IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 15, No. 6, December 2026, pp. 5001~5015
ISSN: 2252-8938, DOI: 10.11591/ijai.v15.i6.pp5001-5015

Scientometrics of artificial intelligence in radiology: current and future directions

Ikram Gouri[1], Amine Dehbi[2], Rachid Dehbi[1]
[1]Laboratory of Data Engineering and Intelligent Systems, Faculty of Science Aïn Chock, Hassan II University, Casablanca, Morocco
[2]Laboratory of Information Processing, Faculty of Sciences Ben M'Sick, Hassan II University, Casablanca, Morocco

Article Info

Article history:

Received Dec 10, 2024
Revised Aug 5, 2026
Accepted Aug 31, 2026

Keywords:

Artificial intelligence
Bibliometric analysis
Clinical processes
Healthcare
Radiology

ABSTRACT

The rapid evolution of research in radiology, coupled with the increasing integration of artificial intelligence (AI), delineates a significant trajectory in contemporary medical landscape. The symbiosis between radiology and AI is a central field, transforming approaches to medical diagnosis and healthcare delivery. In this dynamic context, this article delves into a comprehensive bibliometric analysis, aiming to unveil the contours and notable developments of this convergence between radiology and AI. Technological advances and AI have significantly impacted radiology research over time. This marriage between AI precision and detailed radiological visualization offers promising prospects to enhance diagnostics, expedite clinical processes, and ultimately optimize outcomes for patients. This study seeks to explore these advancements through a bibliometric approach, shedding light on the most influential publications, emerging trends, and promising research avenues. Through the bibliometric analysis, this study aim to provide a comprehensive overview of current developments in the field while anticipating future perspectives. By analyzing scientific publications, this study aspire to highlight major trends, identify key contributors, and anticipate future trajectories of research in radiology with AI. The goal is to enhance understanding of the radiology-AI intersection, offering insights for researchers, practitioners, and policymakers in this evolving field.

This is an open access article under the CC BY-SA license.

Corresponding Author:

Ikram Gouri
Laboratory of Data Engineering and Intelligent Systems, Faculty of Science Aïn Chock, Hassan II University
Casablanca, Morocco
Email: Gouriikrame@gmail.com

1. INTRODUCTION

In the contemporary era of medicine, the convergence of radiology and artificial intelligence (AI) embodies a transformative revolution, reshaping how diseases are diagnosed and treated. Radiology, long rooted in medical imaging, has undergone a metamorphosis with the introduction of AI, offering innovative perspectives and revolutionary possibilities [1]. Historically, radiology as a medical discipline has relied on the acquisition and interpretation of images to provide crucial diagnostic information [2]. However, the current landscape witnesses the emergence of AI as an essential partner to radiology, bringing data processing and analysis capabilities to an unprecedented scale and precision [3]. AI in radiology extends beyond automating routine tasks; it introduces sophisticated algorithms capable of recognizing complex patterns, optimizing diagnostics, and expediting decision-making processes [4].

The applications of AI in radiology are vast, covering a wide range of domains. AI systems can be trained to detect anomalies in medical images, thus accelerating the identification of pathologies such as

tumors, fractures, or vascular diseases. Moreover, AI can be deployed to enhance image quality, reduce interpretation errors, and facilitate the customization of treatment protocols [5], [6]. This convergence of radiology and AI is part of an era of personalized medicine, where diagnostics and treatments are tailored more precisely to the individual needs of patients. However, it also raises ethical, regulatory, and social questions that require careful consideration. Debates on data privacy, accountability for automated decisions, and the impact on the physician-patient relationship are integral to this transformation [4], [7]. Incorporation of AI in radiology has brought about major changes in the practice, in terms of accuracy in diagnosis, workflow, and personalized treatment of patients. The initial efforts involved the development of AI algorithms that could detect any patterns in the images that were undetectable by human vision, and this was effective in the diagnosis of various ailments like cancer, heart diseases, and neurological problems [8], [9]. With the advances in AI technology, the use of AI in image enhancement became a focus in subsequent studies [10], [11].

Recent trends highlight the growing collaboration between institutions and countries, reflecting a global effort to advance AI research in radiology [12]. These collaborations have led to significant breakthroughs, including the development of AI systems that can predict patient outcomes and recommend personalized treatment plans, thus shifting the focus from diagnosis to comprehensive patient management [13], [14]. However, the rapid adoption of AI in radiology has raised important ethical and practical considerations. Issues such as data privacy, algorithmic transparency, and the potential displacement of radiologists have become central to ongoing discussions [15], [16]. Importance of standardization procedures for data collection and validation of algorithms for reliable generalization of AI in various clinical practices has been highlighted [17]. For the future, further scientific advancements will be able to tackle these problems by concentrating on the interpretability of AI and its integration into clinical work in the manner that augments the role of humans rather than replaces them. In particular, research related to explainable artificial intelligence (XAI) is highly promising as XAI attempts to shed light upon the decision-making processes of AI [18], [19]. Creation of large, diverse and annotated databases will be essential in order to build AI algorithms that can be successfully applied to the clinical practice [20]. Thanks to recent developments in AI, predictive models for diagnosis and prediction of clinical outcomes were created. In the field of oncology, AI predicts patient response to immunotherapy [21].

