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ORIGINAL RESEARCH

Artificial Intelligence and Radiomics in Primary Liver Cancer Imaging: A Bibliometric and Visualized Analysis

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Background: Combining artificial intelligence (AI) with radiomics for primary liver cancer (PLC) enhances diagnostic precision, sharpens risk stratification, and facilitates personalized treatment. The study aims to conduct a bibliometric analysis of this field, explore its research status and emerging hotspots, and provide data support and academic insights for subsequent research.

Methods: A bibliometric analysis of 2890 publications on PLC, AI, and radiomics from 2008 to 2025 was performed, using data retrieved from the Web of Science Core Collection (WoSCC) and Scopus, followed by manual screening and deduplication. The finalized dataset was analyzed and visualized using tools such as VOSviewer, CiteSpace, and R to examine trends in annual publication counts, the geographic distribution of research, the institutions involved, journals, authors, references, and keywords.

Results: Publication output has increased rapidly since 2018. China (n = 1603, 55.47%) was the leading contributor, and Sun Yat-sen University (n = 186, 6.44%) was the most productive institution. Of all authors, Song, Bin (n = 42) was the most prolific author. *Frontiers in Oncology* and *Radiology* were identified as the most productive and influential journals, respectively. The most frequently occurring keywords were "hepatocellular carcinoma", "deep learning", and "magnetic resonance imaging", while "image reconstruction", "liver cancer classification", and "deep supervision" have emerged as prominent recent research hotspots.

Conclusion: Applications of AI and radiomics in imaging for PLC are gaining increasing attention. Future trends are expected to focus on enhancing algorithmic accuracy and advancing clinical prediction of microvascular invasion, postoperative outcomes after hepatectomy, and the effectiveness of transarterial chemoembolization.

Keywords: liver neoplasms, hepatocellular carcinoma, artificial intelligence, radiomics, bibliometrics

Introduction

Primary liver cancer (PLC) is one of the most common malignant tumors in the digestive system and the leading cause of death from cancer worldwide.[1] The main pathological types include hepatocellular carcinoma (HCC), intrahepatic cholangiocarcinoma, and combined hepatocellular-cholangiocarcinoma, among which HCC is the most common.[2] According to the 2022 Global Cancer Statistics, the incidence of PLC (4.3%) and mortality (7.8%) rank sixth and third in cancer worldwide, posing a serious threat to public health.[3] Due to the lack of reliable early warning signs, most patients have progressed to the intermediate and advanced stages at the time of diagnosis, resulting in limited treatment options and poor prognosis.[4,5]

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Medical imaging plays a key role in the diagnosis and treatment of PLC, thereby improving early detection and clinical decision-making.[6] Although ultrasound remains the primary screening tool due to its practicality, computed tomography (CT) and magnetic resonance imaging (MRI) provide more detailed tumor information thanks to their superior spatial resolution and tissue contrast.[7–9] However, traditional imaging techniques have limitations in detecting small lesions and in differentiating benign from malignant masses.[10,11]

To address these limitations, artificial intelligence (AI)-integrated radiomics has significantly advanced the accurate diagnosis and treatment of PLC.[12] By quantifying tumor texture and morphology, radiomics has revealed phenotypic heterogeneity and microenvironmental characteristics, providing an objective basis for clinical management.[13] Although traditional radiomics faces challenges such as high-dimensional data and complex workflows, the integration of deep learning (DL) and machine learning (ML) has effectively simplified the process of feature extraction and analysis.[14–16] Specifically, convolutional neural network (CNN) models leverage their powerful pattern-recognition capabilities to process multidimensional data, achieving high-precision classification and improving efficiency.[17,18] This synergy has led the research to shift from empirical methods to data-driven precision medicine, which has demonstrated significant achievements in lesion differentiation, microvascular invasion (MVI) prediction, and recurrence risk assessment.[19–21] Furthermore, the rapid growth of multi-omics is expanding this paradigm. The synergy between AI and multidimensional data enables characterization of the PLC phenomenon, bridging macroscopic imaging with microscopic molecular landscapes to enhance precision medicine.[22] Recent molecular studies have further elucidated the biological basis underlying imaging phenotypes in PLC, including key regulatory genes, microRNA networks, and potential therapeutic targets, which provide complementary insights for radiomics and AI-based precision diagnosis and treatment.[23–26]

Due to the rapid growth of radiomics and AI in PLC diagnosis and treatment, it's challenging for a systematic review to fully grasp research trends. Bibliometrics, as a method for analyzing academic literature both qualitatively and quantitatively, can objectively reflect the development of the field by analyzing indicators such as annual output and key authors. It also compensates for the shortcomings of quantitative analysis in systematic reviews.[27,28] Although many bibliometric studies on liver cancer exist, a comprehensive bibliometric analysis of this interdisciplinary field is still lacking.[29,30]

Therefore, this study employs bibliometric methods to systematically analyze the literature on PLC, radiomics, and AI. By analyzing annual publication output, key countries and institutions, leading authors, core journals, highly cited papers, and keyword trends, the study objectively uncovers the field's developmental path, research trends, and future directions, offering insights for future research.

Materials and Methods

Data Sources and Search Strategies

The complete process from initial literature search to data visualization analysis is shown in Figure 1. Our data are obtained from the Science Citation Index Extended Edition of the Web of Science Core Collection (WoSCC) and the Scopus databases. In WoSCC, the search was conducted using Topic (TS) to search AI, radiomics, PLC, CT, MRI, and other related terms. In Scopus, the search was performed using the TITLE-ABS-KEY field for the same set of terms. The search strategy is detailed in Appendix 1 of the Supplementary Materials. The literature search scope is limited to English-language articles and reviews. The time span is from January 1, 2008, to December 31, 2025, incorporating Early Access content. After collecting all publications, two authors (RZF and CG) independently screened the titles and abstracts of the retrieved records and conducted a cross-review for a second round of verification. Any controversies or inconclusive publications were resolved by two experienced radiologists (ZPY and HSC).

