

REVIEW ARTICLE

Artificial intelligence in radiation dose optimization research: A bibliometric mapping

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Abstract

In radiation dose optimization, artificial intelligence (AI) plays a crucial role in improving image quality, treatment planning, and patient safety in medical imaging and radiotherapy. Although research in this field is growing rapidly, publication patterns, intellectual structure, themes, and co-authorship remain poorly understood. This study therefore aimed to systematically visualize the global AI research landscape in radiation dose optimization through a bibliometric approach. Data were retrieved from the Scopus database, obtained through a structured search strategy, yielding a final dataset of 738 publications. We performed bibliometric analysis with BiblioSpy[®], data cleaning with OpenRefine, and network visualization and keyword co-occurrence analysis with VOSviewer. The results showed a substantial increase in publication output since 2018, reaching its highest annual output in 2025 with 187 publications; data for 2026 reflect an incomplete year, reflecting growing scholarly attention to AI-driven radiation dose optimization in medical imaging and radiotherapy. The United States and China led in research productivity and international collaboration. *Medical Physics* and *IEEE Transactions on Medical Imaging* showed high citation performance and were the two publications with the strongest scholarly influence. The keyword analysis revealed the main research topics: computed tomography, deep learning, machine learning, image reconstruction, and dose prediction. Co-authorship analysis also showed a strong trend toward large-scale, international collaboration. In conclusion, this research provides a thorough bibliometric analysis of AI research in radiation dose optimization, highlighting key trends, emerging areas, and international research collaborations to guide future studies and clinical practice.

Keywords: Bibliometrics; VOSviewer; Artificial intelligence; Dose optimization

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1. Introduction

In recent years, artificial intelligence (AI) has significantly reshaped medical imaging and radiotherapy, becoming a key tool for optimizing radiation doses. The integration of AI, especially through deep learning algorithms and convolutional neural networks, has driven notable advancements in reducing unnecessary radiation exposure while

maintaining high diagnostic quality.¹⁻³ Recent studies demonstrate that AI-powered methods can significantly refine dose estimation, streamline patient positioning, and improve real-time adaptive radiotherapy, thereby enhancing both treatment efficacy and safety. These advances are especially important in critical areas such as pediatric imaging, where minimizing radiation risk while maintaining high-quality imaging is essential.⁴⁻⁶

Leveraging these developments, the clinical use of AI in radiation dose management is transforming conventional workflows, offering automated segmentation, real-time treatment planning, and improved quality assurance. AI algorithms have been thoroughly tested for their ability to reduce planning time, improve dose conformity, and ultimately enhance patient outcomes.⁷⁻⁹ Recent pilot studies have highlighted the potential of AI in enabling personalized treatment protocols and adaptive therapies, which are essential for healthcare systems around the world to maintain a balance between innovation and patient safety. Challenges, including generalizability of the model, ethical concerns, and regulatory compliance, are critical issues that need to be addressed for the model to be widely adopted in clinical practice. By examining existing literature and recent advancements, this study aims to offer a comprehensive overview of the current state of AI in radiation dose management, paving the way for future advancements and integration into clinical practice.¹⁰⁻¹²

The literature on AI in radiation dose optimization is varied, covering approaches from deep learning^{13,14} for image reconstruction to hybrid AI and Monte Carlo for radiotherapy planning. In computed tomography (CT) imaging, deep convolutional models¹⁵ and generative adversarial networks have been used to substantially reduce image noise and artifacts with up to 90% dose reduction without affecting diagnostic confidence. These techniques can improve image quality and may improve scan-range calculation and patient positioning, helping set the stage for more efficient, patient-specific radiation protocols. Hybrid AI–Monte Carlo approaches also enable fast, accurate dose calculations that can support adaptive treatment workflows and more accurately model dose in complex anatomical structures. Although these methodologies have strong technical promise, they need thorough validation across diverse populations and clinical settings to be reliable and generalizable.¹⁶⁻²¹ The potential of AI in the clinical field further highlights its transformative impact. Research has shown the successful integration of AI tools into automated organ and tumor segmentation, substantially improving treatment accuracy and reducing manual planning time. AI algorithms for adaptive radiotherapy have also enabled better target coverage and minimized exposure to nearby

critical structures, improving therapeutic outcomes. Furthermore, AI's integration into quality assurance has facilitated the early detection of treatment errors, further underscoring its significance in patient safety and efficiency. Radiation dose reductions have been seen in adult and pediatric imaging with AI-driven workflow automation, such as patient positioning and scan range optimization, and even further gains have been made in standardizing treatment protocols and making treatments more accessible in resource-challenged environments.²²⁻²⁵ However, the ethical and regulatory aspects of using AI for radiation dose optimization have become important topics of discussion. Data privacy concerns, algorithmic bias, and the lack of harmonized regulatory frameworks across regions are highlighted as challenges. These challenges require strong validation procedures and multidisciplinary involvement to ensure the safety and equity of AI system applications. While regulators struggle to keep up with technology, understanding of the need for rigorous quality management and monitoring is growing. Professional bodies and consensus statements worldwide highlight the need for transparency, accountability, and human oversight in AI use for clinical decisions, as well as ethical guidelines and best practices for the safe use of AI.²⁶⁻³¹

Moreover, emerging trends indicate considerable research gaps, especially in pediatric imaging and in multimodal applications beyond CT. Although AI has achieved great success in dose optimization for adult CT imaging, little work has addressed dose optimization in other modalities (such as positron emission tomography and magnetic resonance imaging) in pediatric patients. New AI tools, such as digital twins and federated learning, show potential for individual and privacy-aware radiation dose planning, but they also highlight the importance of multisite validation and harmonization. To fully leverage the potential of AI in comprehensive radiation dose management, future research efforts should be directed toward increasing the diversity of datasets, creating modality-specific AI models, and building harmonized regulatory frameworks.³²⁻³⁶

Accordingly, this study addresses the following research questions (RQs):

- (i) RQ1: Which source titles combine high productivity with strong citation performance in AI in radiation dose optimization research?
- (ii) RQ2: What temporal inflection points can be identified in the development and impact trajectory of AI in radiation dose optimization research?
- (iii) RQ3: How do citation trajectories differentiate older citation classics from more recent high-impact contributions in AI in radiation dose optimization

research?

- (iv) RQ4: How do national productivity, citation impact, and international collaboration jointly shape the global knowledge landscape of AI in radiation dose optimization?
- (v) RQ5: Which themes in AI in radiation dose optimization function as motor, basic, niche, emerging, or declining themes?
- (vi) RQ6: What authorship patterns characterize AI in radiation dose optimization research in terms of solo, small-team, and multi-author collaboration?

2. Methodology

Bibliometrics refers to the systematic collection, organization, and analysis of bibliographic information derived from scientific publications.^{37,38} Beyond descriptive indicators such as publication year, source journal, and prolific authors,³⁹ bibliometric research also incorporates advanced analytical techniques, including document co-citation analysis. Consequently, a rigorous literature review requires an iterative, systematic process that begins with identifying suitable keywords, followed by comprehensive database searching and detailed analytical procedures.^{40,41}

This method supports the development of a comprehensive bibliography while improving the reliability and validity of the findings.⁴² This study focused on high-impact publications as they provide valuable information on the theoretical underpinning of the research area. Elsevier's Scopus database was chosen as the primary source to collect the data and ensure the accuracy and consistency of the retrieved data.^{43–45} Only peer-reviewed journal articles and conference proceedings were included to maintain dataset quality, while books and lecture notes were excluded.⁴⁶ Initially, publications from 2000 to 2026 were retrieved from Scopus because of the broad coverage of its databases.