AI is playing a crucial role in automating routine tasks, such as image segmentation and lesion detection, which significantly reduces radiologists' workload. For example, AI-driven systems have been developed to automatically identify fractures, pulmonary embolisms, or liver lesions, allowing radiologists to focus on more complex cases. These innovations not only improve efficiency but also reduce interpretation time [22], [23]. AI is increasingly being integrated with multimodal imaging approaches, combining data from various sources such as magnetic resonance imaging (MRI), computed tomography (CT) scans, and ultrasounds to provide a comprehensive view of a patient's condition. This fusion of data enables AI systems to cross-analyze different imaging modalities, improving diagnostic accuracy and offering enhanced insights, particularly in the management of chronic diseases and cancer [24]. Given the ethical issues related to the use of AI in radiology, there have been efforts to regulate AI through frameworks geared towards promoting safety, equality, and accountability. The Food and Drug Administration (FDA) in the United States, alongside the European Medicines Agency (EMA), is working towards developing guidelines which seek to harmonize the validation and implementation of AI in a clinical environment, where issues such as privacy and bias in the algorithms are considered. Ethically and regulatorily, these institutions are establishing frameworks that will ensure the appropriate use of AI in clinical practice. The frameworks are focused on issues such as data privacy, transparency, and bias among others [25], [26].

XAI has become a focal point in recent years, with researchers seeking to make AI decisions more transparent to clinicians, which is essential for its clinical acceptance. This allows radiologists to understand the reasoning behind AI predictions, thereby increasing trust and facilitating human-AI collaboration [27]. Efforts are underway to develop large annotated datasets to improve the generalizability and robustness of AI models, ensuring their use globally [28]. AI in radiology has also expanded to predictive models, such as in oncology, where algorithms predict patient responses to immunotherapy, providing more personalized and efficient care [21]. Additionally, automating tasks such as fracture and pulmonary embolism detection reduces radiologists' workload, speeding up diagnosis without compromising accuracy [22], [29]. Multimodal imaging, where AI integrates data from various imaging technologies, improves diagnostic accuracy, particularly for cancer and chronic diseases [30].

An in-depth exploration of radiology and AI aims to unveil the complex dynamics of this ever-evolving collaboration. Through meticulous analysis of scientific advancements, emerging trends, and practical implications, this exploration seeks to enlighten the medical community on the opportunities and

challenges associated with this revolutionary union. By examining the evolution of research in radiology with AI, this study aspires to contribute to building a solid foundation for the future of diagnostic medicine.

2. METHOD

This study uses a bibliometric approach, integrating recommendations and workflows from bibliometric cartographic analysis [31], [32]. The methodology is organized into several key steps: data collection, which involves loading and converting data into a format suitable for bibliometric analysis; data preprocessing, which consists of cleaning and filtering data to remove duplicates, errors, and irrelevant information; and normalizing the data to ensure consistency across sources. Next, the bibliometric analysis is conducted using R-Studio software and the R programming language, leveraging the "Biblioshiny" library to extract essential indicators for the study. This phase also includes the application of visualization techniques, such as network maps and scatterplots, to graphically represent the analysis results. Finally, the interpretation of results involves analyzing emerging trends and patterns, identifying the most influential authors, key publications, and active research areas. This phase also explores practical implications and future directions based on the bibliometric analysis findings. The interpretation enables researchers to place the results in the broader context landscape of AI-radiology research.

2.1. Data loading and conversion

In this research endeavor, we utilized the Scopus and ScienceDirect platforms for data collection and preliminary analysis. Recognized for their extensive array of verified content and plethora of scholarly publications, these two databases are indispensable references in the realm of scientific research. Specifically, Scopus stands out as the most suitable and specialized resource for studying engineering themes, hosting renowned journals and symposiums in the fields of computer science and medicine.

