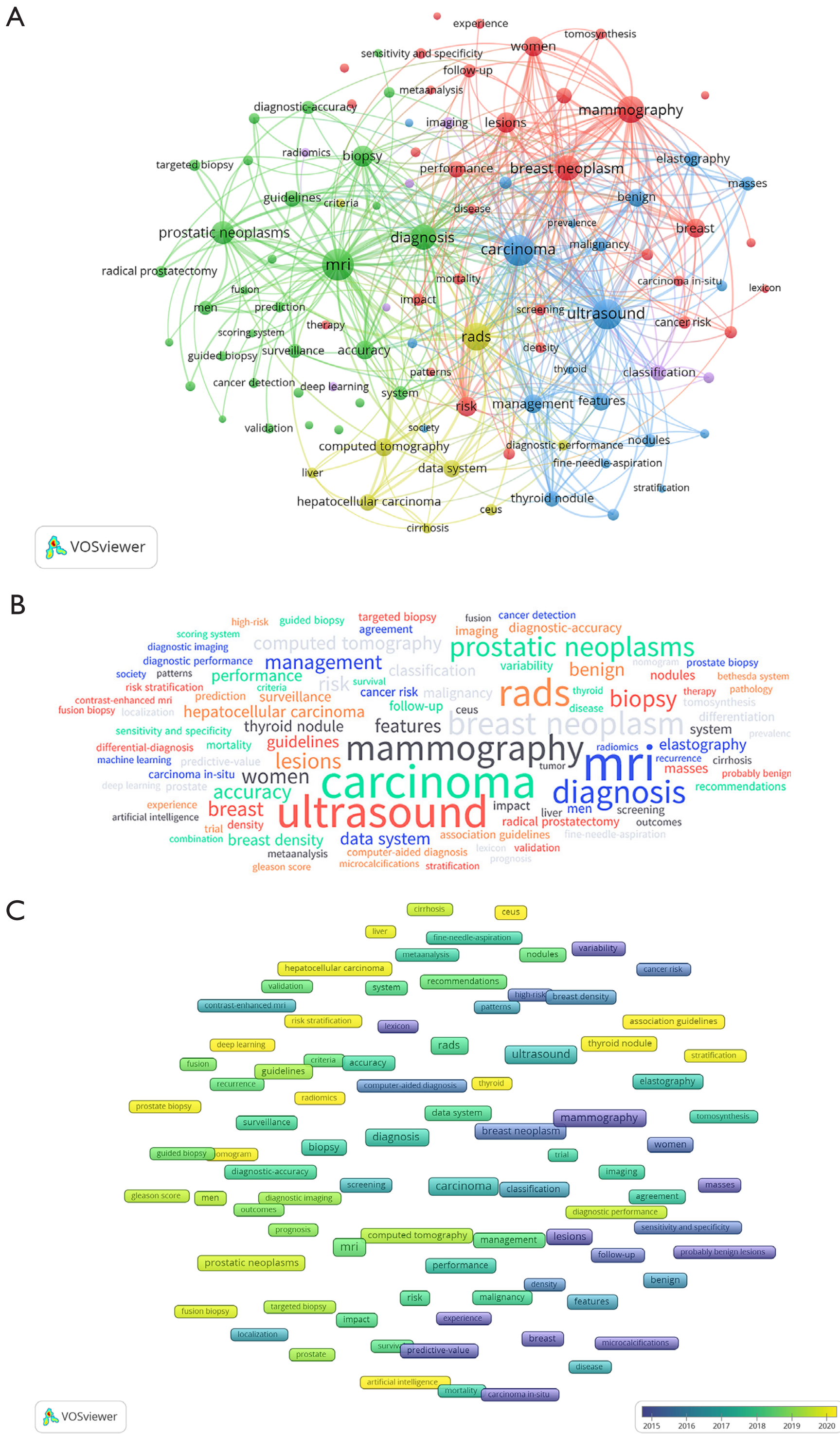

Figure 7 Distribution of the top 100 keywords. (A) The co-occurrence of the top 100 keywords. The 100 keywords that occurred more than 68 times were divided into 5 clusters and coded in different colors: cluster 1, red; cluster 2, green; cluster 3, blue; cluster 4, yellow; and cluster 5, purple. Each node represents one keyword, the size of the nodes represents the frequency of occurrences, and the thickness of the line and distance between nodes indicate the tightness of the relationship. (B) Word cloud of keywords. The font size indicates the frequency of the keywords. (C) The overlay map of the top 100 keywords.

