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Research

Research on the developments of artificial intelligence in radiomics for oncology over the past decade: a bibliometric and visualized analysis

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Abstract

Objective To assess the publications' bibliographic features and look into how the advancement of artificial intelligence (AI) and its subfields in radiomics has affected the growth of oncology.

Methods The researchers conducted a search in the Web of Science (WoS) for scientific publications in cancer pertaining to AI and radiomics, published in English from 1 January 2015 to 31 December 2024.The research included a scientometric methodology and comprehensive data analysis utilising scientific visualization tools, including the Bibliometrix R software package, VOSviewer, and CiteSpace. Bibliometric techniques utilised were co-authorship, co-citation, co-occurrence, citation burst, and performance Analysis.

Results The final study encompassed 4,127 publications authored by 5,026 individuals and published across 597 journals. China (2087;50.57%) and USA (850;20.6%) were the two most productive countries. The authors with the highest publication counts were Tian Jie (60) and Cuocolo Renato (30). Fudan University (169;4.09%) and Sun Yat-sen University (162;3.93%) were the most active institutions. The foremost journals were *Frontiers in Oncology* and *Cancer*. The predominant author keywords were radiomics, artificial intelligence, and oncology research.

Conclusion Investigations into the integration of AI with radiomics in oncology remain nascent, with numerous studies concentrating on biology, diagnosis, treatment, and cancer risk evaluation.

Keywords Bibliometric analysis · Artificial intelligence · Deep learning · Radiomics · Oncology

1 Introduction

Radiomics encompasses the high-throughput extraction of numerous quantitative attributes from radiological images, including CT (computed tomography) and MRI (magnetic resonance imaging) scans. This new technique is predicated on the notion that automated or semi-automated software analysis of medical imaging data can uncover more information than visual evaluation by physicians alone [1]. Advanced imaging analysis can elucidate the connection between

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nuanced radiological abnormalities and particular elements of the underlying pathobiology, including the tumour microenvironment (TME) [2]. The amalgamation of radiomics with artificial intelligence (AI) reveals new opportunities for personalised medicine and the advancement of more effective cancer treatments.

As technology progresses, the difficulties facing AI become progressively complex. To sustain its relevance and competitiveness, the scientific community has developed the notion of machine learning (ML). Machine learning is the scientific field that examines how computers acquire knowledge from data. To tackle the difficulties associated with managing large datasets and unstructured data, researchers have created convolutional neural networks (CNN) and recurrent neural networks (RNN). The emergence of these technologies has made deep learning (DL) a viable possibility. Deep learning approaches demonstrate enhanced flexibility and can be adapted with tweaks for diverse applications. Besides classification, deep learning algorithms extensively investigate segmentation, registration, and lesion detection [3].

The recent surge in research endeavors centered on leveraging AI in tumor diagnosis and treatment within the domain of radiomics, accompanied by the proliferation of related academic publications, underscores the pressing imperative for researchers to discern the most recent advancements in this field. In this context, it is imperative to present a comprehensive overview of global research trends and focal points in this domain, thereby providing guidance for the future direction of research initiatives.

Bibliometric analysis serves as a visual analysis method that has been extensively applied across various research fields to identify hotspots [4–7]. This technique utilizes mathematical and statistical methodologies to quantitatively assess the various characteristics of literature. The present paper aims to deliver a thorough overview of the use and advancement of AI in radiomics for oncology over the last 10 years. The bibliometric analysis employed in this study offers insights into current research advancements, significant focal points, and upcoming trends. The study's findings are expected to facilitate the comprehension of prospective research trajectories among novice researchers.

2 Methods

2.1 Database base

The Science Citation Index Expanded (SCI-Expanded) from the Web of Science Core Collection (WoSCC), developed by Clarivate Analytics, served as the data source. The WoSCC is the most commonly utilised and recognised database for scientific or bibliometric research, a viewpoint supported by multiple published works. It encompasses around 9,000 of the globe's most esteemed high-impact journals and over 12,000 academic conferences.

2.2 Searching strategy

In order to comprehensively identify relevant literature in the field, a search formula was constructed with the assistance of the MeSH database and subsequently reviewed and endorsed by all authors. The search strategy was described as follows: (TS = "Neoplasms" OR "Tumors" OR "Neoplasia" OR "Neoplasias" OR "Neoplasm" OR "Tumor" OR "Cancer" OR "Cancers" OR "Malignant Neoplasm" OR "Malignancy" OR "Malignancies" OR "Malignant Neoplasms" OR "Neoplasm, Malignant" OR "Neoplasms, Malignant" OR "Benign Neoplasms" OR "Neoplasms, Benign" OR "Neoplasm, Benign" OR "Benign Neoplasm" OR "Carcinoma" OR "Carcinomas" OR "Epithelioma" OR "Epitheliomas" OR "Malignant Epithelial Neoplasms" OR "Epithelial Neoplasm, Malignant" OR "Malignant Epithelial Neoplasm" OR "Neoplasm, Malignant Epithelial" OR "Neoplasms, Malignant Epithelial" OR "Epithelial Neoplasms, Malignant" OR "Epithelial Tumors, Malignant" OR "Epithelial Tumor, Malignant" OR "Malignant Epithelial Tumor" OR "Malignant Epithelial Tumors" OR "Tumor, Malignant Epithelial" OR "Carcinoma, Anaplastic" OR "Anaplastic Carcinoma" OR "Anaplastic Carcinomas" OR "Carcinoma, Spindle-Cell" OR "Carcinoma, Spindle Cell" OR "Spindle-Cell Carcinoma" OR "Spindle-Cell Carcinomas" OR "Carcinoma, Undifferentiated" OR "Undifferentiated Carcinoma" OR "Undifferentiated Carcinomas" OR "Carcinomatosis" OR "Carcinomatoses") AND (TS = "Artificial Intelligence" OR "Intelligence, Artificial" OR "Computer Reasoning" OR "Reasoning, Computer" OR "AI (Artificial Intelligence)" OR "Machine Intelligence" OR "Intelligence, Machine" OR "Computational Intelligence" OR "Intelligence, Computational" OR "Computer Vision Systems" OR "Computer Vision System" OR "System, Computer Vision" OR "Systems, Computer Vision" OR "Vision System, Computer" OR "Vision Systems, Computer" OR "Knowledge Acquisition (Computer)" OR "Acquisition, Knowledge (Computer)" OR "Knowledge Representation (Computer)" OR "Knowledge Representations (Computer)" OR "Representation, Knowledge (Computer)" OR "machine learning" OR "deep learning" OR "Unsupervised Learning" OR "Neural networks" OR "Convolutional Neural Network" OR "Reinforcement Learning" OR "Natural Language Processing" OR "Natural Language Process" OR "Artificial neural network") AND (TS = "radiomics"). The language was limited to English, and the document types were limited to original articles and reviews.

Two authors independently searched and reviewed the literature published between January 1, 2015 and December 31, 2024, collected pertinent information on January 1, 2025. The following information was downloaded and stored in plain text format: the paper's title, keywords, abstract, authors, institution, and bibliographic record. Figure 1 shows how the search results were made to be more precise. After the authors saved the plain text files of the retrieved documents from WoSCC, CiteSpace V (version 6.1.R6) was used for file de-duplication.

2.3 Data analysis and visualization

The visualisation of bibliometric analysis was conducted with R language software (version 4.2.3), VOSviewer (version 1.6.20), and CiteSpace (version 6.1.R6). The bibliometrix R tool was employed to extract data regarding keywords, countries, and years. Subsequently, R software was utilised to create heatmaps that visually depicted the frequency of publications nationwide during a designated time frame. VOSviewer can create and exhibit extensive bibliometric maps in multiple formats, including labelling, density, cluster density, and scatter views. Thus, the interconnections of nations/regions, institutions, authors, journals, references, citations, and keywords can be illustrated using VOSviewer [8].CiteSpace can be employed to analyse and visualise simulation networks, as well as to identify and illustrate patterns and outbreaks in research. In bibliometric analysis, co-authorship, co-citation, and co-occurrence analysis are the predominant metrics [9].Co-authorship analysis is the assessment of relationships among authors, countries, or organizations based on the quantity of collaboratively produced works [10]. Co-occurrence analysis is a quantitative tool that examines the relationship between distinct objects based on their simultaneous occurrence. Co-citation analysis illustrates the strength of relationships among cited things based on the quantity of citing items [11].