Data Collection and Processing

Following the above screening process, 1874 and 2594 eligible publications were identified from WoSCC and Scopus, respectively. Complete information, including the title, author, abstract, keywords, and references, was extracted from the marked result list of the WoSCC and converted to a plain-text file for export. For Scopus, records were obtained from the marked result list and exported in "CSV with All Fields" format. Using Python (version 3.11), the CSV files from Scopus

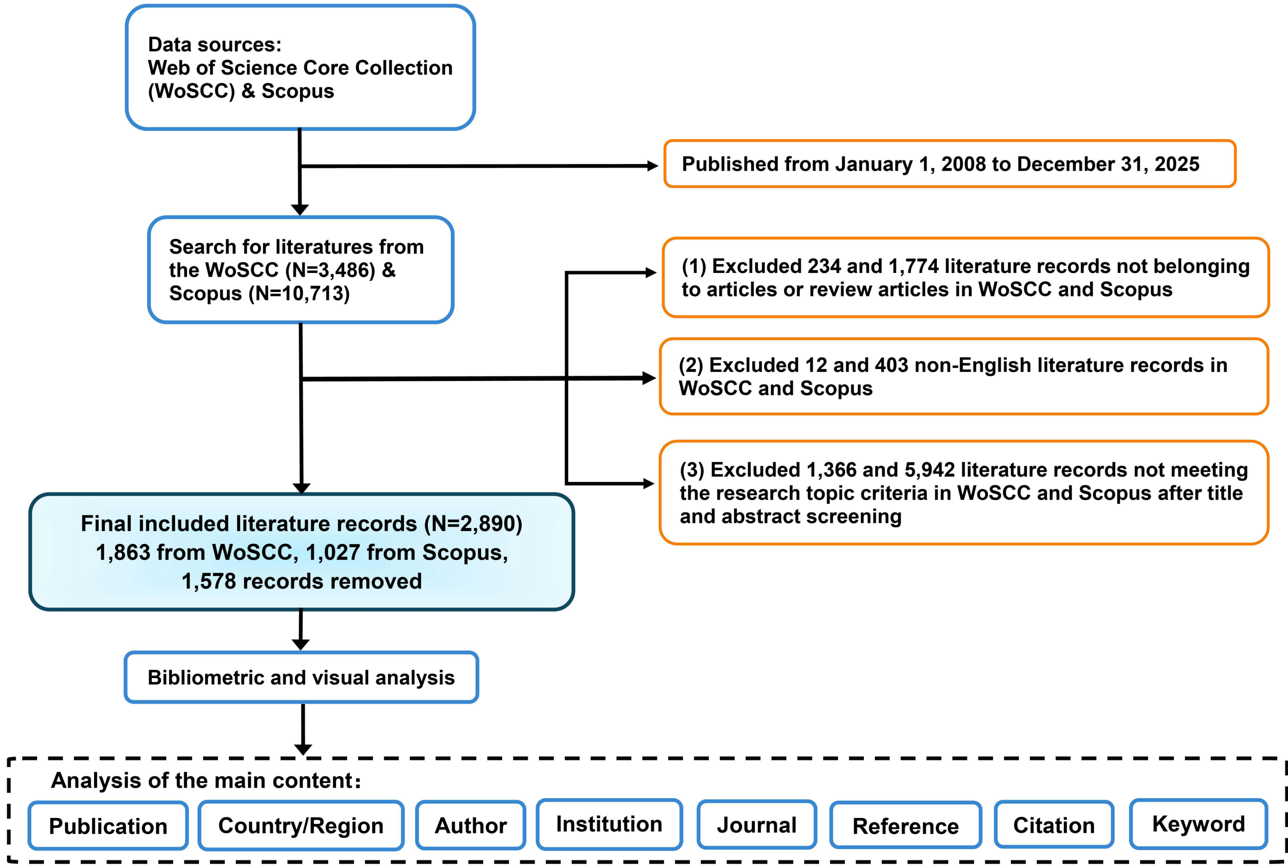

Figure 1 Flowchart of literature sources, screening, and data visualization analysis.

and the TXT files from WoSCC were converted into a unified plain-text format that is consistent with the complete records and citation reference structure of WoSCC. Firstly, data cleaning was carried out to ensure data quality, including deduplication of the same Digital Object Identifiers, exclusion of withdrawn publications, and exclusion of records in which the author field contains "[Anonymous]". Secondly, the institutional data were optimized by eliminating virtual institutions and by standardizing and merging duplicate institutions. Finally, a manual review was conducted. After this process, a total of 2890 publications were included in the analysis.

Visualization and Data Presentation

Data management and preliminary statistical analysis, including visualization of annual publication trends and literature types, were conducted using Microsoft Excel 2021. For more advanced bibliometric visualization, the appropriate tool should be selected based on its analytical advantages. VOSviewer (version 1.6.20) was used to draw the network of collaborations between countries/regions and institutions as well as the network diagram of co-cited journals. To enhance the graphical presentation, Pajek (version 6.01) was used to optimize the layout of network nodes, while Scimago Graphica (version 1.0.53) was integrated to generate a world map to display international cooperation.[31] CiteSpace (version 6.4.R1 Advanced) was used for studying temporal dynamics and research frontiers. This included generating chronological diagrams of author collaborations and evolution diagrams of keywords, a dual-map overlay of journals, and capturing references and keywords exhibiting strong citation bursts over time.[32] Additionally, the log-likelihood ratio (LLR) algorithm in CiteSpace was used for cluster analysis of co-cited references to identify emerging trends, while the R software (version 4.5.2) package ggplot2 was used for visualizing specific journal indicators.

Results

Annual Publications and Trend

Publication volume signifies research activity. Figure 2A illustrates that between 2008 and 2018, the annual publication count remained low, not exceeding 77. Since 2018, the number of publications has increased significantly, accounting for approximately 80% of total publications from 2020 to 2025. To quantify this nonlinear acceleration trend, Figure 2A employs a cubic polynomial fit. The $R^2 = 0.9881$ indicates a good fit. The overall growth trend is clear, and it is still on the rise. Specifically for the types of literature (Figure 2B), the number of Articles has consistently been the largest and has increased rapidly, in line with the overall trend. Although the base for Reviews is relatively small, it has increased in parallel since 2018.