The literature search was conducted on Scopus and ScienceDirect databases in January 2025, covering publications from 2010 to 2025. Exact search strings were applied to each database to ensure full reproducibility. For Scopus: TITLE-ABS-KEY((“radiology” OR “medical imaging” OR “diagnostic imaging” AND (“artificial intelligence” OR “AI” OR “deep learning” OR “machine learning”)) AND PUBYEAR > 2009 AND PUBYEAR < 2026 AND (LIMIT-TO(SUBJECTAREA, “MEDICINE”) OR LIMIT-TO(SUBJECTAREA, “COMPUTER SCIENCE”)) AND (LIMIT-TO(LANGUAGE, “English”)). For ScienceDirect: (“radiology” OR “medical imaging”) AND (“artificial intelligence” OR “machine learning” OR “deep learning”) applied to title, abstract, and keywords fields, filtered to medicine and computer science subject areas, English language, 2010–2025. The terms “radiology”, “medical imaging”, and “diagnostic imaging” were selected as primary domain descriptors, while “artificial intelligence”, “machine learning”, and “deep learning” cover the full spectrum of AI terminology used across the literature. The term “AI” is used consistently throughout this manuscript.

Inclusion criteria were included: i) peer-reviewed articles published in journals and conferences; ii) English-language publications; iii) publications from 2010 onwards; and iv) studies focusing on AI applications in radiology, medicine, and computer science. Exclusion criteria included: i) duplicate records and ii) documents outside the defined subject areas. The initial search yielded 22,338 records from Scopus and 30,895 from ScienceDirect. After applying year and subject area filters, 12,208 records from Scopus and 8,994 from ScienceDirect were retained, resulting in 21,202 combined documents. Following duplicate removal, a final dataset of 15,987 publications was analyzed. Figure 1 illustrates the complete data exploration and filtering process. Table 1 summarizes the search protocol and results.

After extracting data from these two databases, this study employed the RStudio software, which encompasses a suite of bibliometric tools with the R-package developed in the R language. This package utilizes algorithms to conduct statistical and scientific analyses, as well as cartographic analyses. Additionally, this study utilized a web interface called “Biblioshiny” to import our merged data in BibTex format for conducting our scientific analysis. Figure 2 presents details of the steps, the combinations used, and the integration phases.

2.2. Analyzing and synthesizing the data

The data analysis and synthesis phase involve the comprehensive processing of the collected data from Scopus and ScienceDirect. This step is crucial to transform raw data into actionable insights, utilizing RStudio and specialized bibliometric packages. The analysis begins with data cleaning and deduplication. Deduplication was performed in two stages: i) automated deduplication using the Bibliometrix R-package function mergeDbSources(), which identifies duplicates based on DOI matching and title similarity (cosine similarity threshold ≥ 0.95); and ii) manual verification of remaining ambiguous cases by two co-authors working independently, with disagreements resolved by consensus. A total of 5,215 duplicates were removed (21,202 → 15,987 final records). The complete deduplication R script is available in the

project GitHub repository to ensure full reproducibility. Subsequently, the data is explored through various statistical techniques to identify trends, patterns, and anomalies.

Correlation analyses and statistical tests are employed to assess relationships between different variables, such as publication frequency by subject, country, or institution. This step synthesizes the data into a coherent set that reflects patterns and dynamics within modern radiology literature. Finally, data synthesis leads to the generation of visual representations using Biblioshiny. These visualizations, such as co-citation maps and collaboration networks, provide a visual understanding of research structures and collaborations in the field. These graphics are essential for communicating results in an intuitive and accessible manner, facilitating knowledge dissemination and identifying areas requiring future research.