The data were then extracted, cleaned, and standardized using OpenRefine. This eliminated duplicate records, standardized author and institution names, and harmonized journal titles.⁴⁷ The clustering and transformation capabilities provided by OpenRefine (version 3.9.3) were then used to resolve minor discrepancies, such as spelling variants and abbreviations.^{48,49} These procedures increased dataset reliability and the accuracy of the bibliometric mapping and visualization analyses that followed. The finalized dataset of publications from 2000 to 2026 was then retained for further analysis. The annual publication and citation trends, yearly bibliometric statistics, top-source analysis, source statistics, subject-area distribution,

top-cited paper analysis, global publication mapping, country statistics, cluster summary statistics, and keyword detail listings in this study were created using BiblioSpy® (version 1).⁵⁰

2.1. Data search strategy

The search strategy was designed to include publications that clearly discussed the use of AI techniques in radiation dose optimization in medical imaging and radiotherapy. Radiation-related terms like “radiation dose,” “radiation exposure,” and “dose optimization” were chosen and used with the keywords of AI technologies such as “artificial intelligence,” “machine learning,” “deep learning,” and “neural network.” The TITLE-ABS-KEY field was used to limit the search to the title, abstract, and keywords of the documents to achieve high topic relevance and low retrieval of irrelevant documents. Only journal articles in English were included to maintain consistency and quality. Other types of documents and sources in languages other than English were excluded.

We excluded several years of early publications (1987, 1992, 1994, 1996–1999) after manually screening the initial search results. These records were standalone publications containing only a single search term and were not necessarily related to the current AI radiation dose optimization research. Their presence would have added noise to the data and could have skewed the field mapping using bibliometrics. Because these records were few and lacked thematic relevance, they were excluded to improve dataset consistency and analytical validity. The final dataset thus represents the period when AI-based methods became a well-defined research area in radiation dose optimization (Table 1).

After the search and screening process, 738 publications were identified as the body of scholarly literature on AI in radiation dose optimization (Figure 1). The retrieved data show the increasing interdisciplinary use of AI techniques in radiation sciences, with most applications in medical imaging and radiotherapy. The inclusion criteria ensured that the selected publications were peer-reviewed scientific publications, enhancing the reliability and academic rigor of the analysis. The dataset also provides a solid basis for bibliometric assessment, allowing one to examine publication trends, the most influential authors, the most important journals, institutional collaborations, and emerging research areas in this field. Moreover, this sophisticated dataset enables advanced bibliometric mapping and visualization analyses, providing valuable insights into the evolution and structure of knowledge and future directions in research on AI for radiation dose optimization.

2.2. Data analysis

VOSviewer is a popular bibliometric software created by Nees Jan van Eck and Ludo Waltman at Leiden University, Netherlands.^{51,52} The software focuses on the visualization of the network and is especially useful for clustering similar items together, co-occurrence of keywords, and creating density maps.⁵³ The data were obtained from the Scopus database in plain text format, with data from 2000 to 2026, and contained the year of publication, title, author(s) names, journal, number of citations, and keywords. The data were subsequently analyzed using VOSviewer version 1.6.20. VOSviewer positions items within a low-dimensional space in which the distance between two items

directly reflects their degree of relatedness and similarity.^{51,54} VOS uses association–strength normalization to quantify the relatedness between items. The association strength between items i and j is calculated using Equation 1⁵⁵:

$$AS_{ij} = \frac{C_{ij}}{w_i w_j} \quad (1)$$

where c_{ij} represents the number of co-occurrences between items i and j , while w_i and w_j represent the total occurrence frequencies of items i and j , respectively.⁵⁵ Higher association–strength values indicate stronger relationships between two items relative to their overall occurrence

Table 1. The search string

Database	Search string
Scopus	TITLE-ABS-KEY (("artificial intelligence" OR AI OR "machine learning" OR "deep learning" OR "neural network") AND ("radiation dose" OR "radiation exposure" OR "radiation level" OR "radiation amount") AND (optimization OR "dose optimization" OR "dose reduction" OR "dose management" OR "dose adjustment")) AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (DOCTYPE , "ar")) AND (EXCLUDE (PUBYEAR , "1987") OR EXCLUDE (PUBYEAR , "1992") OR EXCLUDE (PUBYEAR , "1994") OR EXCLUDE (PUBYEAR , "1996") OR EXCLUDE (PUBYEAR , "1997") OR EXCLUDE (PUBYEAR , "1998") OR EXCLUDE (PUBYEAR , "1999"))

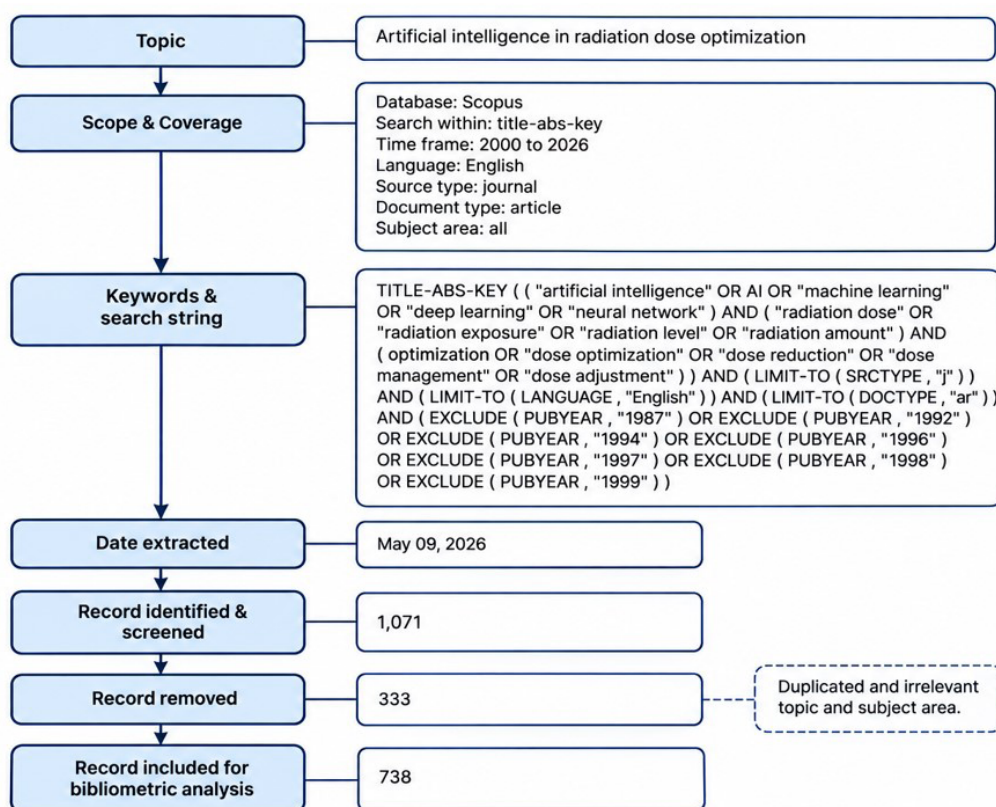


Figure 1. Bibliometric study flow diagram

frequencies. According to Appio *et al.*⁵⁶, the LinLog/modularity normalization approach was implemented. Keyword co-occurrence analysis is particularly useful for exploring the development of a research area over time.⁵⁷ It has proven effective in identifying popular topics across various disciplines.⁵⁸ Meanwhile, citation analysis helps identify key research issues, emerging trends, and methodological approaches, while revealing the historical relevance of a discipline's principal areas of focus.⁵⁹ Document co-citation analysis is among the most frequently applied bibliometric methods^{56,60}, with its results relying on network theory to map and identify the underlying structure and relationships within the data.⁶⁰

3. Results

3.1. Research question 1: Which source titles combine high productivity with strong citation performance in AI in radiation dose optimization research?

As shown in Figure 2 and Table 2, *Medical Physics* was the most productive source, with 83 publications, followed by *European Radiology* (29 publications) and *Physics in Medicine and Biology* (23 publications). *Physica Medica* and *European Journal of Radiology* contributed 19 and 18 publications, respectively, while *IEEE Transactions on Medical Imaging* and *Academic Radiology* recorded 17 and 15 publications each. *Frontiers in Oncology* and *Quantitative Imaging in Medicine and Surgery* each produced 15 publications, and *Radiotherapy and Oncology* recorded the lowest output among the top 10 sources with 11 publications.