The H-index is a statistic utilised to assess the scientific influence of an author, country, or region. This denotes the quantity of academic publications or scholars/countries/regions that have produced H articles, with each work cited a

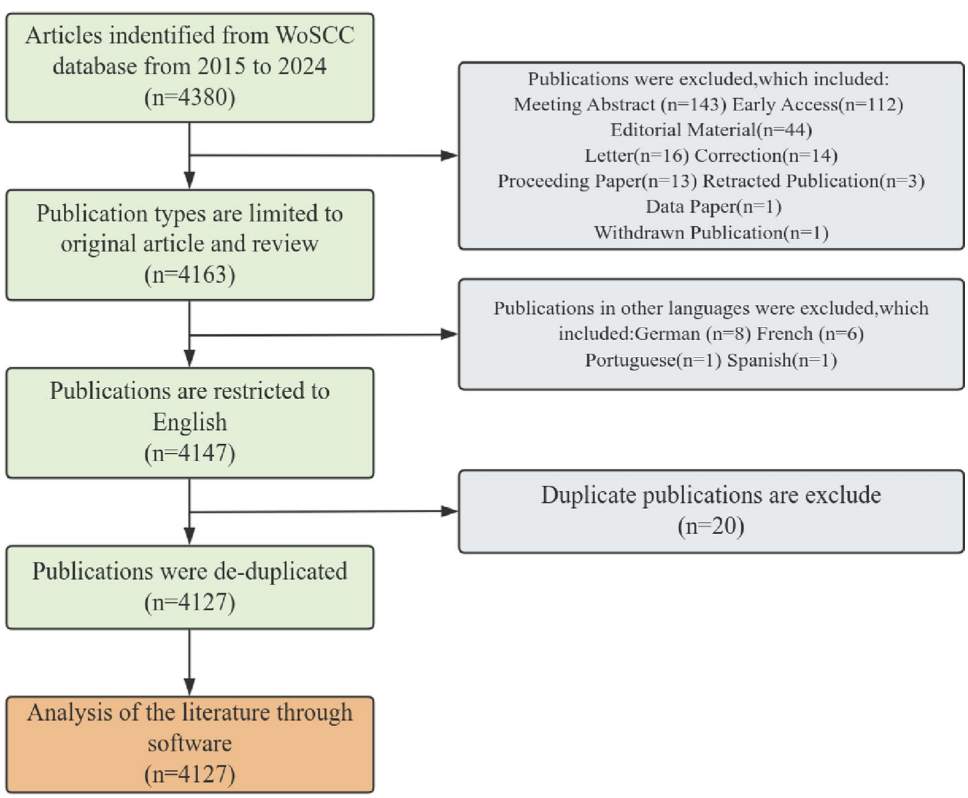

Fig. 1 The screening flow chart of this study

minimum of H times. The H-index was calculated using the Journal Citation Reports (JCR) 2023 to get the Impact Factor (IF) for different journal categories. The data were subsequently converted to Microsoft Excel 2024 for additional analysis.

2.4 Research ethics

The data sources of our study were available from the public databases. So the permission from the ethics committee is not needed.

3 Results

3.1 Global trend of publications and citations

A total of 4127 pertinent papers were gathered, and their publication and citation metrics were later analysed. As of January 1, 2025, the total citations for AI in radiomics within oncology research, the average citation rate, and the h-index are reported by WoSCC. Figure 2a illustrates a pronounced rising trajectory in global publications and citations from 2015 to 2024, with the most substantial increase occurring between 2020 and 2021, reflecting a 63.75% rise in annual publications. In 2015, the number of publications was merely 6, but it surged to 1101 by 2024. The data reveals that 92.39% of the total articles published in the past decade were released in the last 5 years. This phenomena can be ascribed to the growing popularity and application of AI. The integration of AI and radiomics could substantially expedite

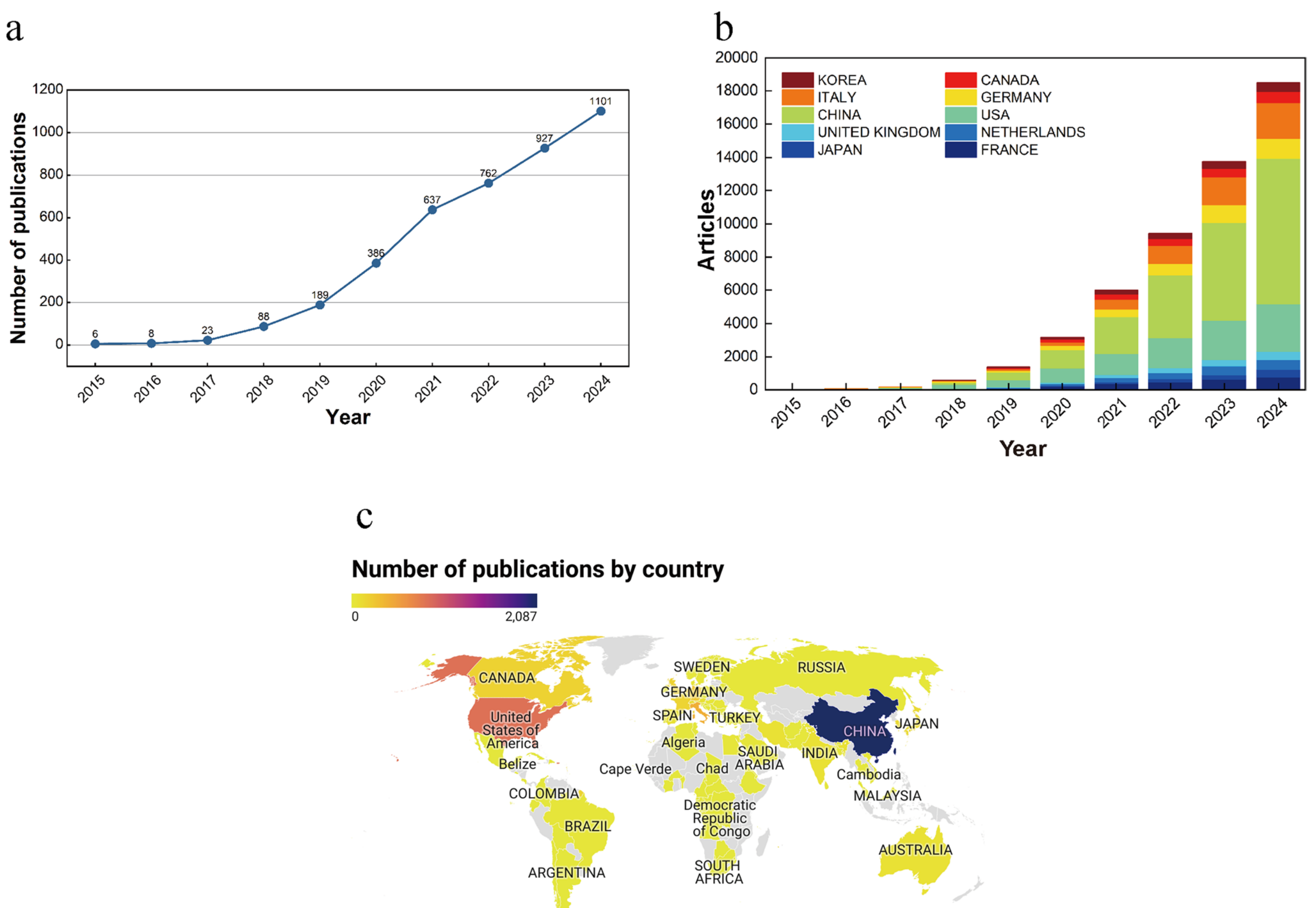

Fig. 2 Number of publications and analysis trends of AI in radiomics for oncology research (**a**) Annual global publication output. **b** Trends in publication output growth for the top 10 countries. **c** A Geo-visualized map built using CiteSpace based on publication volume by country/region

its progress and provide innovative insights for cancer research. This region is set to become a significant research hub in the next years. The publishing of further related articles is expected in the forthcoming years.

3.2 Distribution by country/region and institution

Since 2015, 89 nations and regions, along with 3874 institutions, have participated in research related to the use of artificial AI and radiomics in cancer. Figure 2c illustrates the geographical distribution of these research activities, highlighting a significant concentration of studies in North America, East Asia, and Western Europe. Table 1 demonstrates that China possesses the largest publication count, totalling 2087, with an H-index of 70. The United States (850), Italy (413), Germany (250), and the Netherlands (207) are in close succession. 'Total Link Strength(TLS)' is a metric used to measure the strength of connections between nodes, often used in co-occurrence network analysis in bibliometrics. It represents the total weight of all connections between a node and other nodes. This metric can help identify which nodes in the network have stronger connections. Among the five most productive countries, China exhibits subpar performance in "TLS", "Citations", and "Average Citations". This may suggest the insignificance of published publications or a deficiency in international collaboration. Nonetheless, the average publication year between releases is commendable, indicating that Chinese research is progressive. A comparative analysis of worldwide publication metrics indicates that articles published in U.S. sources (897) exhibit a pronounced superiority in performance at TLS, substantially surpassing those from the Netherlands (418) and China (411), which rank second and third, respectively. Nevertheless, the Netherlands, Cyprus, Israel, and Poland exhibited average citations over 50, signifying that they produced articles with an average of over 50 citations per article, which is exceptional among all countries. The nine universities with the highest publication volumes are located in China, with Fudan University being the foremost global publisher (Table 2). This phenomenon aligns with the broader landscape of global academic publishing, where Chinese universities consistently demonstrate remarkable productivity in terms of publication volume. Upon rigorous evaluation employing criteria such as citation metrics and additional article attributes, Maastricht University emerges as a notable outlier, securing the 10th position among the world's leading institutions. Figure 2b illustrates a substantial increase in the annual publication rate of scholarly articles in these countries, particularly during the last five years. Italy initially led the research, but China surpassed it in 2020 and has since maintained its dominance.