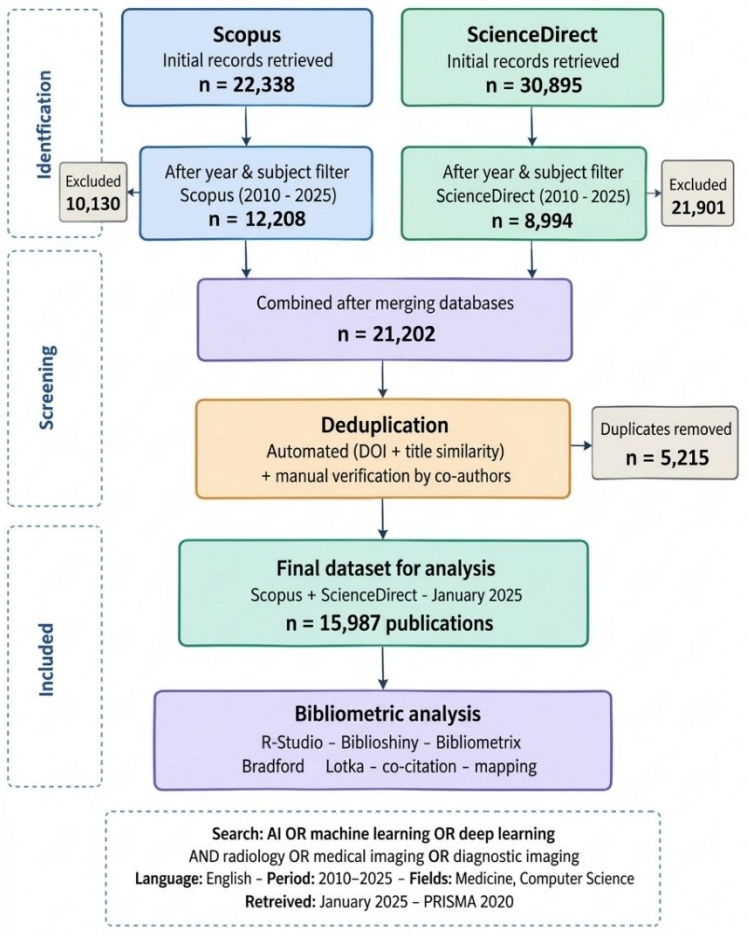


Figure 1. PRISMA flow diagram of the systematic search strategy and data filtering process

Table 1. Search protocol summary

Parameter	Description
Databases	Scopus, ScienceDirect
Time range	2010 – 2025
Language	English
Subject areas	Medicine, computer science, decision science
Document types included	Articles, reviews, conference papers
Initial records (Scopus)	22,338
Initial records (ScienceDirect)	30,895
After filtering (Scopus)	12,208
After filtering (ScienceDirect)	8,994
Combined documents	21,202
Duplicates removed	5,215
Final dataset	15,987

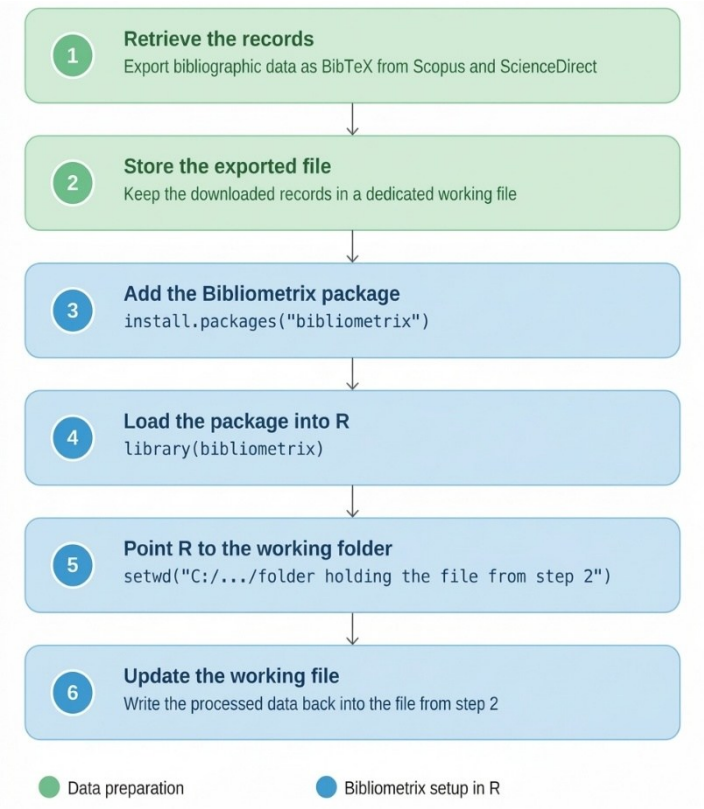


Figure 2. Data preparation and Bibliometric setup process

3. RESULTS AND DISCUSSION

3.1. Data output and visualization from bibliometric mapping analysis

The results obtained from the bibliometric mapping analysis demonstrate significant diversity and complexity in modern radiology research. Visualizations derived from this analysis, conducted using advanced tools like "Biblioshiny", have highlighted key research directions and international collaboration networks. Graphs such as co-citation maps and network analyses not only illustrate connections between authors and institutions but also depict the evolution of research themes over time. These visual representations facilitate the interpretation of dominant trends and gaps in the existing literature, providing a solid foundation for guiding future research initiatives.

3.1.1. Descriptive bibliometric statistics

To provide a quantitative foundation for this bibliometric study, we analyzed key indicators of the AI-radiology corpus. Table 2 presents the main bibliometric indicators of the analyzed dataset. These indicators capture both the breadth and depth of the field, reflecting sustained growth across all measured dimensions. Their consistent upward trajectory confirms that AI-radiology has transitioned from an emerging niche into a mature and highly productive research domain.