Among these sources, *IEEE Transactions on Medical Imaging* received the highest total number of citations (2,071), followed by *Medical Physics* (1,939) and *European Radiology* (1,145).

However, *IEEE Transactions on Medical Imaging* had the highest citations per publication ($C/P = 121.824$) and the highest citations per cited publication ($C/CP = 147.929$), with the highest e-index value (44.37), despite its comparatively low publication count. This was followed by *Radiotherapy and Oncology* ($C/P = 44.364$, $C/CP = 48.8$) and *European Radiology* ($C/P = 39.483$, $C/CP = 40.893$). Concerning the h-index, *Medical Physics* had the highest ($h = 25$), while *European Radiology* ($h = 18$), *Physics in Medicine and Biology* ($h = 10$), and *Physica Medica* ($h = 10$) had lower values. Moreover, *Medical Physics* had the highest g-index (43), followed by *European Radiology* (29) and *Physica Medica* (18). The m-index values varied from 0.417 (*Physics in Medicine and Biology*) to 2.25 (*European Radiology*), and *Medical Physics* had an m-index of 2.083. *Medical Physics* (424) and *European Radiology* (247) had the highest number of citing authors, and *Medical Physics* (71) had the highest number of cited papers (NCP), followed by *European Radiology* (28) and *Radiotherapy and Oncology* (10).

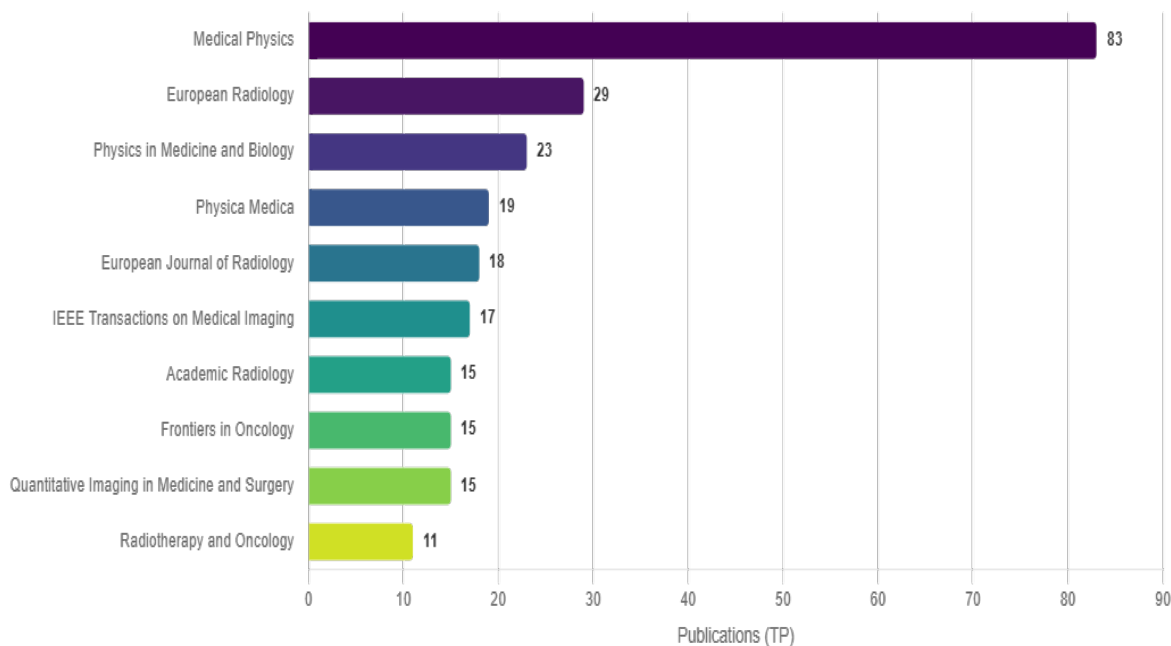


Figure 2. Top sources of publications

3.2. Research question 2: What temporal inflection points can be identified in the development and impact trajectory of AI in radiation dose optimization research?

Publication activity remained low until the mid-2010s and increased markedly thereafter (Figure 3, Table 3). Production was very low and sporadic from 2001 through 2014, with only a single publication in some years (2003, 2011, and 2012) and a maximum of three publications in 2014, suggesting it was still in an early exploratory stage. It began to increase gradually from 2015 onward, rising to 6 publications in 2015 and 8 in 2016. The first significant inflection point was around 2017–2019, when annual publications rose from 7 to 22, indicating a shift from the emerging phase to the growth phase. The biggest structural change occurred between 2020 and 2021, with publications rising from 51 to 77, then continuing to rise to 78 in 2022 and 87 in 2023, before peaking in 2025 with 187 publications. In 2026, publications fell to 82, but this year was only partially covered.

As shown in Figure 3, the citation trajectory differed from the publication-output trend. Citation activity was high relative to publication output and unevenly distributed, with 130 citations to 2 publications in 2006 and 255 citations to 6 publications in 2015, indicating that a few foundational publications had a disproportionately strong impact. This inflection point is sharp between 2016 and 2018, with total citations increasing from 244 to 1,723 and publications entering a growth phase. Citations

reached a peak of 2,883 in 2021, the highest point on the citation curve, and have been in a steady decline since then: 2022 (1,832), 2023 (1,150), 2024, 2025, and 2026. This post-2021 divergence of continued increase in publication volume and decreasing total citations is the most striking inflection in the impact trajectory, as typically seen in citation accumulation of more recently published works.

3.3. Research question 3: How do citation trajectories differentiate older citation classics from more recent high-impact contributions in AI in radiation dose optimization research?

The top 10 most cited papers on AI in radiation dose optimization display a clear distinction between total citation accumulation and annualized citation rate, reflecting differences in publication age (Table 4). Wolterink *et al.*⁶¹, published in *IEEE Transactions on Medical Imaging*, ranked first with 977 total citations and a citations-per-year (C/Y) rate of 97.7, the highest among all listed works. Wang *et al.*⁶² followed with 418 total citations and a C/Y of 46.44, while Shan *et al.*⁶³, despite being the most recently published paper in the top 10, accumulated 415 total citations at a C/Y rate of 46.11 (Table 4). Fan *et al.*⁶⁴ and Nguyen *et al.*⁶⁵ recorded 344 and 331 total citations, respectively, with C/Y values of 43 and 41.38. The remaining entries, Greffier *et al.*⁶⁶, Bohoudi *et al.*⁶⁷, Ravishankar *et al.*⁶⁸, You *et al.*⁶⁹, and Wu *et al.*⁷⁰, recorded total citations ranging from 319 down to 225, with C/Y values spanning from 45.57 to 22.5.

Table 2. Source statistics

Source title	Publisher	TP	TC	NCA	NCP	C/P	C/CP	h	g	m	e
Medical Physics	John Wiley and Sons Ltd	83	1,939	424	71	23.361	27.31	25	43	2.083	30.66
European Radiology	Springer Science and Business Media Deutschland GmbH	29	1,145	247	28	39.483	40.893	18	29	2.25	27.24
Physics in Medicine and Biology	Institute of Physics	23	316	168	18	13.739	17.556	10	17	0.417	13.27
Physica Medica	Associazione Italiana di Fisica Medica	19	359	129	14	18.895	25.643	10	18	1.25	15.49
European Journal of Radiology	Elsevier Ireland Ltd	18	300	166	15	16.667	20	11	17	1.833	12.69
IEEE Transactions on Medical Imaging	Institute of Electrical and Electronics Engineers Inc.	17	2,071	95	14	121.824	147.929	9	17	0.818	44.37
Academic Radiology	Elsevier Inc.	15	162	116	13	10.8	12.462	7	12	0.538	9.7
Frontiers in Oncology	Frontiers Media SA	15	169	109	14	11.267	12.071	6	12	0.75	10.3
Quantitative Imaging in Medicine and Surgery	AME Publishing Company	15	233	101	11	15.533	21.182	8	15	1.333	12.45
Radiotherapy and Oncology	Elsevier Ireland Ltd	11	488	93	10	44.364	48.8	7	11	0.778	20.71

Abbreviations: C/CP: Citations per cited publication; C/P: Citations per publication; e: e-index; g: g-index; h: h-index; m: m-quotient; NCA: Number of contributing authors; NCP: Number of cited publications; TC: Total citations; TP: Total publications.