A web-based visualisation map was created using VOSviewer to examine international cooperation in radiomics research articles related to advancements in AI for cancer (Fig. 3a). Countries or regions that exhibited high co-occurrence were then categorized by identical coloration. Countries or regions with similar colors were recognized as demonstrating enhanced collaboration and establishing clusters. The extent of collaboration is signified by the breadth of these lines. The United States (897) possesses the largest total contact power, signifying its predominant role in global cooperation. The nations exhibiting the highest level of cooperation with the U.S. are Brazil, Israel, Finland, Colombia, and Slovenia. The green cluster, on the other hand, is predominantly led by China, which engages in the most collaboration with Australia, Egypt, Saudi Arabia, Singapore, and Malaysia. The red cluster, predominantly comprising German entities, collaborates extensively with various countries, including England, Austria, Turkey, Greece, Poland, Portugal, and Romania. As illustrated in Fig. 3b, the global collaboration network demonstrates substantial involvement from

Table 1 Top 10 producing countries related to AI in radiomics for oncology research

Rank	Countries	Articles	Percentage	Total link strength	Citations	Avg. pub. Year	Avg. citations	H-index
1	CHINA	2087	50.57%	411	30,308	2022.3996	14.5223	70
2	USA	850	20.60%	897	33,155	2021.52	39.0059	78
3	ITALY	413	10.01%	392	9189	2022.0872	22.2494	44
4	GERMANY	250	6.06%	365	5679	2021.796	22.716	41
5	NETHERLANDS	207	5.02%	418	11,761	2021.7536	56.8164	43
6	CANADA	190	4.60%	341	5112	2021.7684	26.9053	38
7	ENGLAND	180	4.36%	385	6254	2021.9444	34.7444	36
8	FRANCE	172	4.17%	252	5003	2021.6105	29.0872	34
9	SOUTH KOREA	134	3.25%	74	3844	2021.6493	28.6866	34
10	JAPAN	130	3.15%	76	1733	2022.3385	13.3308	23

Table 2 Top 10 producing institutions related to AI in radiomics for oncology research

Rank	Institution	Articles	Percentage	Total link strength	Citations	Avg. pub. Year	Avg. citations
1	Fudan Univ	169	4.09%	243	3142	2022.2308	18.5917
2	Sun Yat Sen Univ	162	3.93%	293	3607	2022.2469	22.2654
3	Chinese Acad Sci	152	3.68%	441	5784	2021.6645	38.0526
4	Shanghai Jiao Tong Univ	127	3.08%	183	1923	2022.2126	15.1417
5	Sichuan Univ	120	2.91%	123	1812	2022.1417	15.1
6	Southern Med Univ	111	2.69%	222	2049	2022.2703	18.4595
7	Zhejiang Univ	92	2.23%	128	1532	2022.087	16.6522
8	China Med Univ	85	2.06%	95	1359	2022.1882	15.9882
9	Beihang Univ	79	1.91%	285	3715	2021.4304	47.0253
10	Maastricht Univ	79	1.91%	142	7381	2021.3165	93.4304

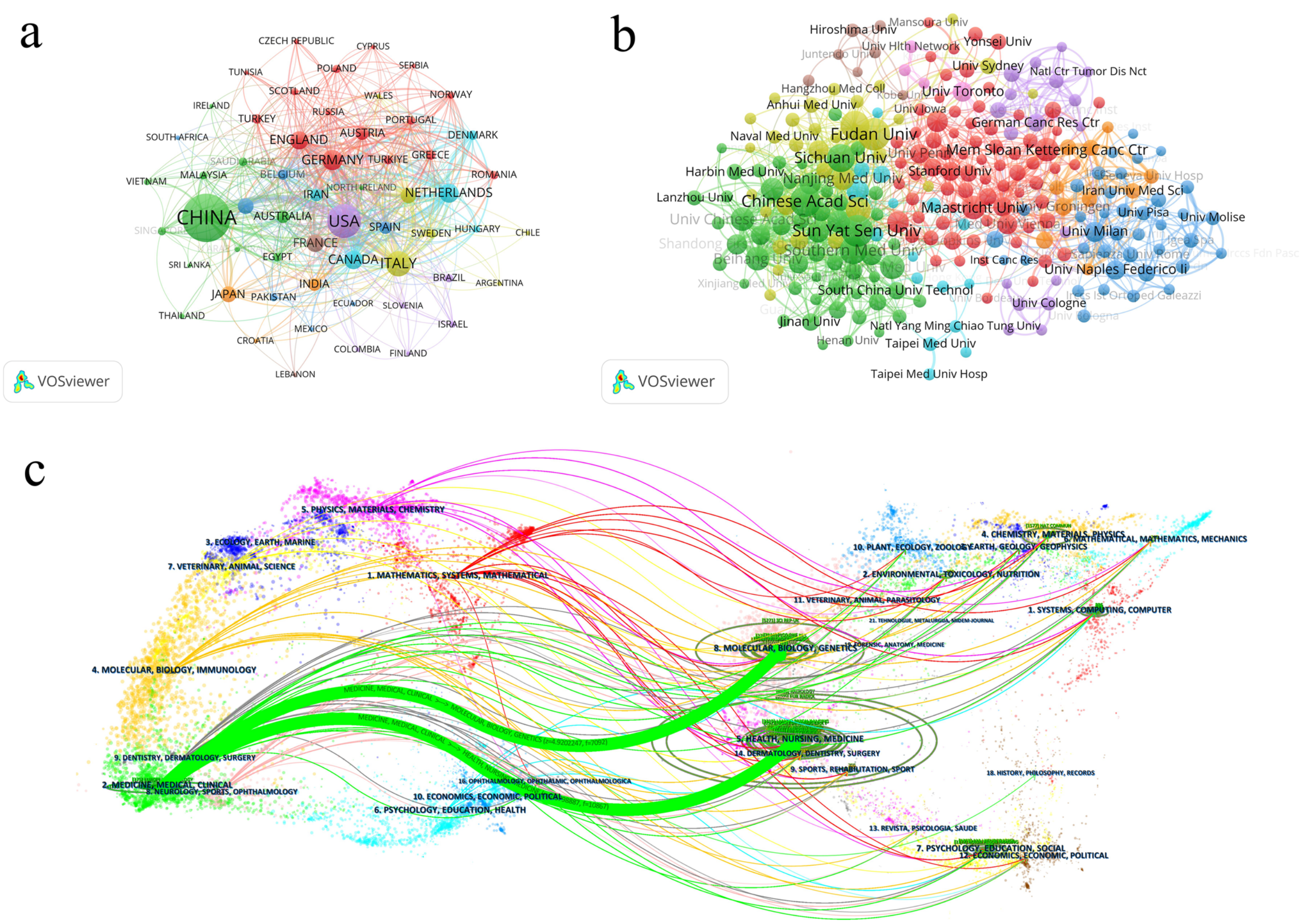

Fig. 3 Visualization map of the VOSviewer network of countries/regions and institutions involved AI in radiomics for oncology. **a** Collaboration analysis by country/region. **b** Collaboration analysis by agency. **c** Double graph superposition of citations of articles on the application of radiomics in neurological diseases (the left side is the cited journal, the right side is the cited journal, and the curve path represents the citation relationship)

numerous organizations, with the Chinese Academy of Sciences exhibiting the highest total link strength. A substantial proportion of these cooperative endeavors is centered on universities and research institutions within their respective nations. In contrast, the green clusters predominantly consist of Chinese universities, while the red clusters primarily

Table 3 Top 10 productive journals for AI in radiomics for oncology research

Rank	Productive journal	Articles (N)	Percentage	IF	H-index	JCR	Total link strength	Citations	Avg. citations
1	*Frontiers in oncology*	394	9.547%	3.5	60	Q2	624,152	5936	15.066
2	*Cancers*	270	6.542%	4.5	53	Q1	440,254	3496	12.9481
3	*European radiology*	175	4.240%	4.7	134	Q1	299,527	5821	33.2629
4	*Diagnostics*	121	2.932%	3	45	Q1	203,907	1166	9.6364
5	*Scientific reports*	119	2.883%	3.8	149	Q1	226,149	3653	30.6975
6	*Academic radiology*	88	2.132%	3.8	87	Q1	137,805	1055	11.9886
7	*Medical physics*	77	1.866%	3.2	159	Q1	142,701	1757	22.8182
8	*Abdominal radiology*	70	1.696%	2.3	67	Q2	105,965	715	10.2143
9	*Journal of magnetic resonance imaging*	67	1.623%	3.3	142	Q1	111,177	1542	23.0149
10	*European journal of radiology*	67	1.623%	3.2	102	Q1	116,109	1775	26.4925