Analysis of Countries/Regions

Figure 3A shows cooperation among countries and the total number of publications from major countries. Correspondingly, Table 1 lists the top 15 countries by the number of publications and their citation and collaboration indicators. China is the most productive country (n = 1603, 55.47%), followed by the USA (n = 538, 18.62%). Although China and the USA maintain certain cooperation, China's scientific research output remains primarily

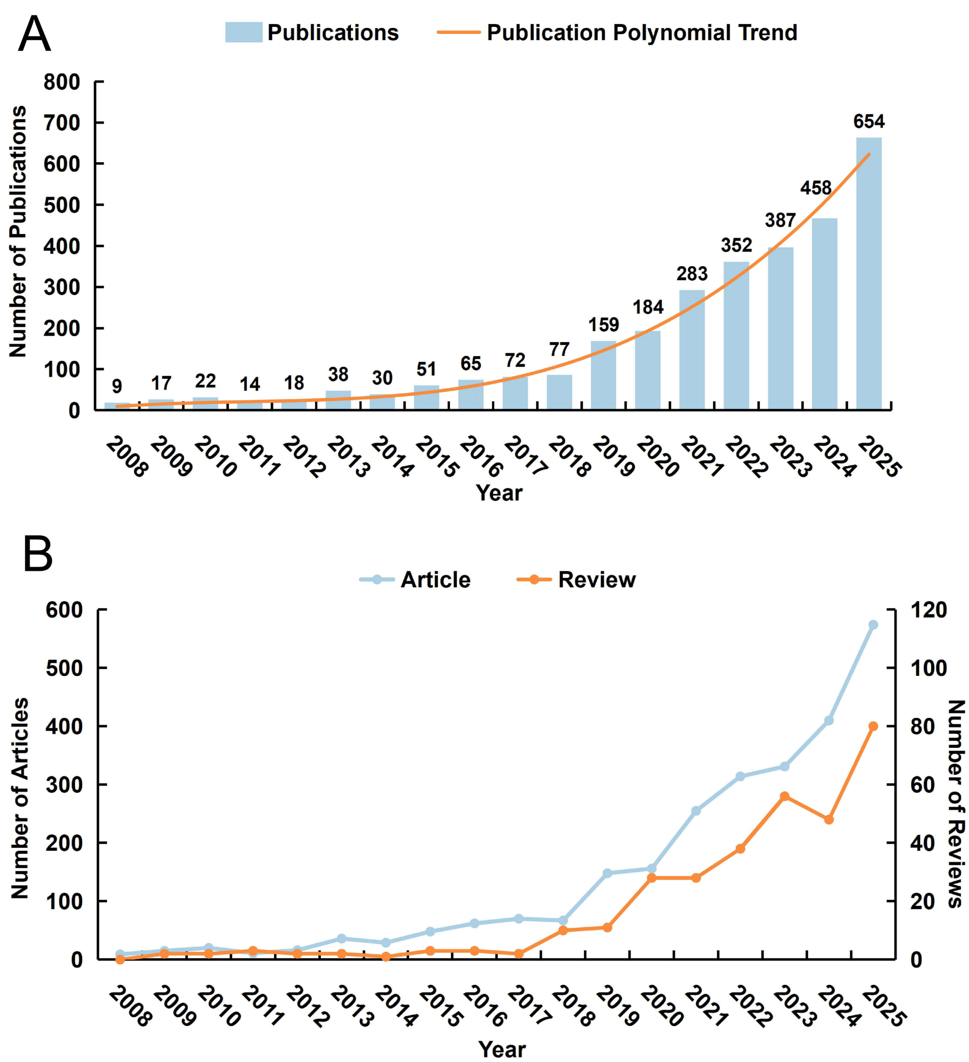

Figure 2 Trends in annual publication volume and distribution of document types from 2008 to 2025. (**A**) Annual number of publications with a polynomial trendline. (The bar shows counts in publications, and the solid line shows the polynomial fitting trend. $y = 0.2057x^3 - 2.4272x^2 + 11.65x + 0.1389$, x = Year – 2007, $R^2 = 0.9881$). (**B**) Annual counts of articles and reviews. (The blue line shows the number of original articles (left Y-axis), and the orange line shows the number of reviews (right Y-axis).).