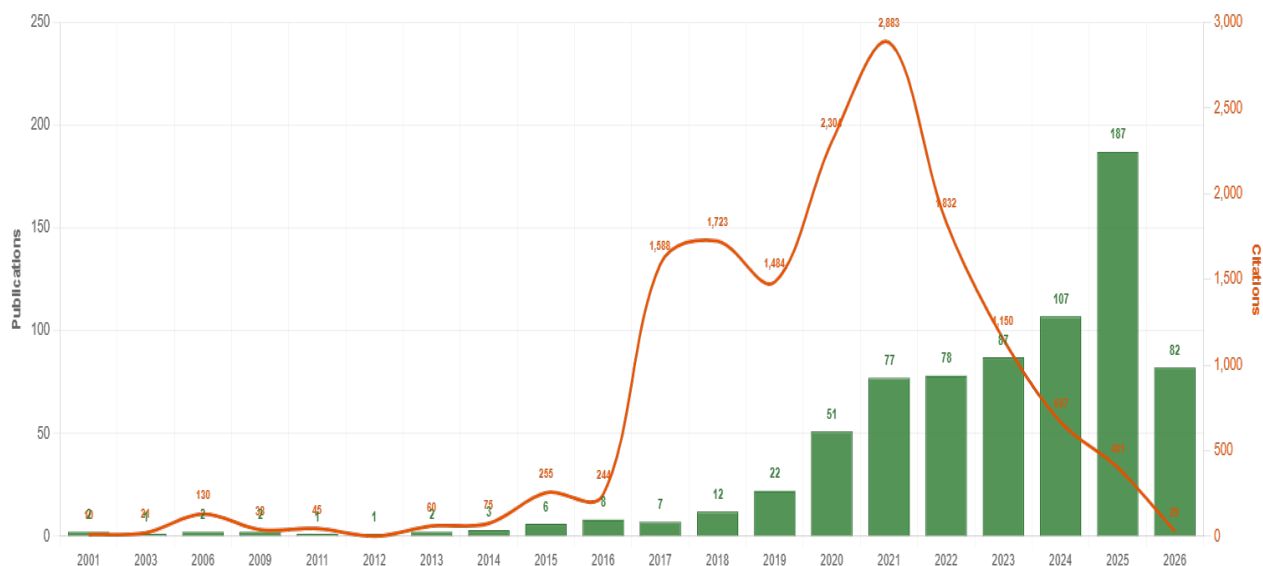


Figure 3. Annual publications and citations

Table 3. Yearly bibliometric statistics

Year	TP	NCA	NCP	TC	C/P	C/CP	h	g	m	e
2001	2	5	2	10	5.0	5.0	1	2	1.0	2.83
2003	1	4	1	21	21.0	21.0	1	1	0.333	4.47
2006	2	13	2	130	65.0	65.0	2	2	0.333	11.22
2009	2	10	2	38	19.0	19.0	2	2	0.222	5.83
2011	1	4	1	45	45.0	45.0	1	1	0.091	6.63
2012	1	5	0	0	0.0	0	0	0	0.0	0.0
2013	2	10	2	60	30.0	30.0	2	2	0.154	7.48
2014	3	16	3	75	25.0	25.0	3	3	0.214	8.12
2015	6	45	6	255	42.5	42.5	6	6	0.4	14.8
2016	8	43	8	244	30.5	30.5	7	8	0.438	13.89

Abbreviations: C/CP: Citations per cited publication; C/P: Citations per publication; e: e-index; g: g-index; h: h-index; m: m-quotient; NCA: Number of contributing authors; NCP: Number of cited publications; TC: Total citations; TP: Total publications.

When assessed using the normalized total citation (NTC) metric, which adjusts for field- and time-based citation variance, the ranking of papers shifts relative to raw citation counts (Table 4). Greffier *et al.*⁶⁶ recorded the highest NTC value of 7.06, followed by Ravishankar *et al.*⁶⁸ with an NTC of 5.58 and Fan *et al.*⁶⁴ with an NTC of 5.1, even though none of these three papers ranked first in total citations. Nguyen *et al.*⁶⁵ recorded an NTC of 4.91, and Wolterink *et al.*⁶¹, the leading authors in both TC and C/Y, recorded a comparatively lower NTC of 4.31. Shan *et al.*⁶³ recorded an NTC of 2.89, and Wang *et al.*⁶² recorded 2.91,

while You *et al.*⁶⁹, Bohoudi *et al.*⁶⁷, and Wu *et al.*⁷⁰ recorded the lowest NTC values of 1.66, 1.28, and 0.99, respectively.

3.4. Research question 4: How do national productivity, citation impact, and international collaboration jointly shape the global knowledge landscape of AI in radiation dose optimization?

The global distribution of publications on AI in radiation dose optimization reveals a concentration of research output among a small number of countries (Figure 4; Table 5). China led global productivity with 209 publications,

followed closely by the United States with 196; together, these two countries accounted for 53.3% of publications from the top 10 countries. Germany ranked third with 66 publications, followed by Japan (59), South Korea (46), and France (39) (Table 5). The top 10 producing nations included Switzerland (33), the Netherlands (30), India (27), and Italy (26). In addition to the above major contributors, the choropleth map shows moderate publication activity in parts of Europe, the Middle East and Southeast Asia, such as Canada (23), Australia (14), Saudi Arabia (8), and Iran (16), and minimal and negligible publication activity elsewhere, including much of Africa, Central Asia, and South America (Figure 4).

Country rankings differed when citation performance was considered alongside publication output (Table 5). Even though the United States was the second most productive in the world in terms of publications, it had the largest absolute number of citations (6,483), resulting in a C/P ratio of 33.08, whereas China's C/P ratio was 20.22. Among the top 10 countries, the Netherlands, with 30 publications, had a disproportionately high C/P of 66.67 and C/CP of 80, the highest efficiency ratios, as well as the highest e-index value of 41.01 outside the two leading producers. However, even with significantly fewer publications (Table 5), South Korea (C/P = 25.87) and Switzerland (C/P = 26.76) also recorded higher C/P values than China (C/P = 20.22). The United States recorded the highest h-index (h = 39),

followed by China (h = 30).

3.5. Research question 5: Which themes in AI in radiation dose optimization function as motor, basic, niche, emerging, or declining themes?

The four thematic clusters differed in density and average degree, representing internal cohesion and external connectivity, respectively (Figure 5; Table 6). Although Cluster 4 (AI) had the fewest documents (170), with keywords like "CNN," "dose reduction," and "computed tomography angiography," it had the highest density (50.0%) and the highest average degree (9.8) among the four clusters. These values position Cluster 4 as a motor theme characterized by relatively high internal cohesion and external connectivity. The theme with the highest density (45.5%) and average degree (8.4) was Cluster 1 (computed tomography), which included terms such as "image reconstruction," "radiation dosage," and "low dose," and had the highest average h-index (12) and the largest total number of citations (7,319), indicating it was a basic and well-established theme that underlies the core research activity of the field (Table 6).