Table 4 Top 10 prolific authors and co-cited authors of AI in radiomics for oncology

Rank	Author	Count (N)	Rank	Co-cited author	Count (N)
1	Tian, Jie	60	1	Lambin P	1587
2	Cuocolo, Renato	30	2	Gillies RJ	1240
3	Fusco, Roberta	25	3	Van Griethuysen JJM	976
4	Granata, Vincenza	24	4	Aerts Hjwl	818
5	Dong, Di	23	5	Zwanenburg A	747
6	Song, Bin	22	6	Sung H	456
7	Li, Jing	18	7	Parmar C	427
8	Petrillo, Antonella	18	8	Siegel RL	402
9	Lambin, Philippe	17	9	Kumar V	358
10	Zhang, Yu	16	10	Liu ZY	344

feature universities from Europe and North America. The underdevelopment of cross-border collaboration is evident, underscoring the necessity for its enhancement in future research endeavors.

3.3 Distribution by journal

An extensive examination of scholarly articles indicates a significant collection of 4127 papers focused on the integration of AI and radiomics inside oncological research. These papers have been distributed throughout 597 academic journals. Table 3 lists the 10 journals with the highest output and citation frequency. *Frontiers in oncology* (394, 9.547%), with an impact factor (IF) of 3.5 and an H-index of 60, was the most often published journal, followed by *Cancer* (270, 6.542%), *European Radiology* (175, 4.240%), *Diagnostics* (121, 2.932%), and *Scientific reports* (119, 2.883%).

The dual map illustrates three primary reference routes. The left side illustrates the research frontier, featuring articles predominantly in medical, neurology, sports, ophthalmology, and clinical journals, whereas the right side depicts the cited region, with articles mainly published in molecular, biology, genetics, health, nursing, medicine, dermatology, dentistry, and surgery journals (Fig. 3c).

3.4 Authors analysis

A total of 5,026 authors engaged in the study. Table 4 presents the ten most prolific authors. Tian Jie authored 60 articles, leading in publication count, succeeded by Cuocolo Renato with 30 papers, Fusco Roberta with 25 papers, Granata Vincenza with 24 papers, Dong Di with 23 papers, Song Bin with 22 papers, Li Jing and Petrillo Antonella with 18 papers, and Lambin Philippe with 17 papers, followed by Zhang Yu with 16 papers. Figures 4a and b demonstrate a distinct link regarding article authorship. In this illustration, each node signifies an author, with larger nodes indicating a greater number of published articles by the author. The presence of bold lines in Fig. 4a signifies a substantial level of collaboration among writers. This statistic unequivocally illustrates the presence of communication and collaboration

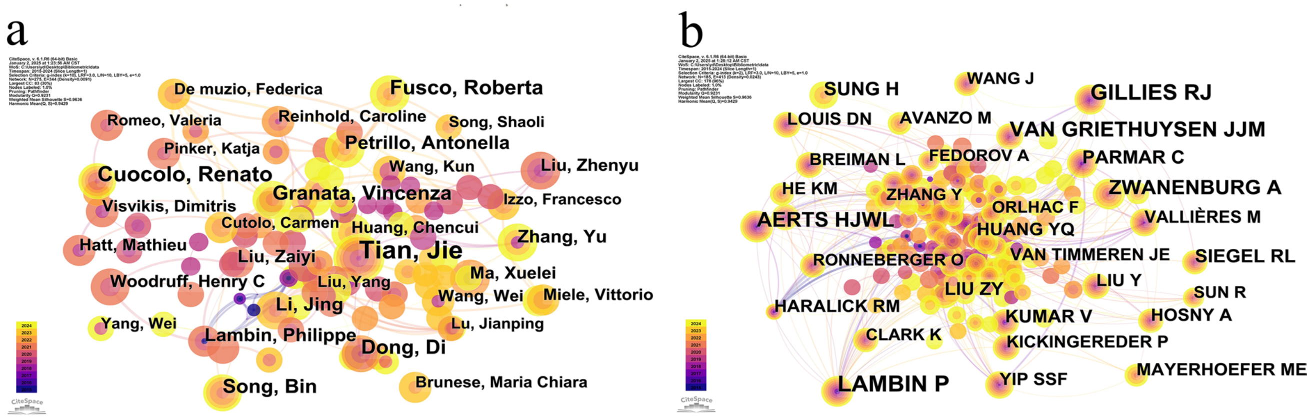

Fig. 4 CiteSpace visualization of authors. **a** Co-occurrence of authors. **b** Co-cited authors. The circle node represents the author of the paper. Links between nodes represent partnerships

among authors in the field. The phrase "co-cited authors" denotes authors who are regularly referenced in publications, serving as significant markers of author contributions. Figure 4b and Table 4 demonstrate that Lambin P (1587) occupies the foremost position, succeeded by Gillies RJ (1240), Van Griethuysen J (976), Aerts Hjwl (818), and Zwanenburg A (747). Numerous authors have made substantial contributions to the fields of radiomics and AI. The existing literature on these topics is a significant resource for scholars in these domains. The fourth most referenced author in our preliminary data is Anonymous (848). Due to our inability to ascertain the precise identity of this author or validate the number of authors represented by Anonymous, we excluded it from our debate. Professor Lambin is a pioneer of the radiomics idea, which he presented in 2012, characterizing it as the systematic identification, extraction, quantification, and analysis of imaging features from radiological images in a high-throughput fashion [12]. Furthermore, he introduced the Radiomics Quality Score (RQS) to evaluate the quality of radiomics research [13]. Professor Gillies has significantly advanced the study of tumour heterogeneity through radiomics signature analysis, elucidating heterogeneous structures inside tumours and establishing a foundation for comprehending tumour biology and formulating personalised treatment strategies [14]. Dr. Van Griethuysen is a principal developer of the PyRadiomics platform, an open-source toolkit for the quantification of radiomics, extensively utilised for the extraction and analysis of features in medical imaging [15]. Dr. Aerts has performed comprehensive research on radiomics feature extraction and analysis techniques, developed numerous sophisticated feature extraction algorithms, and extracted a substantial array of intensity, shape, texture, and wavelet characteristics from CT, MRI, and other medical imaging modalities. He conducted the inaugural extensive clinical use of radiomics including 1019 lung cancer patients [16]. Dr. Zwanenburg is a principal contributor to the Imaging Biomarker standardization Initiative (IBSI) and has participated in formulating comprehensive standardization criteria to enhance the reproducibility and comparability of radiomics study outcomes [17].

3.5 References analysis

A co-citation analysis was conducted on the 4,127 included publications, revealing that among the top 10 most co-cited articles, seven pertained to radiomics, two to oncology, and one to AI (Fig. 5a and Table 5). The articles co-cited over 500 times were exclusively focused on radiomics. They are regarded as dependable sources for subsequent relevant study. Zwanenburg A et al. [17] was co-cited the most, with 576 citations. Gillies RJ et al. [14] had the highest centrality (0.64), indicating that this article was highly influential and acted as a bridge between several research topics.

Looking at the total number of citations on the WOS datebase for the 4127 documents included, the ten most cited articles were identified (Table 6). Van Griethuysen et al. [15], published in 2017, was the most cited. The annual increase in the citation count is evident, with a current total of 3729 citations, representing an average of 414.33 citations per annum. It is noteworthy that five articles are present in both Tables 5 and 6. This observation lends further credence to the prominence of these research domains and suggests that the concepts articulated in these publications have offered researchers significant insights, thereby explaining their frequent citation across a range of research domains. An analysis of these references shows that the combination of AI and radiomics is constantly being constructed. By constantly combining the two, it can provide completely new ideas and methods for diagnosis and treatment in oncology.