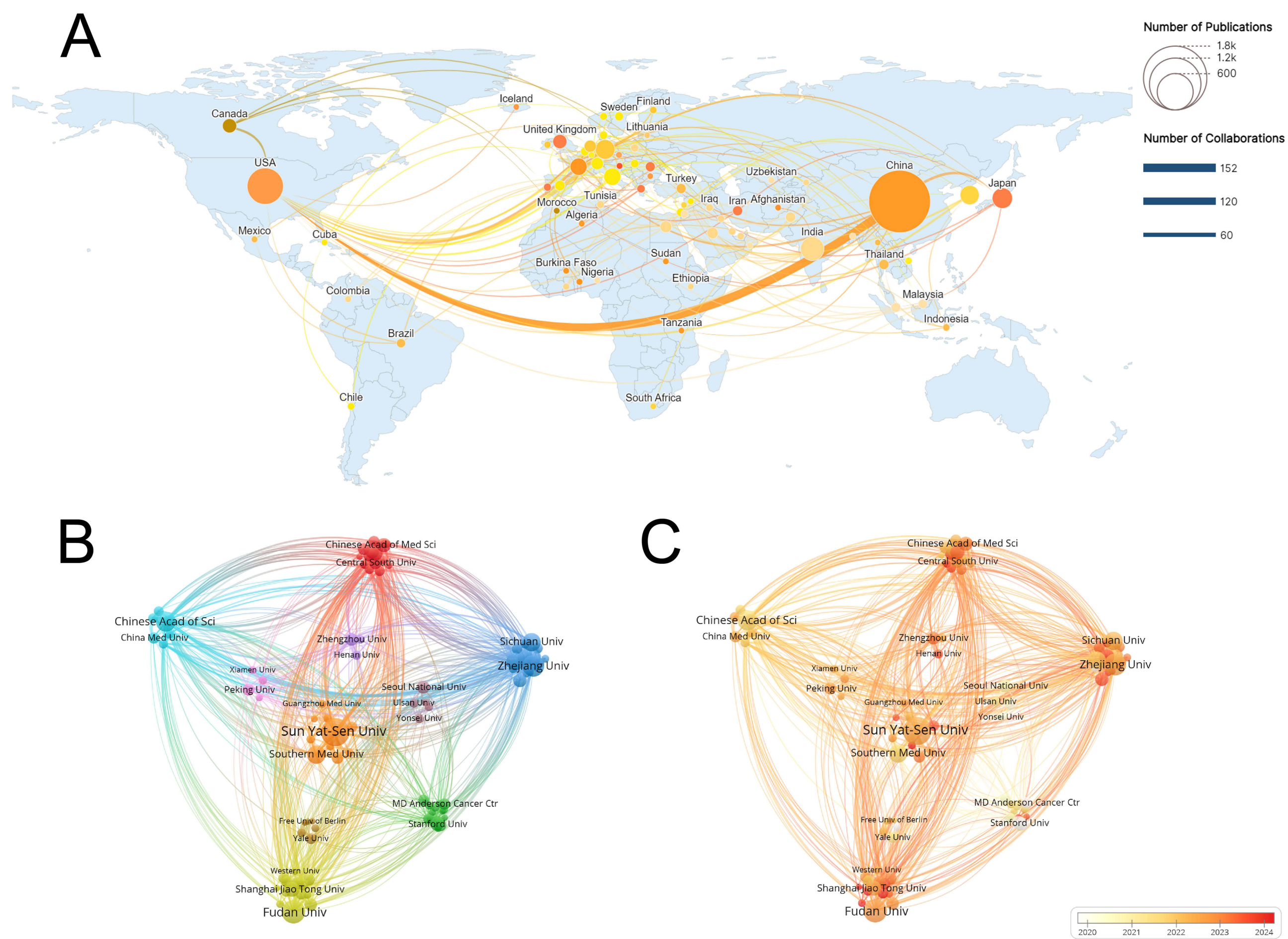

Figure 3 Analysis of countries/regions and institutions in the fields of AI and radiomics in PLC. (**A**) Global distribution of total publications and collaboration network by countries/regions. (**B**) Co-authorship network of institutions. (Node size represents the number of publications; links indicate collaboration relationships.). (**C**) Co-authorship network of institutions with a temporal overlay. (Based on B, different shades represent the average publication year of institutional works.).

driven by domestic collaboration, comprising 1331 single-country publications. In contrast, the multi-country publication ratios in Saudi Arabia, Switzerland, and the United Kingdom all exceed 80% (Table 1). In terms of influence, China achieved the highest total citations (TC = 30,773) due to its substantial publication volume, yet its

Table 1 The Top 15 Most Productive Countries in AI and Radiomics for PLC

Rank	Countries/Regions	Publications	Percentage (% of 2890)	TC	AC	SCP	MCP	MCP_Ratio
1	China	1603	55.47%	30,773	19.20	1331	272	16.97%
2	USA	538	18.62%	16,202	30.12	201	337	62.64%
3	India	219	7.58%	3687	16.84	172	47	21.46%
4	Japan	159	5.50%	3348	21.06	104	55	34.59%
5	Germany	143	4.95%	4406	30.81	56	87	60.84%
6	South Korea	137	4.74%	4267	31.15	92	45	32.85%
7	Italy	109	3.77%	2389	21.92	57	52	47.71%

(*Continued*)

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Table 1 (Continued).

Rank	Countries/Regions	Publications	Percentage (% of 2890)	TC	AC	SCP	MCP	MCP_Ratio
8	France	107	3.70%	3437	32.12	35	72	67.29%
9	Canada	68	2.35%	2603	38.28	23	45	66.18%
10	United Kingdom	67	2.32%	2359	35.21	12	55	82.09%
11	Switzerland	47	1.63%	1579	33.60	7	40	85.11%
12	Netherlands	45	1.56%	1842	40.93	11	34	75.56%
13	Egypt	41	1.42%	687	16.76	20	21	51.22%
14	Saudi Arabia	39	1.35%	791	20.28	4	35	89.74%
15	Spain	29	1.00%	1094	37.72	9	20	68.97%

Abbreviations: TC, Total Citations; AC, Average Citations; SCP, Single-Country Publications; MCP, Multi-Country Publications; MCP_Ratio, Multi-Country Publication Ratio.

average citations per literature (AC = 19.20) was relatively low. Notably, although the Netherlands had fewer publications (n = 45), its AC (40.93) was high.

Analysis of Institutions

Chinese institutions led PLC, AI, and radiomics research (Table S1). Sun Yat-sen University is a leading contributor (n = 186, 6.44%) to DL radiomics for HCC. Meanwhile, Stanford University demonstrated strong academic influence, with an average of 45.61 citations. GE Healthcare (n = 73) was the only enterprise organization in the top 20. Figure 3B shows 10 different clusters based on inter-agency collaboration. Figure 3C further illustrates a significant increase in recent activities, with major Chinese universities, such as Sun Yat-sen University and Zhejiang University, strengthening their cooperation efforts since 2022. While cross-border cluster cooperation mostly occurred before 2022.

Analysis of Journals

Statistics were compiled for the top 30 journals in the field by publication volume to examine the relationships among publication count, TC, and impact factor (IF), yielding Figure 4A. The findings revealed that fourteen journals had published more than 40 relevant articles. Among these, *European Radiology* had the highest TC (4307), while *Radiology* possessed the highest IF (15.2) (Table S2). *Frontiers in Oncology* contributed the most publications (n = 148, H-index = 28), followed by *Abdominal Radiology* (n = 92, H-index = 22) and *European Radiology* (n = 88, H-index = 36) (Table S2).

To better understand how journals are interconnected, the co-citation network was analyzed. Figure 4B indicates close interdisciplinary integration among radiology, hepatology, surgery, oncology, and computational medicine and image processing. The significant co-citation connections suggest frequent knowledge sharing among these fields. This is further supported by the dual-map overlay (Figure 4C), which shows that research published relies heavily on the fields of health, nursing, medicine, molecular, biology, and genetics. Additionally, disciplines such as systems, computing, and computer science also contribute to PLC, AI, and radiomics research.

Analysis of the Authors

According to Price's Law, authors who publish at least five articles can be regarded as core authors. There are 497 core authors in this research field, and the 10 most productive authors are shown in Table S3. Meanwhile, the most cited authors are also listed (Table S4). From the timeline of author cooperation (Figure 5A), it is evident that the authors within each cluster cooperate closely, whereas links between clusters are relatively small. The three main author clusters