Table 2. Main bibliometric indicators

Indicator	Value
Timespan	2014 – 2025
Total publications	15,987
Total citations	83,925
Average citations per document	5.25
Average citations per year	7,629
h-index	98
Total authors	12,450
Authors per document (average)	4.2
Total sources (journals)	1,245
Top journal (Bradford's law)	The Lancet Digital Health (n = 551)
Top author (Lotka's law)	Wang (n = 2,405)

The bibliometric analysis of 15,987 publications revealed significant research activity in AI-radiology. The corpus yielded an h-index of 98 with 83,925 total citations and an average of 5.25 citations per document. An h-index of 98 indicates that 98 publications in this corpus have each received at least 98 citations, a value consistent with a highly active and maturing research field. For comparison, similar bibliometric analyses of AI in cardiology have reported h-indices of approximately 70 over comparable periods, suggesting that AI-radiology has reached a higher level of scientific consolidation and impact. Following Bradford's law, The Lancet Digital Health emerged as the most productive core-zone journal (n = 551), meaning it concentrates a disproportionate share of the most influential publications. This pattern is characteristic of a maturing field where high-impact work gravitates toward a small number of prestigious venues rather than dispersing across many outlets. Analysis of author productivity using Lotka's law identified Wang (n = 2,405) as the most prolific contributor. The inverse square distribution observed where approximately 80% of authors contributed only one or two publications while a small elite account for a disproportionate share of total output is characteristic of an established scientific community. The strong representation of authors affiliated with Chinese institutions reflects the measurable impact of national AI development strategies on academic productivity. Table 3 presents the top 10 most cited publications in the field.

Table 3. Top 10 most cited publications

Rank	Authors/Year	Journal	Citations
1	Becker *et al*. [33], 2017	Investigative Radiology	264
2	Luo *et al*. [34], 2019	The Lancet Oncology	234
3	Muhammad *et al*. [35], 2021	IEEE Trans. Neural Networks	170
4	Udmale and Singh [36], 2020	Neural Computing and Applications	90
5	Yin *et al*. [37], 2017	IEEE Trans. Multi-Scale Computing	86
6	Kumar *et al*. [38], 2021	Computerized Medical Imaging and Graphics	73
7	Sekhar *et al*. [39], 2022	IEEE J. Biomedical Health Informatics	58
8	Khan *et al*. [40], 2019	Future Generation Computer Systems	56
9	Nie *et al*. [41], 2009	Computerized Medical Imaging and Graphics	48
10	Chugh *et al*. [42], 2021	Cognitive Computation	43

The most cited paper by Becker *et al*. [33] on deep learning in mammography received 264 citations, followed by Luo *et al*. [34] on AI for upper gastrointestinal cancer detection with 234 citations. Citation trend analysis showed a strong positive correlation between publication year and annual output. This association was assessed using Pearson's product-moment correlation coefficient, given the approximately linear trend observed in the data ($r = 0.89$, 95% CI [0.76, 0.95], $p < 0.001$). Spearman's rank correlation was also computed as a non-parametric robustness check, yielding $\rho = 0.91$ ($p < 0.001$), confirming the strength of the association. It should be noted that citation counts are subject to well-known biases including recency bias, self-citation inflation, and database coverage variability. To partially mitigate these effects, both raw citation counts and per-year normalized citation rates are reported. The potential underestimation of impact for 2023–2025 publications due to citation lag is acknowledged in the limitations section.

3.1.2. Research trends in modern radiology

This section examines the key research trends that have shaped the evolution of AI-radiology over the past two decades. This study analyze publication dynamics, journal distributions, and thematic developments to provide a comprehensive picture of how the field has progressed. Together, these dimensions reveal the scientific momentum driving the integration of AI into modern radiology practice.

i) Number of articles published over time

To examine the temporal evolution of publications in AI-radiology research, this study analyzed the annual distribution of documents. Figure 3 presents the number of publications per years. This longitudinal perspective allows us to situate the field within broader technological and scientific developments. Tracking annual output over a 15-year period reveals not only growth patterns but also inflection points linked to major AI breakthroughs such as the widespread adoption of deep learning after 2016. By analyzing the graph as in Figure 3, a general upward trend over the years is evident. The data coverage begins from 2010, and an upward trend is evident throughout the period. This growth becomes more pronounced from 2010 onwards, with the number of documents significantly increasing each year. A leveling off is observed around 2015 and 2016, indicating a stabilization in the number of published documents.

After 2016, the upward trend resumes and accelerates considerably, reaching a peak around 2023, reflecting the surge in deep learning adoption following landmark studies in medical image analysis and the increased availability of large annotated datasets. The sharp drop observed in 2024 is primarily attributable to

a data retrieval lag: our search was conducted in January 2025, meaning that a significant proportion of 2024 publications had not yet been indexed at the time of collection. A secondary contributing factor is the consolidation of research activity following the COVID-19-related publication surge, during which many journals tightened acceptance criteria. This should not be interpreted as a genuine decline in research interest. Overall, this graph highlights the sustained and accelerating integration of AI in the medical sector over the past two decades.