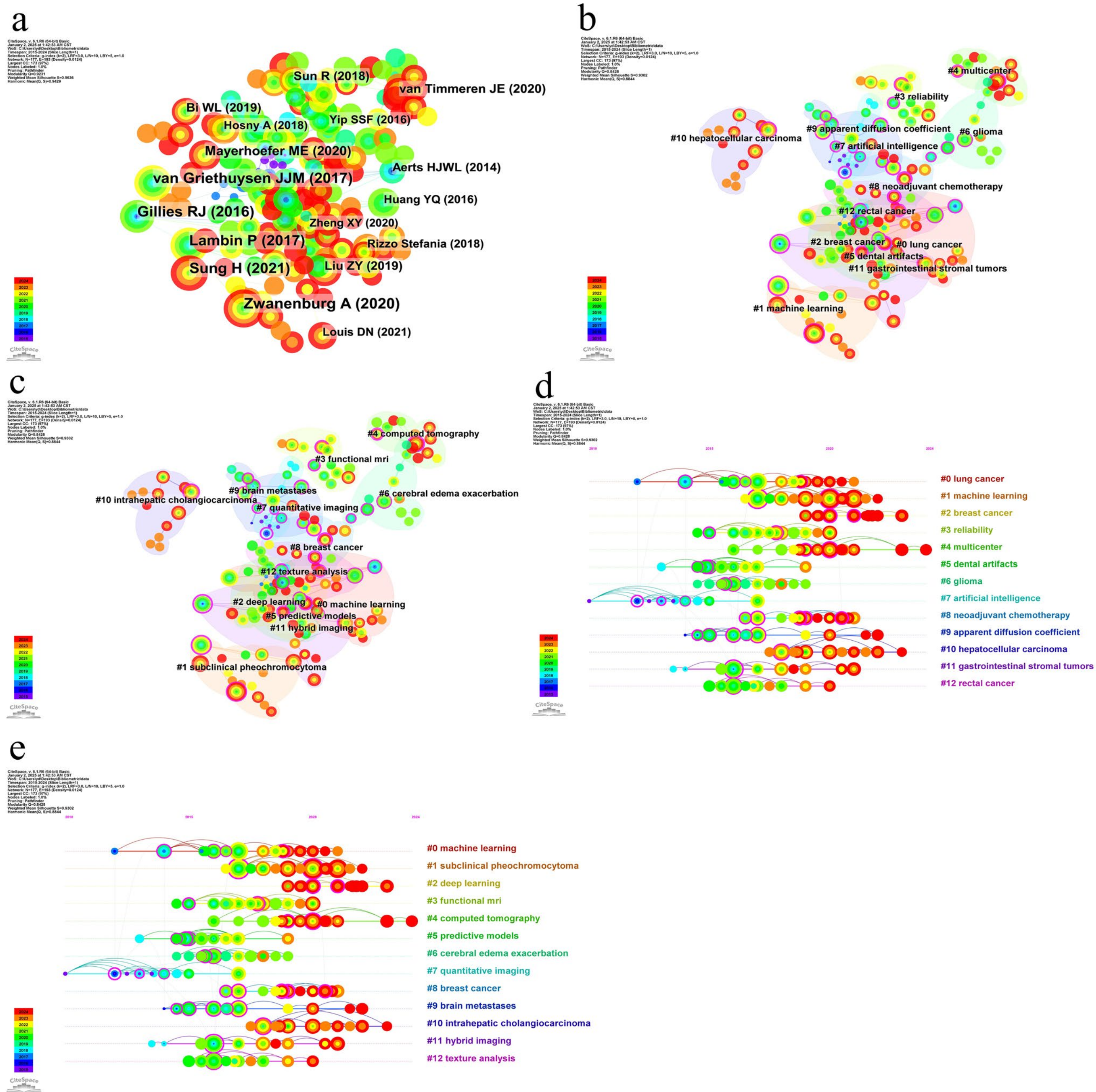

Fig. 5 Analysis of references related to AI in radiomics for oncological studies. **a** Network of co-cited references. **b** Literature co-citation clustering (LLR algorithm). **c** Literature co-cited clustering (LSI algorithm). **d** Literature co-citation clustering timeline (LLR algorithm). **e** Literature co-citation clustering timeline (LSI algorithm)

We conducted co-citation class clustering of references by identifying co-cited literature (Fig. 5b, c) to uncover themes and patterns in the research domain. Latent Semantic Indexing (LSI) excels with extensive datasets and is proficient at recognizing semantic similarities within the literature. The Log-Likelihood Ratio (LLR) is proficient in detecting robust correlations between literature and research boundaries. The findings from this analysis indicate that machine learning, deep learning, and other technologies are frequently applied in radiomics for a variety of diseases such as lung cancer, breast cancer, tumor brain metastasis, which may be involved in a variety of aspects such as diagnosis, treatment, metastasis prediction, survival prediction(Table 7). To enhance the monitoring of contemporary research hotspots, we developed a timeline of literature co-citation clustering (Fig. 5d, e). It excels at evaluating pivotal nodes and research focal

Table 5 Top 10 most cited papers according to CiteSpace on AI in radiomics for oncology

Rank	Co-citations (N)	Centrality	First author	Year	Title	Journal	DOI
1	576	0.15	Zwanenburg A	2020	The Image Biomarker Standardization Initiative: Standardized Quantitative Radiomics for High-Throughput Image-based Phenotyping	*Radiology*	10.1148/radiol.2020191145
2	515	0.64	Gillies RJ	2016	Radiomics: Images Are More than Pictures, They Are Data	*Radiology*	10.1148/radiol.2015151169
3	508	0.49	Lambin P	2017	Radiomics: the bridge between medical imaging and personalized medicine	*Nature Reviews Clinical Oncology*	10.1038/nrclinonc.2017.141
4	501	0	Van Griethuysen JJM	2017	Computational Radiomics System to Decode the Radiographic Phenotype	*Cancer Research*	10.1158/0008-5472.CAN-17-0339
5	471	0.02	Sung H	2021	Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries	*CA: A Cancer Journal for Clinicians*	10.3322/caac.21660
6	233	0.09	Mayerhoefer ME	2020	Introduction to Radiomics	*Journal of Nuclear Medicine*	10.2967/jnumed.118.222893
7	188	0	Bray F	2020	Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries	*CA: A Cancer Journal for Clinicians*	10.3322/caac.21492
8	170	0.22	Van Timmeren JE	2020	Radiomics in medical imaging-"how-to" guide and critical reflection	*Insights into Imaging*	10.1186/s13244-020-00887-2
9	159	0.09	Bi WL	2019	Artificial intelligence in cancer imaging: Clinical challenges and applications	*CA: A Cancer Journal for Clinicians*	10.3322/caac.21552
10	158	0.02	Liu ZY	2019	The Applications of Radiomics in Precision Diagnosis and Treatment of Oncology: Opportunities and Challenges	*Theranostics*	10.7150/thno.30309

Table 6 Top 10 most cited papers according to the Web of science database on AI in radiomics for oncology

Rank	Total Citations	Avg. Ann. Cit	First author	Year	Title	Journal	DOI
1	3729	414.33	Van Griethuysen	2017	Computational Radiomics System to Decode the Radiographic Phenotype	*Cancer Research*	10.1158/0008-5472.CAN-17-0339
2	1845	230.63	Hosny	2018	Artificial intelligence in radiology	*Nature Reviews Cancer*	10.1038/s41568-018-0016-5
3	977	139.57	Bi, Wenya Linda	2019	Artificial intelligence in cancer imaging: Clinical challenges and applications	*CA: A Cancer Journal for Clinicians*	10.3322/caac.21552
4	860	143.33	Mayerhoefer, Marius E	2020	Introduction to Radiomics	*Journal of Nuclear Medicine*	10.2967/jnumed.118.222893
5	800	100	Sun, Roger	2018	A radiomics approach to assess tumour-infiltrating CD8 cells and response to anti-PD-1 or anti-PD-L1 immunotherapy: an imaging biomarker, retrospective multicohort study	*Lancet Oncology*	10.1016/S1470-2045(18)30413-3
6	706	117.67	Van Timmeren, Janita E	2020	Radiomics in medical imaging-how-to guide and critical reflection	*Insights into Imaging*	10.1186/s13244-020-00887-2
7	679	61.73	Parmar, Chintan	2015	Machine Learning methods for Quantitative Radiomic Biomarkers	*Scientific Reports*	10.1038/srep13087
8	563	80.43	Liu, Zhenyu	2019	The Applications of Radiomics in Precision Diagnosis and Treatment of Oncology: Opportunities and Challenges	*Theranostics*	10.7150/thno.30309
9	443	49.22	Braman, Nathaniel M	2017	Intratumoral and peritumoral radiomics for the pretreatment prediction of pathological complete response to neoadjuvant chemotherapy based on breast DCE-MRI	*Breast Cancer Research*	10.1186/s13058-017–0846-1
10	366	45.75	Hosny, Ahmed	2018	Deep learning for lung cancer prognostication: A retrospective multi-cohort radiomics study	*Plos Medicine*	10.1371/journal.pmed.1002711

Table 7 Reference co-citation clustering information

Cluster ID	size	Silhouette	Mean (Year)	Top terms(LSI)	Top terms(LLR)
0	18	0.86	2017	Machine learning	Lung cancer
1	15	0.969	2019	Subclinical pheochromocytoma	Machine learning
2	14	1	2021	Deep learning	Breast cancer
3	13	0.977	2017	Functional mri	Reliability
4	13	0.951	2019	Computed tomography	Multicenter
5	13	0.877	2015	Predictive models	Dental artifacts
6	13	0.897	2016	Cerebral edema exacerbation	Glioma
7	12	0.984	2013	quantitative imaging	Artificial intelligence
8	12	0.793	2019	Breast cancer	Neoadjuvant chemotherapy
9	12	0.909	2017	Brain metastases	Apparent diffusion coefficient
10	12	0.943	2020	Intrahepatic cholangiocarcinoma	Hepatocellular carcinoma
11	10	0.949	2017	Hybrid imaging	Gastrointestinal stromal tumors
12	10	0.975	2017	Texture analysis	Rectal cancer

points within the literature. The timeline indicates that the predominant research focal points since 2020 are primarily cancer and machine learning.