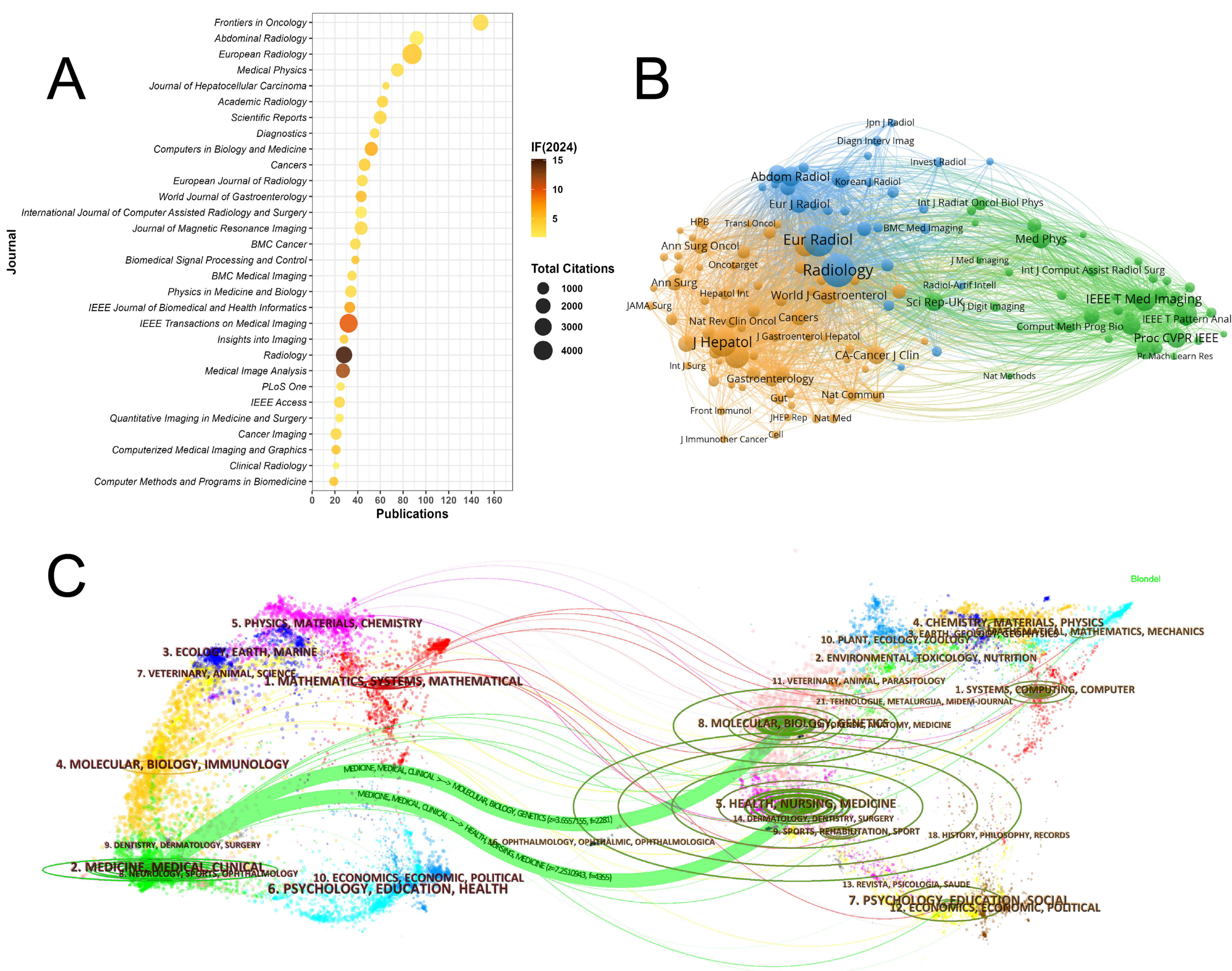

Figure 4 Analysis of journals on AI and radiomics in PLC. **(A)** Top 30 most published journals. (Journals are listed on the Y-axis against publication count on the X-axis. Node size indicates total citations, and color gradient represents the 2024 Impact Factor (IF).). (**B**) Co-citation network of cited journals. (Node size represents the number of citations; links indicate co-occurrence relationships.). (**C**) The dual-map overlay of journals. (The citing subject categories are on the left, the cited subject categories are on the right, and the colored paths represent the citation relationships.).

identified were “learning radiomics (#0)”, “intrahepatic cholangiocarcinoma (#1)”, and “preoperative gadoxetic acid-enhanced mri (#2)”. Notably, Song, Bin, the most prolific author, is situated within cluster #1, with his research output primarily concentrated in the period following 2019.[33,34] Figure 5B shows the co-cited network diagram of authors. The top three authors with influence in this field are Professor Hyuna Sung of the USA, Professor Philippe Lambin of the Netherlands, and Professor Josep M. Llovet of Spain.

Analysis of References and Co-Cited References

The 15 papers with the highest citation frequency were listed in Table 2, along with their respective publication venues.[35–49] Notably, Li Xiaomeng’s team published a paper on H-Dense U-Net in *IEEE Transactions on Medical Imaging* in 2018, which ranks first with 1785 citations.[35] The co-citation network divides highly cited papers into 12 clusters (Figure 5C), covering topics such as AI, texture analysis, clinical PLC diagnosis and treatment. Among these, “radiomics (#0)” is currently the largest cluster. Multiple clusters jointly promote their research progress. When combined with burst citation analysis (Figure 5D), Gillies et al reported a very strong citation burst (Strength = 41.40).[35,38,50–67] The papers published by Li Xiaomeng, Jorge A. Marrero, and Julie K. Heimbach have been highly cited in recent years.[35,66,67]