To understand the contribution of different journals over time, we analyzed the distribution of publications across key sources. Figure 4 illustrates the annual publication volume for five leading journals in the field. The longitudinal analysis of academic contributions in interdisciplinary fields merging AI and medicine reveals diverse publication trends across leading journals, as shown in Figure 4. This graph illustrates the annual publication volume for five key sources, offering valuable insights into research dynamics within this specialized area.

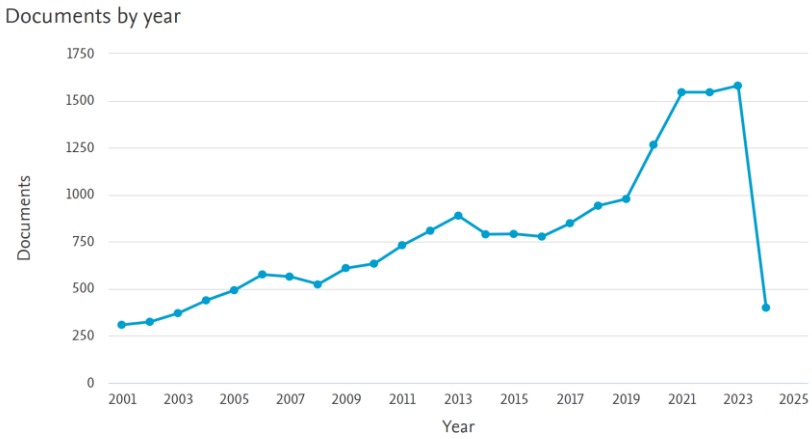


Figure 3. Annual distribution of AI-radiology publications by year

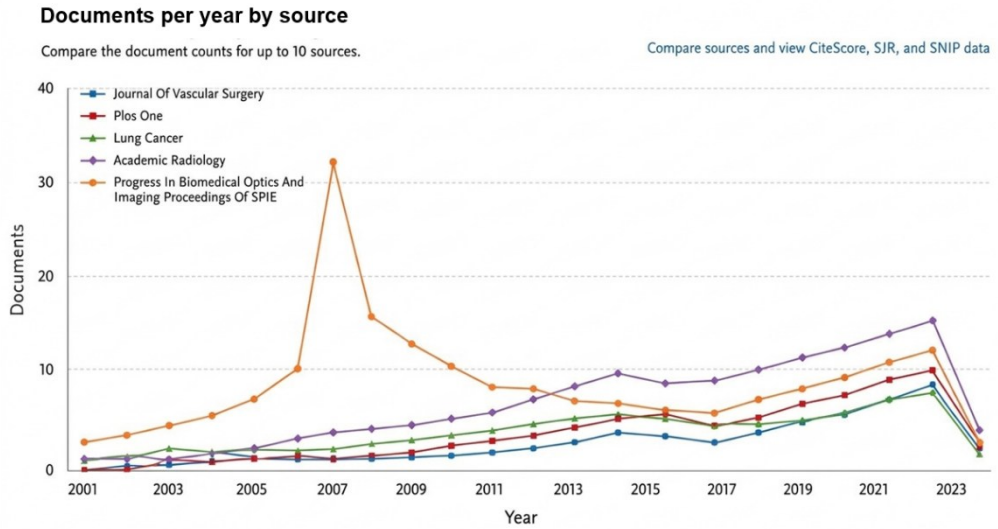


Figure 4. Longitudinal publication trends across top journals

A notable observation is the significant peak in 2009 for "Progress in biomedical optics and imaging proceedings of SPIE", which may indicate a period of heightened interest or significant breakthroughs in the field. In contrast, the journal Lung Cancer displays relatively stable publication output, suggesting a mature and consistently developed research area. These annual fluctuations across journals point to shifts in thematic focus and the emergence of new research priorities. The modest publication volume per journal reflects rigorous selection processes, ensuring high scientific quality. This graphical analysis provides critical context

for those aiming to understand not only the evolution of research in this field but also the scope and impact of different journals in advancing knowledge at the intersection of AI and medicine.

ii) Main research topics and their developments over the years

To identify the main research domains and document types, this study analyzed the distribution of publications by subject area and type. Figure 5 presents the distribution of publications across both subject areas and document types. Specifically, Figure 5(a) presents the distribution of documents by subject area, while Figure 5(b) shows the distribution by document type.