3.6 Keywords analysis

Keywords are distilled and derived from an article's content to encapsulate its subject matter and essence. High-frequency keywords frequently suggest prevalent subjects within the study domain. The keyword co-occurrence network is an analytical method grounded in text content. The authors gathered 213 keywords and determined the 25 most frequently referenced keywords using keyword burst analysis (Fig. 6). The year denotes when these terms initially emerged in the database. Strength denotes the magnitude of the keyword's citation increase over a specified timeframe. A greater value indicates increased attention garnered by the term within that timeframe. The terms "Begin" and "End" indicate the years during which the citation growth of the keyword commenced and concluded. This signifies a substantial rise in the citation count for this keyword throughout this timeframe. The red bars on the right side of the graph indicate the particular years during which the keyword experienced an increase in citations. The greater the length of the red segment of the bar, the more attention the keyword garnered during that timeframe. The analysis reveals that the predominant burst keywords pertain to radiomics, artificial intelligence, and oncology research. The initial advancements in this field include textural features, heterogeneity, lung cancer cells, segmentation, classification, computer-aided diagnostics, and CNNs. Subsequent to this seminal work, a plethora of other subjects have emerged as the focal point of research endeavors. These subjects include texture analysis, FDG PET, tumor heterogeneity, radiogenomics, high-grade glioma, performance, imaging biomarkers, volume, imaging phenotypes, parameters, risk stratification, and ductal adenocarcinoma. In recent years, surgery, epidemiology, magnetic resonance imaging (MRI), staging, and systematic review have emerged as pivotal terms for outbreaks. Figure 6a illustrates a distinct association among the terms. The illustration demonstrates that the size of each node corresponds to the significance of the keyword, with larger nodes representing keywords of greater importance. The thickness of the line in Fig. 6a signifies the strength of the correlation between two terms. To identify focal points in the research domain, the terms were grouped. The data were examined using LSI and LLR processing, yielding Fig. 6b, c. Table 8 illustrates that the Silhouette metric reflects cluster quality, with values spanning from − 1 to 1. A number approaching 1 indicates greater similarity within clusters, increased differentiation across clusters, and improved clustering efficacy. Cluster 0, with 25 publications and an average publication year of 2020, exhibits exceptional clustering quality (silhouette = 1), primarily associated with Cluster 4, which comprises 17 publications, with an average publication year of 2020, and also exhibits exceptional clustering quality (silhouette = 1), primarily associated with machine learning and texture analysis. Cluster 12 has 17 publications, with an average publication year of 2020 and exceptional clustering quality (Silhouette = 1), primarily concerning magnetic resonance imaging, nasopharyngeal carcinoma, prostate cancer aggressiveness, and pancreatic cancer. To enhance the monitoring of recent research trends, a keyword co-citation

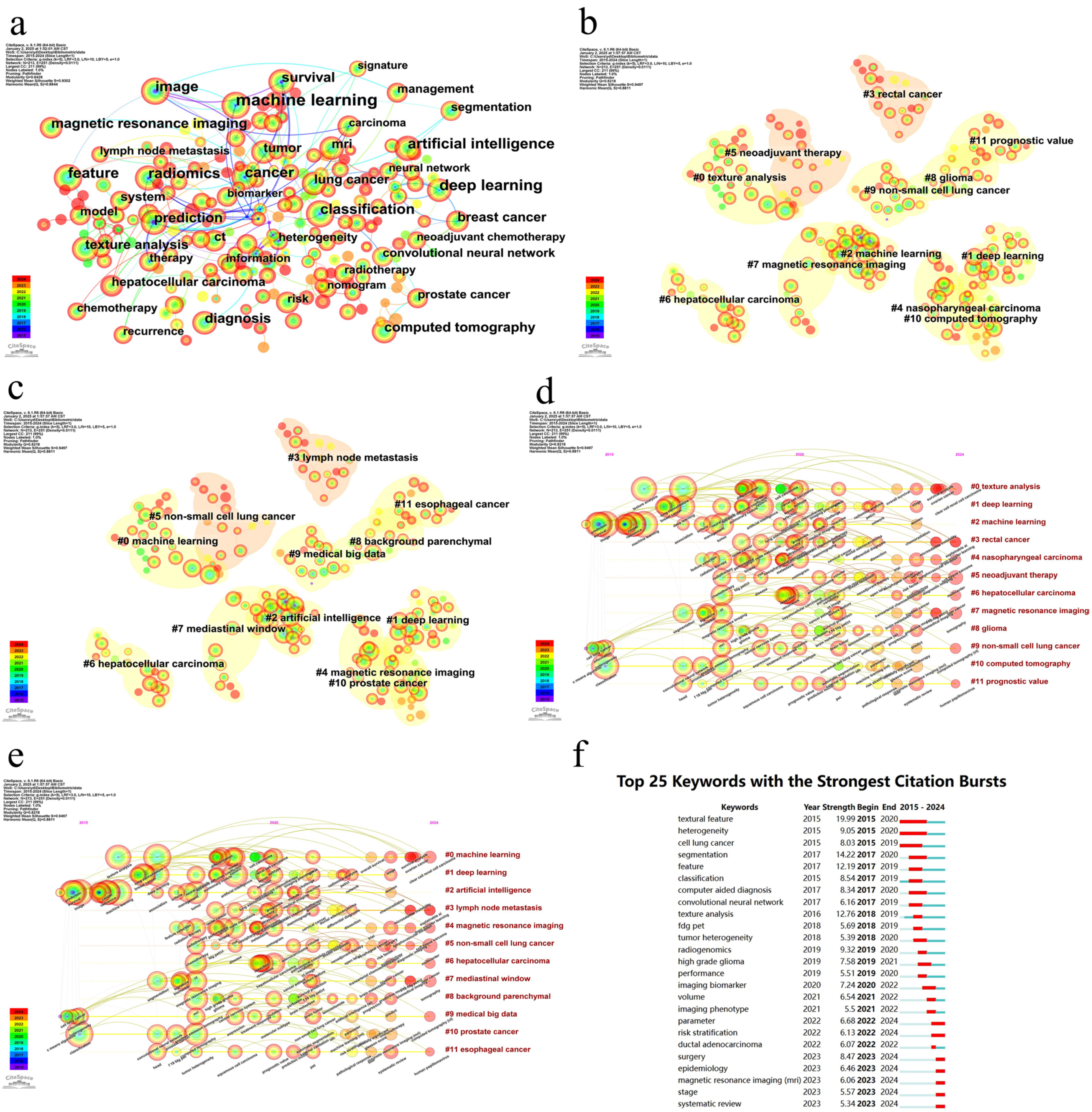

Fig. 6 CiteSpace visualisation of AI in radiomics for oncology research keywords. **a** Visualisation and analysis of keywords in related studies **b** Keyword clustering analysis (LLR algorithm) **c** Keyword clustering analysis (LSI algorithm) (**d**) Keyword clustering timeline (LLR algorithm) (**e**) Keyword clustering timeline (LSI algorithm) (**f**) The top 25 keywords with the strongest citation bursts

clustering timeline was developed (see Figs. 6d, e). The timeline reveals that since 2020, the predominant research trends have been centered on cancer and artificial intelligence.

4 Discussion

In recent years, AI has swiftly emerged as a fundamental component of the medical domain, particularly in oncology. This study conducted a thorough bibliometric analysis of the application of AI in radiomics for oncology research over the past decade, utilising the bibliometric packages of R software, as well as the visualisation tools Citespace and VOSviewer.