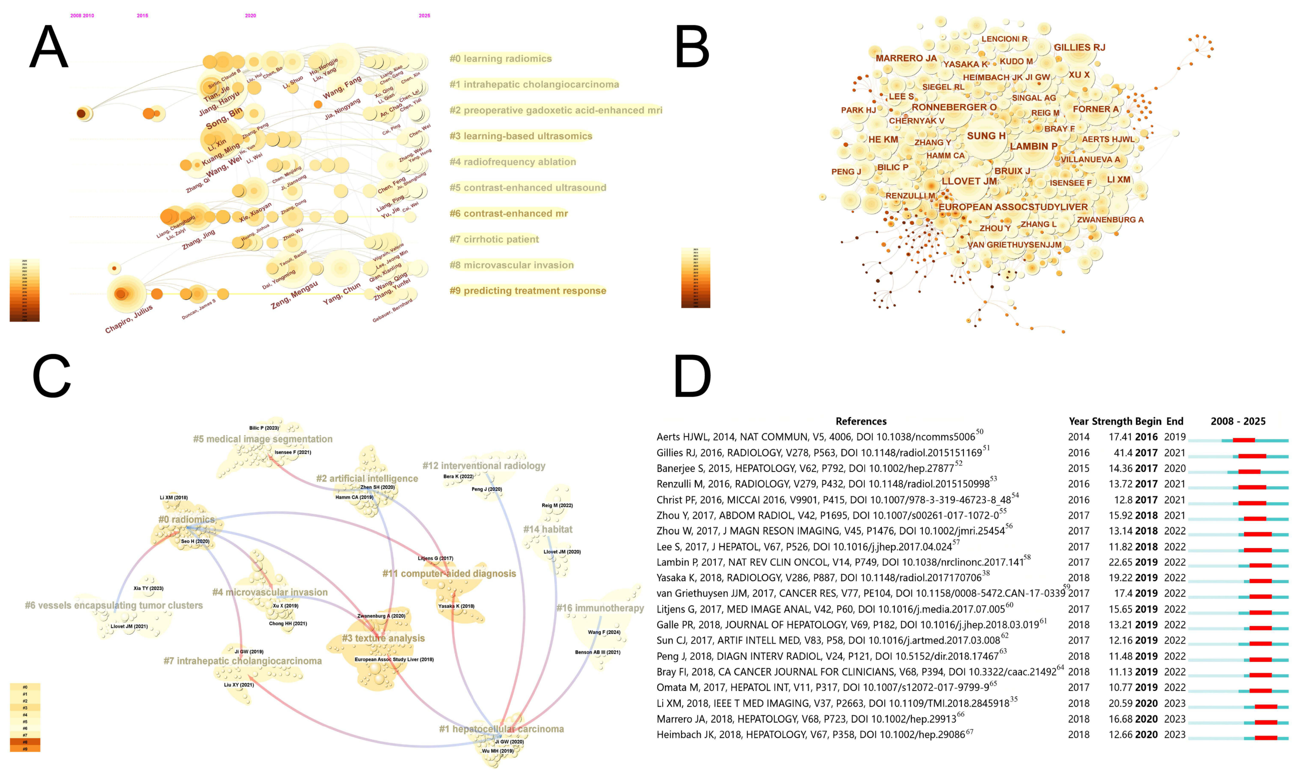

Figure 5 Analysis of core authors and references on AI and radiomics in PLC. (**A**) Timeline chart of the author collaboration network. (Closely collaborating authors are clustered along the timeline, with their key publication titles highlighted on the right. Node color indicates the year, and node size indicates publication frequency.). (**B**) Co-citation network of cited authors. (Node color indicates the year; node size indicates citation frequency.). (**C**) Landscape view of reference co-citation clusters. (Smaller numbers indicate larger clusters, with #0 as the largest; node size represents citation frequency; arrows on dependency paths indicate the direction of citation flow between clusters.). (**D**) Top 20 references with the strongest citation bursts. (The red bars indicate the duration of the citation burst.).

Keywords and Hotspots Analysis

When keyword analysis was performed on the research literature of AI and radiomics in PLC field, a co-occurrence network was constructed based on the keywords after merging (Figure 6A). The keywords that appeared more than 200 times included "hepatocellular carcinoma", "deep learning", "magnetic resonance imaging", "machine learning", "computed tomography", and "artificial intelligence". Detailed data and centrality metrics for the top 25 keywords are presented in Table S5.

To further understand the evolution trend of research hotspots, the keywords in the timeline analysis revealed 11 main clusters (Figure 6B). This timeline shows that the research context starts from basic image processing, and then, with the

Table 2 Top 15 Most Cited Papers on AI and Radiomics in PLC

Rank	Title	First Author	Journal	Year	TC
1	H-DenseUNet: Hybrid Densely Connected UNet for Liver and Tumor Segmentation From CT Volumes[35]	Li, Xiaomeng	IEEE Transactions on Medical Imaging	2018	1,785
2	The Liver Tumor Segmentation Benchmark (LiTS)[36]	Bilic, Patrick	Medical Image Analysis	2023	605
3	Radiomic Analysis of Contrast-enhanced CT Predicts Microvascular Invasion and Outcome in Hepatocellular Carcinoma[37]	Xu, Xun	Journal of Hepatology	2019	565
4	Deep Learning with Convolutional Neural Network for Differentiation of Liver Masses at Dynamic Contrast-enhanced CT: A Preliminary Study[38]	Yasaka, Koichiro	Radiology	2018	475

(*Continued*)

Table 2 (Continued).

Rank	Title	First Author	Journal	Year	TC
5	Transformation-Consistent Self-Ensembling Model for Semisupervised Medical Image Segmentation[39]	Li, Xiaomeng	IEEE Transactions on Neural Networks and Learning Systems	2021	420
6	Modified U-Net (mU-Net) With Incorporation of Object-Dependent High Level Features for Improved Liver and Liver-Tumor Segmentation in CT Images[40]	Seo, Hyunseok	IEEE Transactions on Medical Imaging	2020	327
7	MA-Net: A Multi-Scale Attention Network for Liver and Tumor Segmentation[41]	Fan, Tongle	IEEE Access	2020	327
8	RA-UNet: A Hybrid Deep Attention-Aware Network to Extract Liver and Tumor in CT Scans[42]	Jin, Qiangguo	Frontiers in Bioengineering and Biotechnology	2020	300
9	Accuracy of the Liver Imaging Reporting and Data System in Computed Tomography and Magnetic Resonance Image Analysis of Hepatocellular Carcinoma or Overall Malignancy—A Systematic Review[43]	van der Pol, Christian B.	Gastroenterology	2019	300
10	Automated Abdominal Segmentation of CT Scans for Body Composition Analysis Using Deep Learning[44]	Weston, Alexander D.	Radiology	2019	278
11	A Survey on U-shaped Networks in Medical Image Segmentations[45]	Liu, Liangliang	Neurocomputing	2020	263
12	Recent Updates of Transarterial Chemoembolilzation in Hepatocellular Carcinoma[46]	Chang, Young	International Journal of Molecular Sciences	2020	260
13	A Radiomics Nomogram for Preoperative Prediction of Microvascular Invasion in Hepatocellular Carcinoma[47]	Yang, Li	Liver Cancer	2019	254
14	Deep Learning for Liver Tumor Diagnosis Part I: Development of a Convolutional Neural Network Classifier for Multi-phasic MRI[48]	Hamm, Charlie A.	European Radiology	2019	248
15	Radiomic Features at Contrast-enhanced CT Predict Recurrence in Early Stage Hepatocellular Carcinoma: A Multi-Institutional Study[49]	Ji, Guwei	Radiology	2020	237

Abbreviation: TC, Total Citations.

rise and continuous development of AI, the research topic shifted to clinical problems directly related to PLC. In the past three years, "image reconstruction", "liver cancer classification", and "deep supervision" have become prominent terms (Figure 6C).