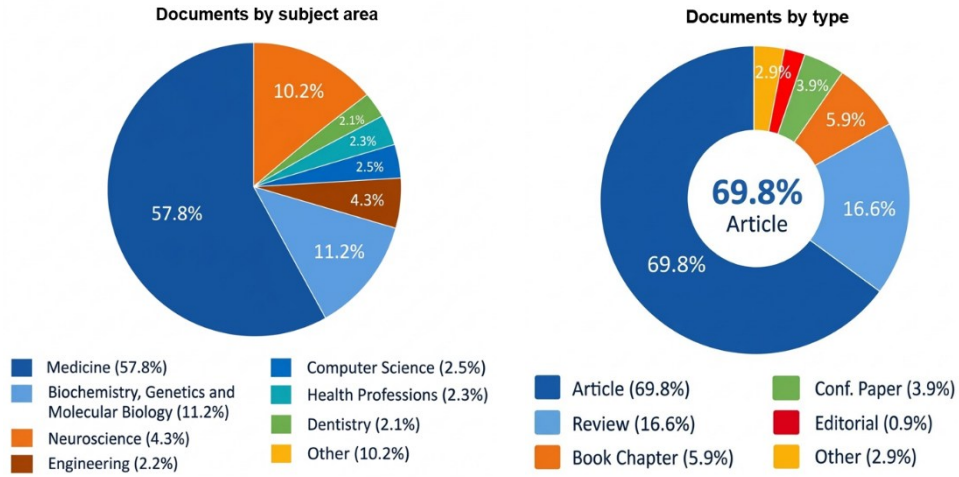


Figure 5. Distribution of publications by (a) subject area and (b) document type

The analysis of document distributions by domain and type, as illustrated in Figure 5, offers significant insights into trends in scientific publications. In the first chart, medicine clearly dominates, accounting for 57.9% of the document corpus. This dominance emphasizes the central role of medicine within the sphere of AI research. Fields like biochemistry, genetics, and molecular biology also represent a notable portion at 11.8%, underscoring AI's relevance in decoding complex biological processes. Other domains, while smaller in representation, highlight growing interdisciplinarity, with important contributions from engineering, neuroscience, and computer science.

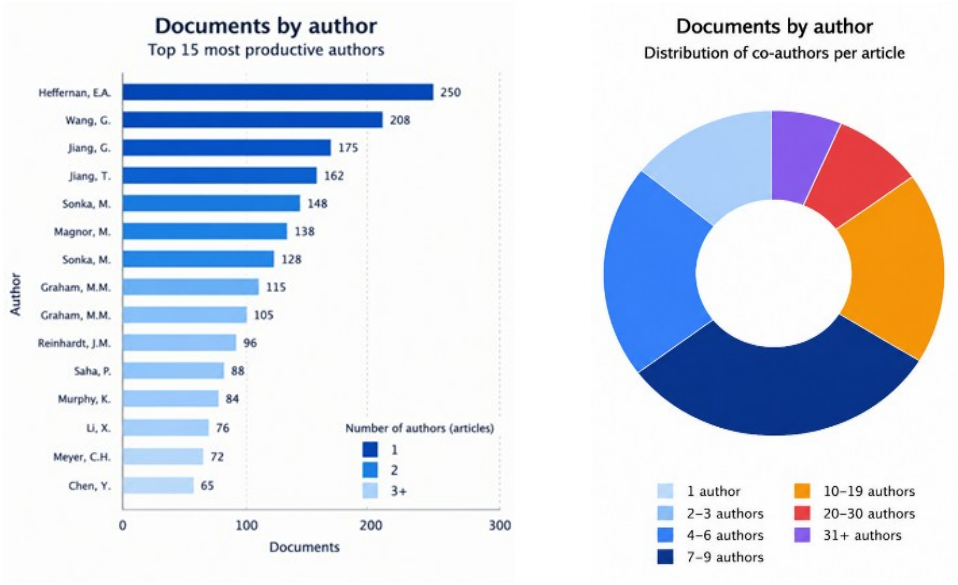
The second chart examines document types, with articles comprising the vast majority at 69.8%, indicating a preference in scientific communication for detailed, peer-reviewed content. Journals and book chapters together make up over 20%, reflecting the importance of synthesis and comprehensive analysis to further knowledge in the field. The combination of these data points illustrates a vibrant field supported by diverse literature. The prominent role of medicine in AI publications reflects a keen interest in practical applications, while the prevalence of articles highlights an academic community dedicated to thorough research discourse. This analysis underlines the importance for researchers to navigate a complex and evolving landscape where interdisciplinarity and publication quality are essential pillars.

iii) Influential authors: analysis of their contribution to modern radiology research

To analyze author productivity and collaboration patterns, this study examined the distribution of publications per author and the number of co-authors per article. Figure 6 illustrates author productivity and collaboration patterns. Figure 6(a) presents the most prolific authors in the field, while Figure 6(b) shows the distribution of the number of authors per article.