Table 8 Top 12 Keywords Cluster Analysis Details

Cluster ID	size	Silhouette	Mean (Year)	Top terms(LSI)	Top terms(LLR)
0	25	1	2020	Machine learning	Texture analysis
1	23	0.95	2019	Deep learning	Deep learning
2	22	0.919	2017	Artificial intelligence	Machine learning
3	17	0.968	2021	Lymph node metastasis pancreatic cancer	Rectal cancer
4	17	1	2020	Magnetic resonance imaging	Nasopharyngeal carcinoma
5	15	0.915	2021	Non-small cell lung cancer	Neoadjuvant therapy
6	15	0.986	2020	Hepatocellular carcinoma	Hepatocellular carcinoma
7	15	0.98	2020	Mediastinal window	Magnetic resonance imaging
8	15	0.869	2020	Background parenchymal	Glioma
9	14	0.97	2018	Medical big data	Non-small cell lung cancer
10	13	0.846	2020	Prostate cancer	Computed tomography
11	11	0.951	2020	Esophageal cancer	Prognostic value
12	5	0.952	2020	Mpmri prostate cancer aggressiveness intelligence	Pancreatic cancer

The objective is to furnish a thorough comprehension of the domain, pinpoint study focal points, investigate prospective research trajectories, and offer motivation for forthcoming enquiries. Our analysis offers an impartial and methodical assessment of the present landscape of AI applications in radiomics, delineates trends, and underscores prospective research goals for the integration of AI and radiomics in tumour diagnosis and treatment. This initiative will assist scientists in swiftly comprehending the present state of research and offer significant insights for choosing study topics. The initial phase of the project analysed publication trends, encompassing nations, institutions, authors, and journals. Keywords were further examined by clustering to discern research hotspots within the domain. This is the most recent bibliometric analysis offering comprehensive insights into the published literature regarding AI in oncology. Fudan University in China is the most active institution, with China being the most prolific country. The leading journal is Frontiers in oncology, while the most prolific author is Tian Jie and the most cited author is Lambin P. The predominant keywords include texture feature, texture analysis, segmentation, and feature. Future research may focus on the optimization of algorithms for feature extraction and machine learning; the prediction of treatment effects, lymph node metastasis, and prognosis for various types of tumors.

In this study, only English-language articles from the WoS database were included in the literature review, which may have introduced some bias. In the process of analyzing the results of the study, we also found some interesting phenomena. For example, China has the highest number of publications, but its "total link strength" and "citations" are not as good as those of the United States (Table 1). We believe there are several reasons for this phenomenon. Chinese AI research in oncology may be more focused on the application level, such as tumor diagnosis and treatment plan optimization using existing AI technologies. Although there is a considerable amount of research in this area, there are relatively few contributions in terms of fundamental theoretical frameworks and innovative technological breakthroughs. In contrast, research in the United States has been more focused on developing fundamental technologies and innovative approaches. These studies are characterized as more forward-looking and original, and are therefore more likely to be the focus of highly cited research. In addition, the United States has significant influence in the global academic community, which ensures that its research results are more frequently identified and cited by international peers. Another interesting phenomenon is that the top 10 most cited papers (Tables 5, 6) are from journals other than the top 10 most productive journals for AI in radiomics for oncology research (Table 3). This may be due to the fact that the most cited papers are more innovative and pioneering than the others, focus on the cutting edge of various research, set standards to inspire other research, or conduct a lot of detailed research, thus gaining favor with the top journals. The reason for the journals with a higher number of articles may be that the journals themselves favor articles in the field of imaging genomics, or they may have lower acceptance criteria, resulting in the publication of many low-quality articles.

Driven by AI technology, radiomics has made tremendous breakthroughs in non-invasive tumor characterisation, classification of benign and malignant tumors, prediction of tumor staging and lymph node involvement, tumor genotype identification, prediction of treatment response, prognosis and multimodal data fusion.

According to our keyword clusters analysis, AI has made substantial progress in the field of texture analysis and feature extraction in recent years (Table 8). The innovation and implementation of deep learning models have led to substantial advancements in the efficacy of feature extraction. Pre-trained models, such as ResNet50, which is based on CNN models, have become increasingly prevalent in the extraction of high-dimensional features from medical images [18]. These models have demonstrated the capability to automatically discern complex patterns and texture features in images with greater efficiency and accuracy compared to conventional manual feature extraction methods. Multimodal medical image segmentation models, such as VISTA3D, have been at the forefront of innovation. They have pioneered the 3D super voxel feature extraction method, which is capable of automatic segmentation and feature extraction of 3D medical images. This method performs well when dealing with complex 3D anatomical structures and improves the accuracy and efficiency of image analysis. Furthermore, these models can also fuse medical image data of different modalities (e.g.CT, MRI, etc.). This fusion method utilizes the strengths of diverse image types to achieve more comprehensive feature extraction and enhance the accuracy and reliability of diagnoses. Concurrently, the TransUNet hybrid architecture is introduced, which integrates the strengths of CNN and Transformer to more effectively capture the long-range dependencies present in images [19].

AI integrated with radiomics can assess and forecast cancer. Narrow-task models have been created to localise lesions and assess the risk of malignancy in lung cancer CT and breast cancer mammography, with applications that have been shown to perform as well as, or sometimes better than expert diagnosticians [20]. In these applications, unprocessed pixel data of the image serves as input for a deep-learning CNN, which is trained using radiologist-labeled ground-truth outputs. Significantly, although the algorithms exhibit remarkable performance for area under the curve, sensitivity, and specificity, they do not assess direct clinical endpoints, like cancer mortality, healthcare expenditures, or quality of life [21].Conversely, others seek to optimize the utility of pre-existing data streams, encompassing patient genomics, routine imaging, unstructured health record data, and comprehensive family history, with the objective of enhancing prediction accuracy. This enhanced predictive capability can facilitate the customization of treatment approaches for individual patients, thereby optimizing outcomes and minimizing unnecessary interventions. In the context of cancer diagnosis, the early detection and precise classification of tumors are crucial for timely intervention, which in turn enhances patient cure rates. Ideally, cancer should be diagnosed in asymptomatic patients, as the development of symptoms typically indicates advanced and incurable disease. Furthermore, given the heterogeneity of cancers in terms of clinical presentations and therapeutic responses, it is crucial to accurately delineate early-stage small tumors to facilitate the selection of optimal therapeutic interventions. However, early-stage primary tumors may exhibit imaging features that are indistinguishable due to their minute size. It is crucial to address and avert false positives, over-detection, over-diagnosis, and over-treatment. The integration of radiomics with machine learning techniques holds promise in the differentiation of various localized liver lesions. The features obtained through this process are instrumental in facilitating non-invasive diagnosis and characterization of liver cancers, offering critical information such as microvascular invasion within the tumor. The employment of artificial intelligence in the classification of various liver pathologies has become a prevalent practice. CNNs, engineered for image recognition tasks, have garnered significant interest in the diagnosis of liver cancer [22]. A substantial body of research employing CT or MR imaging has adopted radiomics to differentiate among distinct liver lesions, attaining areas under the ROC curve (AUC) ranging from 0.7 to 0.95. These investigations have demonstrated robust performance on both the training set and the test and validation sets. The research encompassed a wide range of classification tasks and differential lesions, including hepatocellular carcinoma (HCC), hemangiomas, cysts, adenomas, local nodular hyperplasia of the liver, cholangiocarcinoma (CC), HCC-CC comorbidities, inflammatory masses, and metastases. Clinical characteristics are integrated into specific models to enhance their efficacy [23–27]. Several studies have used AI or radiological features extracted from gadolinium acetate-enhanced MRI, dynamic contrast-enhanced MR or contrast-enhanced CT images to predict microvascular invasion in HCC and mass-type CC [28]. The AUC varied between 0.75 and 0.98, with the majority of studies exhibiting an AUC exceeding 0.85. A study indicated that patients devoid of microvascular invasion (MVI) had markedly extended recurrence-free survival (RFS). All studies were incorporated into the validation set [29–32]. Accurate preoperative prediction of MVI significantly impacts surgical planning, including judgements about the degree of resection and the suitability of ablative therapy. The elevated AUC values and predictive capability indicate that AI and radiomics can effectively ascertain the existence or absence of MVI preoperatively, facilitating a more tailored surgical strategy and enhancing postoperative results and recurrence-free survival in patients with HCC.