Cluster 2 (deep-learning), the largest cluster by document count (355) and total citations (7,985), recorded a comparatively lower density (41.7%) relative to Clusters 1 and 4, despite an average degree of 8.2 and the most recent average publication year (2023.2), suggesting its

Table 4. Top cited papers

#	Reference	Title	Source	TC	C/Y	NTC
1	61	Generative adversarial networks for noise reduction in low-dose CT	<i>IEEE Transactions on Medical Imaging</i>	977	97.7	4.31
2	62	3D conditional generative adversarial networks for high-quality PET image estimation at low dose	<i>NeuroImage</i>	418	46.44	2.91
3	63	Impact of loss functions on the performance of a deep neural network designed to restore low-dose digital mammography	<i>Artificial Intelligence in Medicine</i>	415	46.11	2.89
4	64	Automatic treatment planning based on three-dimensional dose distribution predicted from deep learning technique	<i>Medical Physics</i>	344	43	5.1
5	65	A feasibility study for predicting optimal radiation therapy dose distributions of prostate cancer patients from patient anatomy using deep learning	<i>Scientific Reports</i>	331	41.38	4.91
6	66	Image quality and dose reduction opportunity of deep learning image reconstruction algorithm for CT: a phantom study	<i>European Radiology</i>	319	45.57	7.06
7	67	Fast and robust online adaptive planning in stereotactic MR-guided adaptive radiation therapy (SMART) for pancreatic cancer	<i>Radiotherapy and Oncology</i>	291	29.1	1.28
8	68	Image Reconstruction: From Sparsity to Data-Adaptive Methods and Machine Learning	<i>Proceedings of the IEEE</i>	252	36	5.58
9	69	Structurally-sensitive multi-scale deep neural network for low-dose CT denoising	<i>IEEE Access</i>	239	26.56	1.66
10	70	Iterative low-dose CT reconstruction with priors trained by artificial neural network	<i>IEEE Transactions on Medical Imaging</i>	225	22.5	0.99

Abbreviations: C/Y: Citations per year; NTC: Normalized total citations; TC: Total citations.

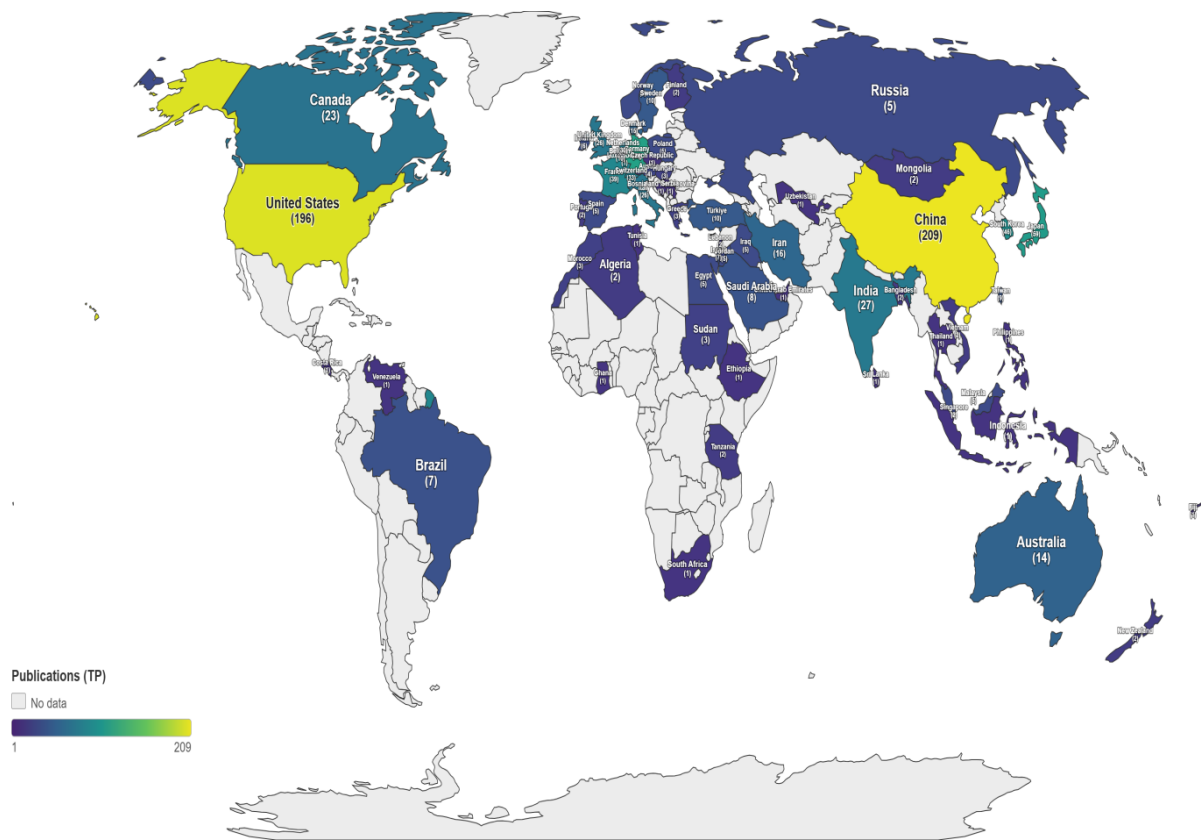


Figure 4. Distribution of publications based on the world map

Table 5. Country publication statistics

Country	TP	NCA	NCP	TC	C/P	C/CP	h	g	m	e
China	209	1,389	165	4226	20.22	25.61	30	61	2.727	46.56
United States	196	1,213	166	6,483	33.08	39.05	39	76	1.625	57.37
Germany	66	491	50	899	13.62	17.98	19	28	0.731	18.52
Japan	59	351	50	945	16.02	18.9	17	29	1.308	20.66
South Korea	46	248	43	1,190	25.87	27.67	15	34	0.577	28.95
France	39	198	32	1,080	27.69	33.75	17	32	1.133	25.69
Switzerland	33	250	26	883	26.76	33.96	13	29	1.444	25.32
Netherlands	30	204	25	2,000	66.67	80	15	30	0.714	41.01
India	27	108	15	198	7.33	13.2	6	14	0.75	11.45
Italy	26	193	21	271	10.42	12.9	10	16	1.25	11.09

Abbreviations: C/CP: Citations per cited publication; C/P: Citations per publication; e: e-index; g: g-index; h: h-index; m: m-quotient; NCA: Number of contributing authors; NCP: Number of cited publications; TC: Total citations; TP: Total publications.

function as a basic theme with emerging characteristics; foundational to the field yet still undergoing active conceptual consolidation (Table 6). In contrast, Cluster 3 (machine learning), with keywords like “GAN,” “VMAT,” and “knowledge-based planning,” has the lowest density (27.8%) and the lowest average degree (5.3) among all four clusters, despite the highest average citations per document (32.93). This lack of internal cohesion and low external connectivity is combined with an earlier average publication year (2022.4) compared to Clusters 2 and 4, and is typical of a niche or fading topic, one that continues to be cited by others from earlier, highly cited publications (e.g., “GAN” with 143.20 average citations; Table 7), but that is not structurally integrated into the thematic core of the field.

3.6. Research question 6: What authorship patterns characterize AI in radiation dose optimization research in terms of solo, small-team, and multi-author collaboration?

The country collaboration network for AI in radiation dose optimization research shows a very small number of high-output countries that are well connected in the core, while countries in the periphery are loosely connected or isolated (Figure 6; Table 8). The United States has the highest PageRank value (1.0000), the highest total link strength (119), and the most links (23), although it has the second-highest number of documents (196) after

China. Although China has the most documents (209) and the most citations (4,226), its PageRank (0.5610) and number of links (13) were relatively low, suggesting that China is a high-productivity node in the collaboration network but less structurally embedded than the United States. Secondary hubs such as Germany (14 links with a total link strength of 49), the Netherlands (14 links with a total link strength of 28), and the United Kingdom (14 links with a total link strength of 28) connected several regional clusters, while countries with very few links and limited total link strength, such as Taiwan (1), Russia (5), and Türkiye (2), showed little network connectivity, and mostly isolated or peripheral collaborative activity.

Conversely, solo and small-team authorship patterns play a minimal, peripheral role in this specialized topic. Instead of isolated actors working independently, small-team collaborations are almost entirely integrated into the expansive, web-like structures of larger clusters. This pattern is highly pronounced in regions such as Malaysia, Jordan, and Iraq, which form a specialized regional sub-cluster (Cluster 2) that remains tethered to the primary global network (Table 8). The relative absence of detached, standalone multi-author or solo-author fragments underscores that isolated research is increasingly unsustainable in this domain, giving way to extensive consortia that bridge mathematical engineering with clinical radiology.