cancers may still go undetected especially in women with thick mammary glands (21). To compensate for the lack of X-rays, routine ultrasound or MRI of the breast is used as a basic imaging technique for breast screening, promoting consistency across modalities (22-24). In addition, ultrasound elastography, CEUS, and Doppler ultrasound can be quantitatively analyzed on the basis of conventional ultrasound, which lowers the false-positive rate, improves diagnostic performance, and reduces the need for biopsy. These benefits not only decrease the cost to healthcare systems but also avoid leveraging an unnecessary psychological burden upon patients (25,26). In addition, ultrasound elastography can predict breast cancer prognosis, guide neoadjuvant chemotherapy regimens, and provide a basis for long-term treatment. Both color Doppler and CEUS can visualize the blood supply inside the tumor, and CEUS can significantly amplify the blood flow signal and provide information about microvascular perfusion, improving specificity (27,28). AI can be used as a computer-aided diagnostic technique to provide higher or equal diagnostic performance to that of radiologists and can be used to assist in diagnosis (29,30). However, Friederike *et al.* pointed out several limitations to the application of AI in clinical practice and that the impact of human-computer interaction on AI and radiologist accuracy cannot be ignored (31).

Green cluster: PI-RADS

PI-RADS is a worldwide, multicenter reporting system that allows radiologists to describe and diagnose untreated prostate lesions in a simple, translatable, and meaningful manner. PI-RADS combines multiparametric magnetic resonance, published data, and expert observations and opinions. The magnetic resonance sequences used for rating include T2-weighted imaging (T2WI), the apparent diffusion coefficient (ADC), diffusion-weighted imaging (DWI), and dynamic contrast enhanced (DCE) MRI (2,16). PI-RADS can guide the detection, localization, staging, and treatment of prostate lesions (32,33). On T2W, focal lesions, nodules, or areas in the transition zone and peripheral zone with traits known to be linked with malignancy and those that differ from the prevailing imaging characteristics of the background can be graded. The central zone and anterior fibromuscular stroma are generally not routinely classified and are considered only when lesions or invasion of surrounding tissues are present. T2WI is the core PI-RADS classification sequence, and DWI-ADC is substantially correlated with the aggressiveness of prostate cancer, which can aid in the identification of atypical nodules, particularly those classified by T2WI as PI-RADS class 3 or higher (2). In clinical settings, DCE is frequently employed to help classify PI-RADS; otherwise, only negative and positive results are reported (2,16,34). The latest version of PI-RADS is PI-RADS v. 2.1, which mainly uses biparametric MR (bpMRI) and does not include DCE. Compared to multiparameter MRI (mpMRI), bpMRI does not require contrast agents, which can reduce costs and improve efficiency (2). Prostate-specific antigen density (PSA level divided by prostate volume) and AI can assist in the classification of PI-RADS, with a PSA density less than 0.15 ng/mL indicating that the probability of prostate cancer is extremely low. PSA density can also be used to improve negative predictive value, and there are already clinical models containing PSA density information (35). The combination of AI and PI-RADS reduces the variability between readers and improves the diagnostic accuracy, especially for primary diagnostics. Diagnosis needs to be based on the whole prostate and to be able to identify prostate lesions that are not visible on mpMRI. Moreover, the algorithm for prostate cancer predicted by MRI has been included in the latest PI-RADS update (36,37).

Blue cluster: Thyroid Imaging Reporting and Data System (TIRADS)

Since 2009, scholars have been developing a thyroid nodule risk grading system based on ultrasound, and the ACR published a grading system for thyroid nodules in 2017 (38,39). Fine-needle aspiration (FNA) or follow-up recommendations based on classification and maximum diameter of nodules can improve the consistency of management recommendations. Indeed, there is a recent problem that there are certain differences between observers regarding FNA recommendations that are difficult to avoid, but these can be minimized through continuous learning and updating of the ACR Thyroid Imaging Reporting and Data System (ACR-TIRADS) (40). ACR-TIRADS does not include the examination of cervical lymph nodes, but lymph node scans are routinely performed clinically to avoid missing hard-to-detect or occult thyroid cancers (4). ACR-TIRADS has a higher degree of specificity compared to several other commonly used grading systems and can reduce unnecessary biopsies, but the sensitivity of this system is lower, and some missed diagnoses can be avoided through follow-up (41). Revisions to the TI-RADS concerning ultrasound elastography and CEUS may be included in the future. Elastography is a semiquantitative method used for assessing tissue hardness and can increase the detection rate of malignant nodules while reducing variation between and within observers (42). Ruan *et al.* proposed a reporting system based on CEUS, which is based on ACR-TIRADS, adding contrast features and significantly improving specificity (43). The application of some AI models can help to improve the diagnostic performance in certain situations, but further research is needed to confirm whether it can aid in clinical judgment (44). Benjamin *et al.* proposed that AI only has a guiding effect on junior physicians, and has no special benefit for experienced doctors and will rather affect judgment and increase diagnosis time (45). AI is constantly evolving, and humans are constantly exploring its value in aiding or assisting in diagnosis.