Our co-citation cluster analysis of references (Table 7) identified themes such as lung and breast cancer, whose presence here may be closely related to individualized treatment of tumors. The integration of AI with radiomics can significantly contribute to tumour treatment. The segmentation of target regions and organs at risk (OARs) is a crucial and time-intensive component in the preparation, delivery, and evaluation of radiotherapy. Following the advent of CT and its application in treatment planning, radiation oncologists have dedicated substantial time to delineating targets and organs at risk. Historically, automatic segmentation has utilised intensity thresholds; however, this approach is not flawless. Recent years have witnessed numerous publications on the application of deep learning (DL) techniques for segmentation. Frequently employed techniques encompass encoder-decoder CNNs and 2D or 3D U-nets [33–35]. Xiao et al. elucidated the efficacy of innovative Refine Net-based 2D and 3D automated segmentation models for CT-derived postoperative clinical target volume (CTV) and organs at risk (OAR) in cervical cancer. The RefineNetPlus3D model achieved DSCs of 0.97, 0.95, 0.91, 0.98, and 0.98 for the bladder, small bowel, rectum, and left and right femoral heads, respectively. The mean manual contouring duration for CTV and OAR in cervical cancer patients was 90–120 min, while the average computation time using RefineNetPlus3D for these OARs was 6.6 s [36, 37]. These findings indicate significant promise for the advancement of adaptive radiotherapy. A recent paper by Liao et al. demonstrated the successful segmentation of 16 abdominal organs-at-risk utilising deep learning techniques, employing 3D U-net as the baseline model. They documented flawless outlines of the liver, kidneys, and spleen. The primary accomplishment of their algorithm is its resilience. Their findings were derived from various CT scans and patients, while the majority of prior investigations utilised more uniform data. Nonetheless, they did not attain good outcomes in the duodenum (DSC < 0.7) [38]. While there remains potential for enhancement in the automatic segmentation of the OAR, it can be asserted with considerable confidence that the segmentation is nearly complete. AI can assist in delineating gross tumour volume (GTV). A 3D U-Net model was employed in a study to segment the lung, main tumour, and affected lymph nodes. The architecture and model hyperparameters were optimised using nnU-Net, a deep learning segmentation approach that does not develop a new network architecture, loss function, or training scheme, encompassing pre-processing, network design, training, and post-processing for each task. Targets were defined by radiation oncologists to produce discovery data and subsequently validated through external resources. Cubes of volume and surface area were utilised for assessment. Although the model surpassed the inter-observer benchmark when verified with internal data (conducted by the same expert) and met the intra-observer benchmark, it failed to exceed the benchmark when evaluated with external data (segmented by separate experts). This outcome may suggest variations in segmentation methodologies and preferences across specialists, as notable discrepancies exist in the manual delineation of tumour regions. AI aid lowered segmentation time by 65% (5.4 min) and interobserver variability by 32%. Consequently, in facilities where residents are employed, or in satellite hospitals lacking constant specialist availability, AI could be essential in aiding residents to generate segmentations that meet the approval of senior radiation oncologists.

AI can also be used to predict a tumor's response to treatment. Regarding DL methods, Xu et al. [39] combined pre-trained CNNs with RNNs to analyse longitudinal CT scans of stage III NSCLC patients before and after treatment. In the validation dataset, the AI approach had high performance in predicting pathological response ($P = 0.016$), and this performance improved as the number of scans analysed increased. Ha et al. [40] trained a CNN to predict response to neoadjuvant chemotherapy based on pretreatment MRI scans and reported an accuracy of 88% for the test dataset. Patients with TNBC (36%) or HER2 + (50%) breast cancer in this study had higher pCR rates than patients with luminal A subtype breast cancer (18%), which is consistent with population-based findings [41]. Jiang et al. [42] created a novel DL-AI biomarker utilising portal phase-contrast enhanced CT images to forecast disease-free survival (DFS) and overall survival (OS). The model was subsequently employed to create detailed column-line plots incorporating clinicopathological features that predicted disease-free survival (DFS) (C-index 0.85, 95% CI 0.83–0.88) and overall survival (OS) (C-index 0.86, 95% CI 0.84–0.89), while also demonstrating advantages from adjuvant chemotherapy across numerous independently validated datasets. Consequently, these researchers propose a non-invasive imaging technique to identify patients who are most likely to benefit from neoadjuvant therapy before treatment begins, contrasting markedly with the existing standard of care that employs post-treatment serial magnetic resonance imaging to evaluate treatment response. The integrated analysis of peritumoral and intratumoral radiological features from DCE-MRI scans in patients with invasive HER2+ breast cancer may facilitate the identification of intrinsic molecular cancer subtypes, enhance understanding of immune responses in the peritumoral environment, and forecast responses to HER2-targeted therapies [43]. In an exploratory study, Mehta et al. [44] demonstrated that pharmacokinetic modelling of baseline dynamic breast MRI helped to identify patients with downregulation of angiogenic pathways after bevacizumab treatment, which may indicate response to therapy.

Integrating radiomics with other types of data, such as genomics and pathology, provides a more complete understanding of cancer. Multimodal data fusion can improve the accuracy of diagnostic and prognostic models. For example, Rao et al. [45] used an unsupervised hierarchical clustering approach to identify novel phenotypes defined by multiparametric MRI features in a TCGA glioblastoma sample library with microRNA and mRNA expression data. The DL model developed by Wang S et al. using CT [46] and Mu W et al. using PET-CT [47] scanning was effective in predicting epidermal growth factor receptor mutation status in NSCLC patients. Yang L et al. [48] using a radiogenomic approach was able to predict KRAF, NRAS and BRAF mutation status in colorectal cancer patients.

The integration of AI and radiomics has emerged as a promising avenue for the acquisition of non-invasive biomarkers, offering a comprehensive reflection of the genetic and immunological characteristics inherent within neoplastic lesions. For instance, radiomic features can be utilized to predict gene mutations and immune phenotypes in non-small cell lung cancer (NSCLC), thereby facilitating personalized treatment strategies. This non-invasive approach has the potential to reduce the necessity for invasive biopsies and to provide real-time information regarding the status of the tumor. Furthermore, AI has the potential to develop tools that facilitate precision follow-up in cancer patients. Radiomic features extracted from post-treatment images can predict recurrence risk and late toxicities, helping to customize follow-up plans. This approach has the potential to optimize the utilization of healthcare resources and enhance patient outcomes.

AI and radiomics have the potential to function as clinical decision support tools, thereby furnishing radiologists and oncologists with supplemental information to facilitate more informed decision-making. The integration of radiomic data with clinical data allows for the provision of personalized treatment recommendations, thereby enhancing the comprehensive management of cancer patients. Specifically, the integration of AI-driven radiomics has the potential to enhance the efficiency of treatment planning, reduce costs associated with trial-and-error approaches, and ultimately improve patient outcomes.

Despite the promising applications of AI in radiomics, several challenges remain. Data standardization, infrastructure support, reproducibility and transparency of radiomic features are critical issues that need to be addressed. In addition, the integration of AI into clinical workflows requires careful consideration of ethical and regulatory issues.

In order to achieve the desired generalization and interoperability of radiomics and AI algorithms in the domain of medical imaging, it is essential that global methodological standards be adopted in clinical workflows [49]. Standard scanning protocols are implemented across organizations to ensure consistency in acquisition parameters. The preprocessing steps, which include filtering, resampling, and morphological image processing, also affect radiomics features. It is therefore necessary to construct standardized processes for these steps. Ensuring data availability, accessibility, and reusability necessitates the stability and reproducibility of radiomics features across hospitals, scanners, and acquisition protocols, a principle that can be applied under the FAIR framework. The involvement of manufacturers in the standardization process is also to be welcomed, as they are responsible for bringing the latest technology to the clinic. Infrastructural support is also crucial for the application of AI in radiomics. This necessitates the allocation of substantial computing resources for the training and deployment of models, as well as the establishment of adequate data storage and processing capabilities. The development of high-performance computing resources is imperative to support the training and deployment of these models. The development of efficient data storage and processing systems is imperative to address the processing demands of large-scale data sets. Addressing the issues of reproducibility and transparency necessitates encouraging researchers to publicize their datasets and codes for universal monitoring. At the same time, it is imperative to establish appropriate ethical guidelines and regulatory frameworks to explore support mechanisms for the integration of AI in radiomics.

In summary, the combination of AI and radiomics has the potential to transform cancer management by providing more accurate diagnostics, personalized treatment plans and improved prognostic assessments. As research continues to address current challenges, the future of AI in oncology radiomics looks promising, with the potential to significantly improve patient outcomes and the efficiency of cancer care.

5 Conclusions

Studies related to the combination of AI and radiomics are developing rapidly in early detection, precision diagnosis, and prognostic analysis of tumours. We summarise publication and citation metrics, including annual growth, most productive countries/regions, most contributing authors, journals and institutions, co-occurring keywords and cutting-edge hotspots. China and the United States are the most productive countries. *Frontiers in oncology* and *Cancer* are the most frequently published journals related to this research. Tian Jie published the most articles and Lambin P and Gillies RJ published the most cited articles. With the development of deep learning algorithms and CNNs, significant progress has been made in imaging-assisted diagnosis of multiple cancer types. Currently, the accuracy of most AI is unsatisfactory and can only be applied to some common diseases, mainly due to insufficient available data. AI also faces challenges in terms of data quality, security and privacy. Nonetheless, we still expect that the deep integration of AI with radiomics can lead to more important advances in identifying early cancers, inferring specific cancer sites, developing personalized treatment plans, describing the tumor microenvironment and predicting future prognosis.

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Declarations

Competing interests The authors declare no competing interests.

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