Discussion

This study analyzed 2890 publications from the WoSCC and Scopus databases related to AI and radiomics in PLC imaging through a systematic bibliometric review. Since 2018, the significant growth in publications can be attributed to multiple factors. The influential paper "Radiomics: the bridge between medical imaging and personalized medicine", published in 2017 by Philippe Lambin, an influential author in the field, played a significant role in popularizing the concept of radiomics.[58] Furthermore, the launch of the Image Biomarker Standardization Initiative (IBSI) and the American College of Radiology's ongoing updates to the Liver Imaging Reporting and Data System (LI-RADS) may have also contributed to accelerating the field's rapid development.[68,69]

At the national and regional levels, China produced the highest number of publications, and Chinese institutions also led research in this area. This is closely linked to the historically high incidence of liver cancer in China.[70] However, there remains a gap in citations per article when compared to European and American research countries. The potential

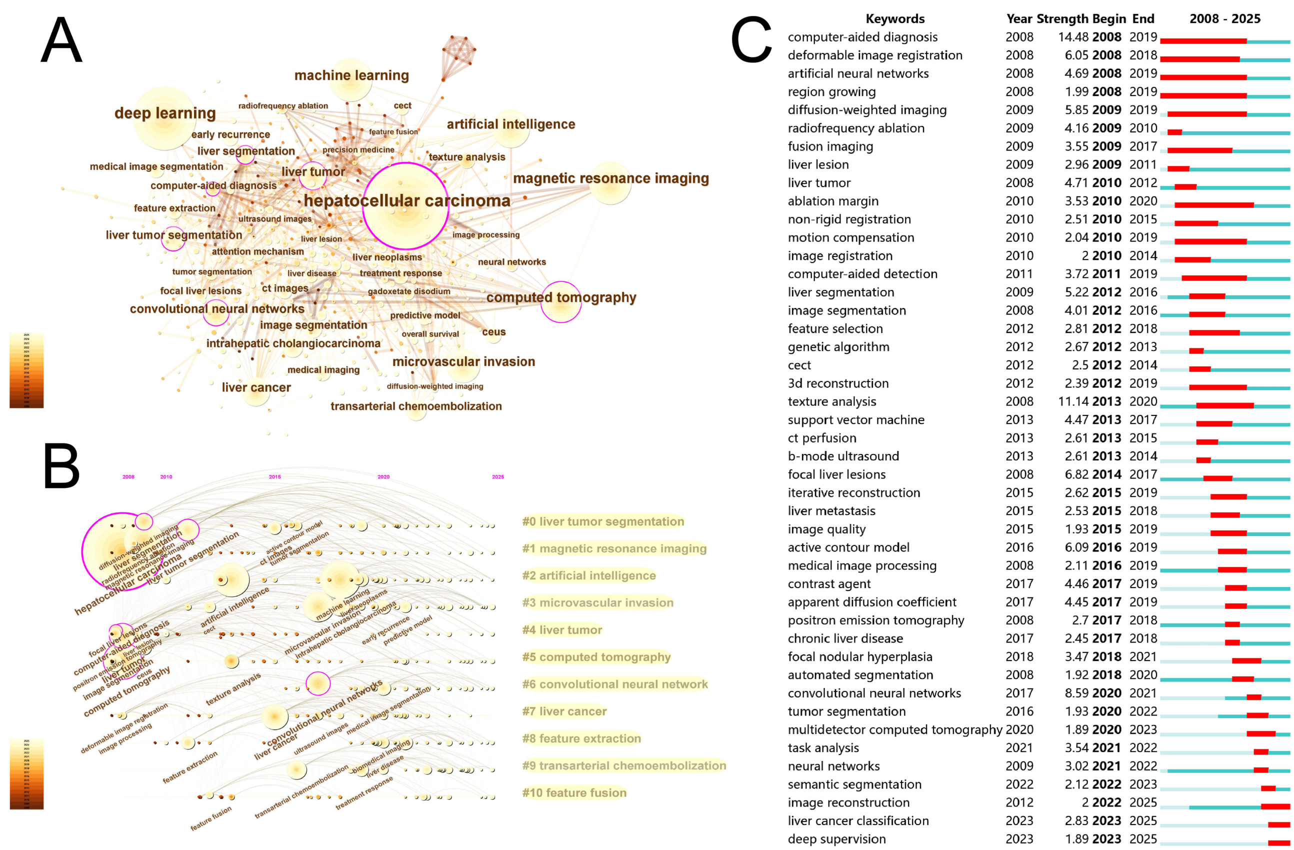

Figure 6 Analysis of keywords on AI and radiomics in PLC. (**A**) Co-occurrence network of keywords. (Node size indicates keyword frequency; node color indicates the year; links depict co-occurrence relationships.). (**B**) Timeline chart of keywords. (Each keyword is positioned according to its first appearance and development over time. The color of each node represents the year, node size reflects keyword frequency, and keywords are grouped into clusters shown on the right.). (**C**) Top 45 keywords with the strongest frequency bursts. (The red bars indicate the duration of the frequency burst.).

reasons are as follows: Firstly, this gap is closely related to the dominant position that Western institutions hold in the global academic network. Research from European and American institutions is often published in high-impact academic journals.[71,72] These journals have significantly higher H-index and IF, which reflect their central position within the global academic network. Their dissemination channels are also more extensive, which may enable articles published in these journals to accrue citations over time. Secondly, European and American countries have abundant academic resources and face lower barriers to collaboration and exchange, enabling them to produce valuable research findings.[73,74] The high rate of multinational collaboration in these regions, compared to lower levels in Asian countries, further supports this observation.

The relatively low level of international collaboration among Asian countries may stem from differences in disease causes and communication costs. The high rate of hepatitis B virus-related liver cancer in Asia and the prevalence of alcoholic hepatitis in the West differ in their pathogenesis and treatment strategies.[75,76] These differences also hinder the development of common ground for collaboration between the two regions parties. Furthermore, the varied language backgrounds across Asia impede complicate and exchanges between countries, limiting academic collaboration both within and between regions. These issues have somewhat obstructed the development of a global research network.