Yellow cluster: Liver Imaging Reporting and Data System (LI-RADS)

The LI-RADS was first proposed in 2011 and was most recently updated in 2018. General ultrasound is used for surveillance in liver cancer; CEUS for diagnosis and staging; and CT or MRI for diagnosis, staging, and treatment response assessment (46). The use of CEUS, CT, and MRI is particularly important in patients with cirrhosis, and some hepatocellular carcinomas (HCCs) can be diagnosed via imaging alone. LR1–5 is a classification of HCC, and liver imaging reporting and data system M (LM-R) includes hepatic malignant lesions that are difficult to diagnose as HCC, reducing the difficulty of classification of undifferentiated HCC and other types of liver malignancies. Additionally, HCC included in LR-M has a poor degree of differentiation, and its prognosis is worse than that of patients with LR-5 (9,47). van der Pol *et al.* calculated the percentage of each type of HCC and overall malignancy via a systematic review, with HCC accounting for 13% and 38% in LR-2 and LR-3, respectively, suggesting that more aggressive management measures should be taken for this type of lesion. Especially for patients with liver cirrhosis, active monitoring can be achieved to achieve early detection and improve the possibility of surgical treatment (3). Radiologists occasionally have difficulty identifying a few useful features with the naked eye, and the application of AI can assist radiologists use the LI-RADS system in evaluations. AI can extract texture features based on pictures be coupled with LI-RADS in disease classification, which can not only improve the accuracy, sensitivity and specificity of diagnostic models but also improve the efficiency of radiologists' reading of images (48).

Purple cluster: application of AI to imaging RADs

AI can quantify knowledge indiscernible to most individuals by converting qualitative activities into quantitative tasks (49). AI extracts a large amount of information from medical images through deep learning (DL), machine learning (ML), convolutional neural networks (CNNs), and other processes and assists RADS in risk stratification (50,51). In addition to conducting risk stratification, AI is able to autonomously identify lesions, deduce tumor genotypes from radiological characteristics, predict clinical outcomes, and evaluate the effects of diseases and treatments on nearby organs (52). The keyword co-occurrence overlay visualization map in *Figure 7C* includes the keywords *artificial intelligence*, *radiomics*, *deep learning*, *machine learning*, *nomogram*, etc. These are current research topics for RADS, and AI is an emerging hotspot. Specifically, the explainability of AI, which involves gaining insight into its assisted judgment principles and explaining the "black box" of AI processes, is likely to be a hotspot for research in the coming years (50,52)

The bibliometric analysis of this study had some limitations and flaws. First, we only included publications from the WOS database, and thus relevant articles were potentially missed. Second, we only included publications in the English language, and some high-quality articles in other languages might have been overlooked. Third, because of their short publication period, recently published articles were excluded. Nonetheless, our bibliometric analysis revealed the current situation, future development trends, and hotspots of RADS research and may serve to provide insight and ideas for researchers in this field.

Conclusions

Research into RADS has proliferated substantially worldwide over the recent years, with the United States producing the most publications. RADS can be applied to most organs of the body, with related BI-RADS, PI-RADS, LI-RADS, and TI-RADS being the most studied systems. In this study, which identified the journals that contributed to the study of RADSs, *European Radiology* was found to have produced the most related publications, and *Radiology* was the most influential journal, with both journals being from the United States. AI is associated with many opportunities and challenges in augmenting RADS-based diagnostic performance and risk stratification, and research on AI and its interpretability will receive increased research attention and focus in the upcoming years.

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Footnote

Conflicts of Interest: All authors have completed the ICMJE uniform disclosure form (available at https://qims.amegroups.com/article/view/10.21037/qims-23-1283/coif). All authors report that this study was supported by the Liaoning Natural Science Foundation (No. 2022-YGJC-52). The authors have no other conflicts of interest to declare.

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