The network splits into two clusters, with Cluster 1

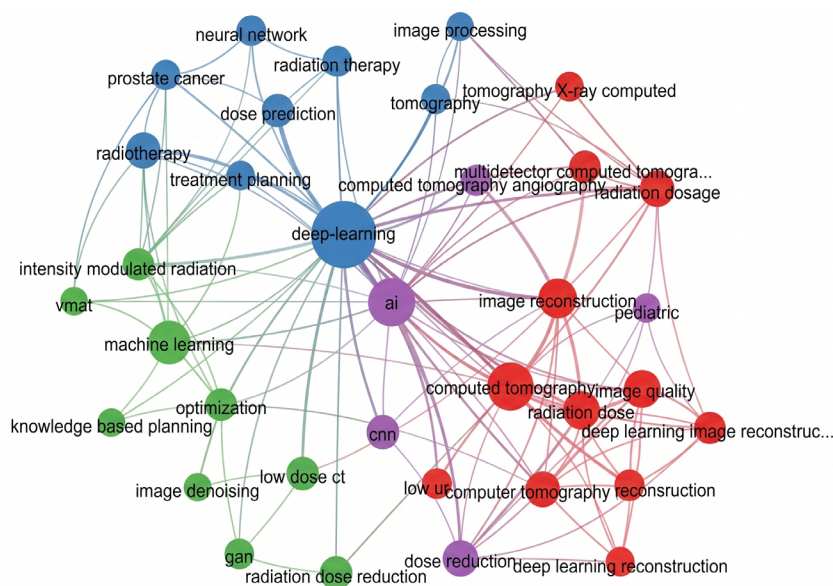


Figure 5. Co-occurrence network. The colours represent four thematic clusters: red, Cluster 1 (Computed tomography); blue, Cluster 2 (Deep learning); green, Cluster 3 (Machine learning); and purple, Cluster 4 (artificial intelligence). Node size represents keyword occurrence, while the connecting lines indicate co-occurrence relationships between keywords.

Table 6. Cluster summary

#	Cluster	Keywords	Links	Link strength	Documents	Citations	Avg. citations	Norm. Cit. (C/P)	Avg. pub. year	Avg. h	Density (%)	Avg. degree	Avg. pagerank
1	Computed tomography	12	30	136	347	7,319	21.09	1.129	2022.9	12	45.5	8.4	0.0262
2	Deep-learning	9	15	86	355	7,985	22.49	1.053	2023.2	9	41.7	8.2	0.0300
3	Machine learning	9	10	26	189	6,224	32.93	0.946	2022.4	9	27.8	5.3	0.0331
4	Artificial intelligence	5	5	22	170	3,341	19.65	1.127	2023.1	5	50.0	9.8	0.0236

comprising most countries, including the main producers (United States, China, Germany, Japan, and France), and an extended, worldwide collaboration network among countries with a long history of research production (Table 8). Jordan, Iraq, and Malaysia (Cluster 2) make up a smaller sub-group of more recent publications (with average year of publication 2025.4, 2025.2, and 2024.6, respectively) and comparatively lower total link strengths (6, 7, and 7, respectively) than the larger Cluster 1, and this indicates an emerging regional collaboration network running somewhat separately from the dominant Cluster 1 core. In Cluster 1, countries with fewer publications (such as Switzerland, Denmark, and Australia) were able to build a denser network of connections and have a higher normalized citation value, compared to less network-embedded countries (such as Israel, Brazil, and Egypt, which had fewer than seven connections despite comparable or higher numbers of publications).

4. Discussion

4.1. Incremental contribution and distinctive analytical dimensions

The bibliometric mapping demonstrated a concentration of publication output among several leading countries, with China and the United States recording the highest publication volumes (Table 5). Unlike approaches based primarily on individual bibliometric indicators, this study integrated productivity and citation metrics with network-structural measures to examine thematic and collaboration patterns (Table 6, Table 8). This combination shows trends that may not have been apparent in individual-metric reviews. For example, China's productivity leadership does not correspond with network centrality (Table 8), or thematic clusters with low numbers of documents can have structurally prominent positions (Table 6); differences that a traditional "top publications and top keywords" review would not highlight.

However, the analytical novelty of this work is constrained by the lack of institutional-level collaboration mapping, funding-source analysis, and interdisciplinary subject-category mapping, which are natural and valuable extensions of the current design but not limiting factors. Data on institutional affiliation may help clarify whether the national citation and centrality advantages seen in the United States and the Netherlands stem from a few high-output, well-resourced institutions, or from national research capacity distributed across many institutions, with implications for research policy. Funding-source analysis could further examine the relationship between research investment and thematic development. Interdisciplinary mapping could also clarify how interconnected computer

Table 7. Keyword details

#	Keyword	Cluster	Doc.	Cit.	Norm. cit.	Avg. pub. year	Avg. cit.	Avg. norm. cit.	Links	Total link strength	Betweenness	Closeness	Page rank
1	Computed tomography	Cluster 1	81	1,448	69,961	2023.1	17.88	0.864	14	108	0.0487	0.6296	0.0304
2	Image reconstruction	Cluster 1	43	1,554	69,299	2022.7	36.14	1.612	12	83	0.0210	0.6071	0.0222
3	Radiation dose	Cluster 1	37	659	40,684	2023.1	17.81	1.100	11	56	0.0158	0.5965	0.0272
4	Image quality	Cluster 1	35	417	35,321	2023.2	11.91	1.009	10	51	0.0106	0.5862	0.0308
5	Radiation dosage	Cluster 1	29	565	43,790	2023.3	19.48	1.510	11	52	0.0259	0.5965	0.0338
6	Computer tomography (CT)	Cluster 1	28	307	25,042	2023.5	10.96	0.894	11	37	0.0253	0.5965	0.0304
7	Multidetector computed tomography	Cluster 1	20	754	38,833	2022.9	37.70	1.942	5	29	0.0004	0.5313	0.0225
8	Deep learning image reconstruction	Cluster 1	19	181	16,252	2023.9	9.53	0.855	8	27	0.0035	0.4722	0.0333
9	Iterative reconstruction	Cluster 1	16	367	15,026	2021.4	22.94	0.939	7	24	0.0057	0.5574	0.0288
10	Low dose	Cluster 1	15	421	14,002	2022.5	28.07	0.933	3	14	0.0000	0.5231	0.0107
11	Deep learning reconstruction	Cluster 1	12	96	7,550	2023.3	8.00	0.629	6	15	0.0004	0.4359	0.0290
12	Tomography X-ray computed	Cluster 1	12	550	15,965	2021.9	45.83	1.330	3	17	0.0000	0.5152	0.0151
13	Deep-learning	Cluster 2	224	6,184	266,960	2023.1	27.61	1.192	31	310	0.4700	0.9189	0.0447
14	Radiotherapy	Cluster 2	30	492	21,459	2021.9	16.40	0.715	8	32	0.0037	0.5484	0.0281
15	Dose prediction	Cluster 2	21	169	11,426	2024.1	8.05	0.544	5	26	0.0007	0.5231	0.0197
16	Radiation therapy	Cluster 2	16	297	16,218	2022.9	18.56	1.014	5	18	0.0010	0.5231	0.0294
17	Neural network	Cluster 2	15	152	9,305	2022.6	10.13	0.620	4	15	0.0004	0.5152	0.0329
18	Treatment planning	Cluster 2	13	147	6,229	2023.2	11.31	0.479	5	13	0.0000	0.5231	0.0227
19	Tomography	Cluster 2	13	188	9,083	2023.8	14.46	0.699	4	16	0.0000	0.5231	0.0237
20	Prostate cancer	Cluster 2	13	127	8,134	2023.5	9.77	0.626	7	23	0.0044	0.5397	0.0373
21	Image processing	Cluster 2	10	229	25,005	2023.7	22.90	2.500	5	20	0.0004	0.5313	0.0314
22	Machine learning	Cluster 3	61	1,126	52,600	2022.3	18.46	0.862	10	31	0.0150	0.5862	0.0429
23	Radiation dose reduction	Cluster 3	22	187	18,293	2023.0	8.50	0.832	3	15	0.0013	0.5231	0.0219
24	Low dose CT	Cluster 3	22	1,172	29,671	2022.5	53.27	1.349	4	20	0.0029	0.5152	0.0314
25	Optimization	Cluster 3	20	341	16,081	2022.2	17.05	0.804	7	17	0.0111	0.5484	0.0503
26	Intensity modulated radiation therapy	Cluster 3	18	300	10,638	2021.6	16.67	0.591	10	27	0.0127	0.5667	0.0356
27	GAN	Cluster 3	15	2,148	24,789	2021.5	143.20	1.653	4	10	0.0052	0.5152	0.0391
28	VMAT	Cluster 3	11	139	7,516	2022.8	12.64	0.683	5	15	0.0003	0.5231	0.0268
29	Knowledge-based planning	Cluster 3	10	514	11,197	2022.0	51.40	1.120	3	6	0.0005	0.5075	0.0300

(Cont'd...)