Radiology is an important journal in this field due to its high IF and disciplinary reputation. Additionally, *IEEE Transactions on Medical Imaging* and *Medical Physics* appear in the co-citation network, reflecting the close integration of medicine and engineering. The core authors have a close network of collaborations, but international collaboration among authors requires strengthening. The high number of sudden citations indicates the primary developmental thread in this field. The focus of the research has shifted from the initial image-based analytics and AI algorithms to clinical applications. The keyword analysis in CiteSpace identified two main research hotspots: technological advancements in radiomics methods and their clinical applications in PLC-related tasks. These hotspots highlight the potential of integrating AI with radiomics in improving the management of PLC.

In the era of medical big data, "liver tumor segmentation" has emerged as the largest topic cluster in AI and radiomics keyword clustering within the PLC field, reflecting a significant and sustained publication trend. AI methods in PLC radiomics have undergone a significant paradigm shift, reflecting higher-level integration of technological advancements.[77] While early traditional ML techniques like k-nearest neighbor, logistic regression, support vector machine, and random forest have served as fundamental components in traditional segmentation pipelines, they face limitations due to reliance on handcrafted features, sensitive parameter settings, and difficulty handling large-scale data.[78–80] Since the advent of DL, CNNs have emerged as the dominant approach, effectively overcoming the limitations of manual feature engineering by directly learning complex patterns from raw data.[81,82] The U-Net introduced by Ronneberger et al[83] is an important CNN-based network widely applied to liver and tumor segmentation.[84] The results of the bibliometric analysis show that articles on U-Net variants, especially for HCC image segmentation, have received a large number of citations, highlighting their wide application and significant influence in addressing challenges such as blurred boundaries and small lesions.[42,85,86] Recently, models based on Transformers have emerged in this field, such as Vision Transformer, Swin Transformer, and Segment Anything Model (SAM). These models have stronger capabilities for capturing long-range dependencies and for performing segmentation with less amount of labeled data.[87] This systematic progression from manual features to CNNs, to models based on Transformer, and to foundational models like SAM, highlights the dynamic nature of AI's continuous breakthroughs in PLC diagnosis and management.

In this context, the potential of AI and radiomics in the clinical application of PLC remains an area of active exploration. Most studies have focused on challenges such as distinguishing uncertain nodules, pathologic grading, and predicting MVI, underscoring the potential value of AI and radiomics in diagnosing PLC.[88–90] Additionally, research has explored individualized treatment evaluation, including the assessment of preoperative transarterial chemoembolization (TACE) efficacy and the prediction of immunotherapy outcomes.[91,92] Positive results in modeling postoperative recurrence and survival outcomes further highlight AI and radiomics promising role in risk stratification and follow-up management.[93,94]

Despite these advancements, the clinical application of AI and radiomics in PLC remains significantly constrained by methodological and technical limitations.[95,96] Besides inherent limitations such as small sample sizes and scarce external validations, the insufficient stability and reproducibility of features remain key challenges.[95,97,98] The radiomics features are highly sensitive to variations in imaging scanners, acquisition parameters, reconstruction algorithms, and feature extraction software.[96,99] Such cross-scanner differences, combined with inter-observer variability, severely hinder the general applicability of radiomics models in multicenter and real-world clinical settings.[100] It is notable that the establishment and promotion of standardized frameworks like the IBSI have significantly improved the consistency in the feature extraction process.[68]

Furthermore, recent keyword burst analysis has revealed related methods such as "image reconstruction", "liver cancer classification", and "deep supervision", suggesting that research focus may be gradually shifting toward improving quantification and interpretability. Although the specific keyword "multimodal fusion" did not emerge as a prominent hotspot in the cluster analysis, the terms "feature fusion (#10)" and those related to imaging technologies, texture analysis, and clinical integration were identified. This suggests a potential trend toward integrating multiple sources of information. Recent literature has shown that combining radiological images with clinical data, pathology, or genomics can significantly improve diagnostic accuracy and prognostic stratification.[96,101] However, such integration methods require rigorous validation to ensure that the increase in model complexity can achieve effective clinical translation.[96] Based on these constantly changing trends, future research in the PLC field is likely to focus on standardizing methods and developing a multi-modal framework that can effectively integrate radiological imaging with multi-source clinical information.

Compared with the focused analysis conducted by Teng et al[102] (n = 906), our study adopted a broader perspective and analyzed 2890 studies. Teng et al conducted a detailed study of core radiomics workflow in HCC, whereas our analysis focuses on the interdisciplinary integration of AI into PLC. Our keyword analysis highlighted key technological trends like "CNNs" and "deep supervision", which were less emphasized in earlier bibliometric studies. However, our broader view might limit depth in certain specialized areas. Additionally, although our study tracks the evolution of AI technology over time, the field's fast-paced innovations may not be fully captured, and recent developments might be underrepresented. Future research combining detailed specialized analysis with comprehensive bibliometric approaches could yield more precise insights into specific technologies or clinical issues.

There are several limitations in this study. First, our study uses the WoSCC and Scopus databases and includes only English literature, restricted to article and review document types. This approach may overlook relevant research findings. Second, although the search strategy, duplication, and synonym normalization cleaning processes have been checked, it remains difficult to eliminate topic drift and label bias. Third, the parameter settings of CiteSpace and VOSviewer affect the network's sparsity and clustering stability to some extent. Fourth, the inability to accurately retrieve the annual citation count for each document from the existing metadata limits the ability to conduct a more detailed assessment of citation influence over time. Nevertheless, the results of our analysis adequately reflect the overall situation in the field.

Conclusion

This bibliometric study highlights the rapid expansion of global research on AI and radiomics in PLC imaging over the past 18 years, emphasizing a shift from methodological exploration to practical application. The analysis indicates that MVI prediction, TACE treatment response, and prognosis prediction are the main research hotspots in the current literature. These findings depict the evolving knowledge landscape in this field and point the way for subsequent academic research, emphasizing the necessity of maintaining sustained attention to these relevant active research areas.

Abbreviations

AI, Artificial intelligence; WoSCC, Web of Science Core Collection; PLC, Primary liver cancer; HCC, Hepatocellular carcinoma; CT, Computed tomography; MRI, Magnetic resonance imaging; DL, Deep learning; ML, Machine learning; CNN, Convolutional neural network; AC, Average citations; TC, Total citations; IF, Impact factor; MVI, Microvascular invasion; TACE, Transarterial chemoembolization; IBSI, Image Biomarker Standardization Initiative; LI-RADS, Liver Imaging Reporting and Data System; SAM, Segment Anything Model.

Disclosure

The authors report no conflicts of interest in this work.

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