Table 7. (Continued)

#	Keyword	Cluster	Doc.	Cit.	Norm. cit.	Avg. pub. year	Avg. cit.	Avg. norm. cit.	Links	Total link strength	Betweenness	Closeness	Page rank
30	Image denoising	Cluster 3	10	297	8,002	2023.4	29.70	0.800	2	8	0.0000	0.4928	0.0197
31	AI	Cluster 4	87	1,844	103,940	2022.9	21.20	1.195	23	113	0.1617	0.7556	0.0346
32	Dose reduction	Cluster 4	31	222	24,167	2023.8	7.16	0.780	11	44	0.0179	0.5965	0.0291
33	GNN	Cluster 4	25	846	21,910	2022.6	33.84	0.876	4	21	0.0000	0.5313	0.0129
34	Computed tomography angiography	Cluster 4	15	279	28,519	2023.2	18.60	1.901	5	26	0.0003	0.5397	0.0154
35	Pediatric	Cluster 4	12	150	13,126	2023.1	12.50	1.094	6	13	0.0029	0.5484	0.0261

Table 8. Country item overview

#	Country	Cluster	Documents	Citations	Norm. citations	Avg. pub. year	Avg. citations	Avg. norm. citations	Links	Total link strength	PageRank
1	China	Cluster 1	209	4,226	20.22	2023.5	384.18	1.838	13	70	0.5610
2	United States	Cluster 1	196	6,483	33.08	2021.8	270.13	1.378	23	119	1.0000
3	Germany	Cluster 1	66	899	13.62	2022.6	34.58	0.524	14	49	0.6003
4	Japan	Cluster 1	59	945	16.02	2022.7	72.69	1.232	7	11	0.3124
5	South Korea	Cluster 1	46	1,190	25.87	2022.1	45.77	0.995	9	19	0.4031
6	France	Cluster 1	39	1,080	27.69	2021.9	72	1.846	10	19	0.4530
7	Switzerland	Cluster 1	33	883	26.76	2023.0	98.11	2.973	11	41	0.4754
8	Netherlands	Cluster 1	30	2,000	66.67	2021.5	95.24	3.175	13	28	0.5651
9	India	Cluster 1	27	198	7.33	2024.1	24.75	0.916	7	9	0.3436
10	Italy	Cluster 1	26	271	10.42	2023.3	33.88	1.302	8	15	0.3780
11	United Kingdom	Cluster 1	26	363	13.96	2023.2	30.25	1.163	14	28	0.5981
12	Canada	Cluster 1	23	581	25.26	2021.7	52.82	2.296	4	11	0.1994
13	Iran	Cluster 1	16	211	13.19	2022.9	23.44	1.466	5	13	0.2367
14	Denmark	Cluster 1	15	386	25.73	2022.2	32.17	2.144	12	20	0.5246
15	Australia	Cluster 1	14	597	42.64	2022.4	54.27	3.876	11	16	0.4857
16	Sweden	Cluster 1	10	273	27.3	2022.3	22.75	2.275	8	13	0.3638

(Cont'd...)

Table 8. (Continued)

#	Country	Cluster	Documents	Citations	Norm. citations	Avg. pub. year	Avg. citations	Avg. norm. citations	Links	Total link strength	PageRank
17	Türkiye	Cluster 1	10	34	3.4	2024.4	4.25	0.425	2	2	0.1555
18	Belgium	Cluster 1	10	238	23.8	2022.4	39.67	3.967	5	9	0.2387
19	Taiwan	Cluster 1	9	47	5.22	2023.9	7.83	0.87	1	1	0.1095
20	Saudi Arabia	Cluster 1	8	50	6.25	2024.8	7.14	0.893	6	9	0.3084
21	Brazil	Cluster 1	7	74	10.57	2022.4	9.25	1.321	6	7	0.3119
22	Israel	Cluster 1	7	93	13.29	2021.3	6.64	0.949	4	4	0.2685
23	Ireland	Cluster 1	6	68	11.33	2024.3	11.33	1.888	4	7	0.2072
24	Russia	Cluster 1	5	25	5	2023.2	5	1	5	5	0.2944
25	Norway	Cluster 1	5	49	9.8	2023.6	12.25	2.45	3	4	0.1641
26	Poland	Cluster 1	5	63	12.6	2023.4	10.5	2.1	3	4	0.1629
27	Spain	Cluster 1	5	92	18.4	2021.4	11.5	2.3	3	4	0.1651
28	Egypt	Cluster 1	5	42	8.4	2024.2	8.4	1.68	4	5	0.2493
29	Jordan	Cluster 2	5	21	4.2	2025.4	7	1.4	4	6	0.2252
30	Iraq	Cluster 2	5	7	1.4	2025.2	2.33	0.467	5	7	0.2635
31	Malaysia	Cluster 2	5	98	19.6	2024.6	16.33	3.267	4	7	0.2250

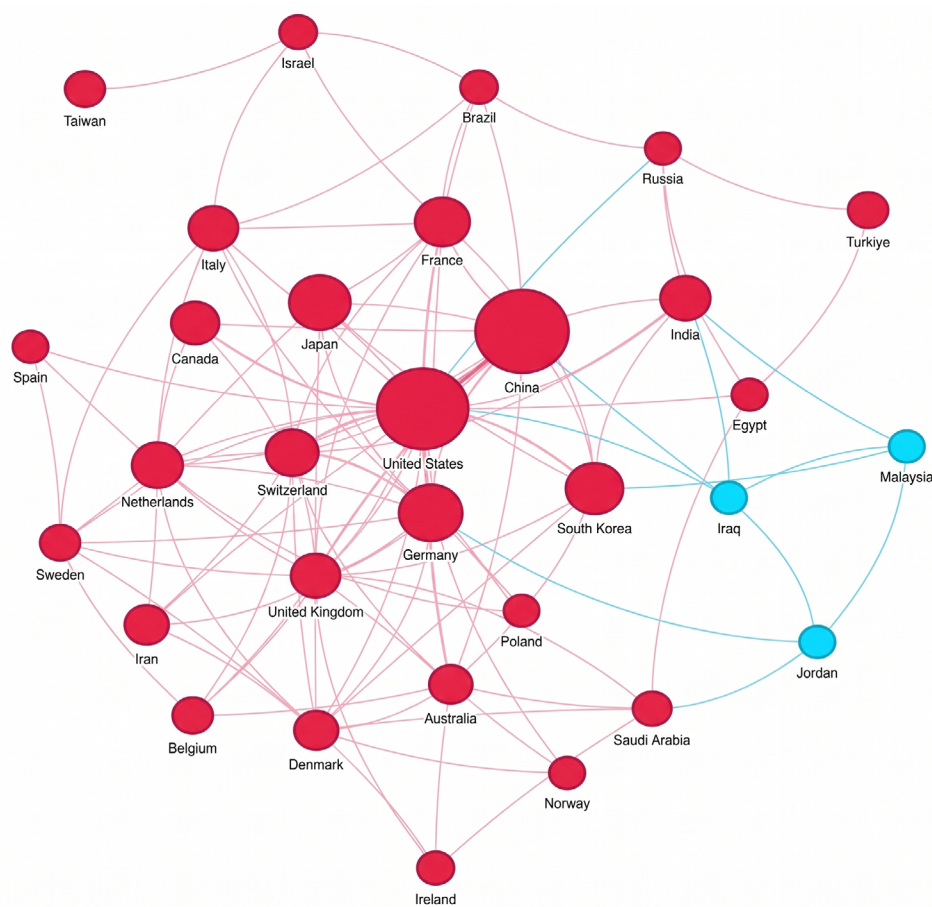


Figure 6. Co-authorship network. Red and blue nodes represent Cluster 1 and Cluster 2, respectively. Node size reflects an author's relative contribution to the publication network, while connecting lines indicate co-authorship relationships between authors.

science, radiology, and biomedical engineering are within this literature. By positioning these three dimensions as the next step in the analysis, rather than an add-on at the end, it would be clearer how future versions of this work would differ from past single-dimensional bibliometric reviews of the field.

4.2. United States–China citation disparity

The United States recorded higher citation performance (6,483; C/P = 33.08) than China (4,226; C/P = 20.22), despite China's higher publication output (Table 5). This difference should be interpreted descriptively, not causally. Several bibliometric characteristics were associated with this pattern. The United States occupied a more central position in the international collaboration network, with a PageRank of 1.0000 and total link strength of 119, compared with China's 0.5610 and 70, respectively (Table 8). In addition, the average publication year of United States-affiliated publications was earlier (2021.8)

than that of China (2023.5), providing a longer period for citation accumulation. These factors may contribute to the observed citation differences; however, the present bibliometric design cannot determine their causal effects or establish differences in underlying research quality. Institutional characteristics, funding patterns, journal visibility, and other unmeasured factors warrant further investigation.

4.3. The Netherlands' elevated citation efficiency

The Netherlands demonstrated exceptionally high citations per publication (C/P = 66.67; C/CP = 80) despite a comparatively smaller publication volume of 30 publications (Table 5), a pattern indicative of citation concentration around a small number of highly influential works rather than broad-based citation performance across the national output. This is further supported by the country's relatively early average publication year (2021.5; Table 8), which afforded a longer accumulation window, and

its high normalized citation value (3.175), suggesting the country's output performs well even after adjusting for field and time effects. However, the top-cited papers reported in Table 4 do not include explicit country-affiliation data, and none of the 10 globally top-cited works can be confidently attributed to Dutch-affiliated corresponding authorship based on the information available; identifying specific representative studies driving this citation efficiency would require supplementary author-affiliation linkage beyond the present dataset. The Netherlands also showed relatively high network connectivity, with a total link strength of 28 across 30 publications (Table 8). This pattern indicates that its publications are relatively well connected within the international collaboration network. However, this analysis cannot determine whether this network position causally contributes to citation performance.

4.4. From iterative reconstruction to deep learning: Clinical implications

The thematic analysis demonstrated strong representation of keywords related to deep learning, machine learning, image reconstruction, and dose prediction, with higher average publication years associated with dose prediction and deep learning image reconstruction, suggesting growing research attention toward these areas, while iterative reconstruction appeared more frequently in earlier publications (average publication year 2021.4; Table 7). These thematic patterns indicate increasing scholarly attention to deep learning-based reconstruction. The broader literature discusses potential applications in dose reduction and image-quality preservation; however, the present bibliometric analysis does not directly evaluate clinical performance, model generalizability, or technological superiority^{61,63} (Table 4). The lower average citation count for “deep learning reconstruction” may partly reflect its more recent publication profile and shorter citation window.

4.5. Bibliometric correlates of identified research gaps

Bibliometric evidence partially and unevenly addresses the research gaps frequently mentioned in this area: pediatric imaging, multimodal applications, and regulatory coordination. The keyword node “pediatric” has a comparatively small number of associated documents (12) and citations (150) in Cluster 4 (Table 7), indicating comparatively lower representation of pediatric dose optimization within the retrieved literature. Similarly, the keywords that span different imaging modalities or treatment areas (e.g., “computed tomography angiography,” with 15 documents, and “pediatric,” with 12 documents) have low numbers of links (5–6) compared to core

keywords (e.g., “deep-learning,” 31 links, and “AI,” 23 links) (Table 7), suggesting that there is a low level of structural integration between modality-specific and cross-cutting AI themes. In contrast, regulatory coordination is not directly represented by a node in the co-occurrence network (Table 7). The limited representation of terms such as “regulation,” “validation,” and “clinical implementation” suggests that these topics are less prominent within the retrieved keyword network. Additional institutional and interdisciplinary analyses could help determine whether this pattern represents a research gap or reflects limitations of keyword-based bibliometric retrieval.

5. Limitations and future research

This study has several limitations. First, the analysis was based exclusively on Scopus. Although Scopus provides broad multidisciplinary coverage and is widely used for bibliometric analysis, publications indexed only in other databases, such as Web of Science, PubMed, IEEE Xplore, or Embase, as well as relevant conference proceedings, may not have been captured. Second, bibliometric retrieval is inherently dependent on the selected search terms and database indexing practices. Despite the structured search strategy, relevant studies using alternative terminology, including radiomics, image-guided radiotherapy, adaptive radiotherapy, knowledge-based planning, image-guided dose management, or modality-specific terms related to CT, positron emission tomography, magnetic resonance imaging, and radiotherapy, may have been omitted if they did not explicitly refer to radiation dose optimization. Consequently, the findings should be interpreted as representing the literature retrieved using the predefined Scopus search strategy rather than the entire body of AI-related radiation dose optimization research.

Furthermore, bibliometric analysis characterizes publication patterns, citation performance, collaboration networks, and thematic structures but does not directly assess scientific quality, clinical effectiveness, technological performance, or patient outcomes. Interpretations concerning technological or clinical progress should therefore be made cautiously and complemented by systematic reviews, meta-analyses, and primary clinical studies.

6. Conclusion

This bibliometric study provides a quantitative overview of the development and structure of research on AI in radiation dose optimization in medical imaging and radiotherapy. Analysis of 738 Scopus-indexed publications demonstrated a substantial increase in publication activity, particularly in recent years, with the highest annual

publication output recorded in 2025. China and the United States were the leading contributors to publication output, while differences were observed in citation performance and international collaboration–network characteristics across countries.

The analysis also identified *Medical Physics* as the most productive source among the leading journals, whereas *IEEE Transactions on Medical Imaging* demonstrated particularly high citation performance. Keyword and thematic analyses showed that CT, deep learning, machine learning, image reconstruction, radiation dose, and dose prediction constitute prominent areas within the literature. The co-authorship analysis further demonstrated the predominance of multi-author and internationally connected research networks.

Overall, these findings characterize the publication, citation, collaboration, and thematic structure of AI-related radiation dose optimization research rather than the clinical effectiveness or technological superiority of specific approaches. The observed thematic patterns identify areas receiving increasing scholarly attention and provide a basis for future systematic reviews and primary studies. Future research may examine questions highlighted within the broader literature, including cross-platform model generalizability, clinical validation, regulatory considerations, and harmonized approaches to AI safety; however, these areas should be regarded as priorities for further investigation rather than conclusions established by the present bibliometric analysis.

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Conflict of interest

The authors report no potential conflict of interest.

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Ethics approval and consent to participate

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Consent for publication

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Availability of data

Not applicable.

Further disclosure

During the preparation of this work, the authors used generative artificial intelligence and AI-assisted technologies to improve the language clarity, phrasing, and structural flow of the manuscript. These tools were used solely to enhance academic writing quality and to assist with formatting the bibliometric analysis presentation. After using these technologies, the authors reviewed, edited, and refined the content to ensure its scientific accuracy and alignment with the empirical data. The authors accept full responsibility for the final content, integrity, and originality of the published paper.

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