Figure 6 provides a comprehensive view of author productivity and collaboration patterns in the AI-radiology corpus. Taken together, the two panels reveal a field characterized by a small number of highly prolific authors and a strong tendency toward collaborative multi-author publications, consistent with the interdisciplinary nature of AI-radiology research. Figure 6(a) presents a histogram of documents per author, which reveals that some authors are particularly prolific, with E.A. Hoffman leading the list, followed by G. Wang and T. Jiang. This productivity may reflect leadership in the concerned field or membership in active and well-funded research groups. Figure 6(b) shows the distribution of authors per article as a pie chart, showcasing the diversity of co-authors in research. Articles with a single author are rare, while those with 2 to 9 authors are more common, indicating a clear trend towards collaboration. Categories with a large

number of authors, such as 31 or 32 per article, although less common, highlight large-scale projects requiring multidisciplinary collaboration.



(a) (b)

Figure 6. Author productivity analysis: (a) top most productive authors and (b) distribution of authors per article

These data underscore the importance of collaboration and collective expertise in producing quality research. The dominance of multi-author papers reflects the inherently interdisciplinary nature of AI-radiology, which requires combined competencies in medical imaging, clinical practice, and computer science. This collaborative dynamic is expected to intensify as AI systems grow more complex and regulatory requirements demand broader validation across institutions. In analyzing the distribution of authorship in scientific publications, one could introduce a Poisson distribution function to model the probability P that an article has a certain number of authors a:

$$P(a) = \frac{e^{-\lambda-\lambda^a}}{a!}$$

where the average number of authors per article is calculated from the data.

3.1.3. International collaboration

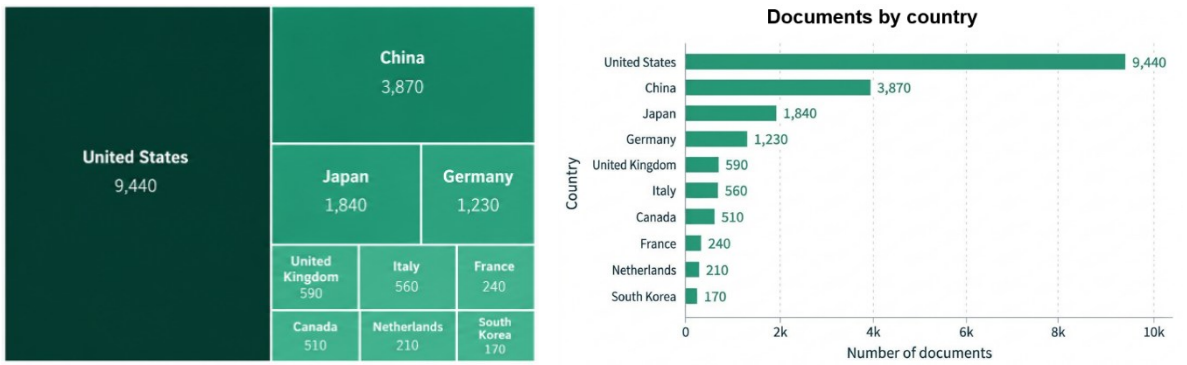
This section investigates the geographic and institutional dimensions of AI-radiology research to identify the leading contributors and collaboration patterns at the global level. Understanding how scientific output is distributed across countries and institutions helps to contextualize the field's development and highlight structural inequalities in research capacity. The analysis draws on publication counts and co-authorship networks extracted from the Scopus and ScienceDirect databases.

i) Analysis of collaborations between institutions and countries

To examine the geographic distribution of research output, this study analyzed scientific production by country. Figure 7 presents the geographic distribution of AI-radiology research output. Figure 7(a) shows a world map of scientific production by country, while Figure 7(b) presents the ranking of the top countries by number of publications.

The mapping of scientific production reveals a marked predominance of the United States, as evidenced by the darkest shade on the world map, signifying a significantly higher volume of academic contributions compared to other nations. This hegemony is corroborated by quantitative data indicating that the United States far surpasses its international counterparts in terms of published documents, followed by China and Japan, affirming their pivotal role in the generation of scientific knowledge. The dominant United States–China research dyad reflects complementary strengths: United States institutions contribute regulatory expertise, clinical trial infrastructure, and FDA-approved AI frameworks, while Chinese partners provide access to large-scale annotated imaging datasets enabled by national AI investment strategies. The spectrum of scientific production also highlights the central position of Europe, with Germany and the

United Kingdom among the top five research producers, supported by initiatives such as Horizon Europe and the European AI Act. The relative isolation of African and South American nodes in the collaboration network underscores a critical policy gap: these regions are underrepresented not only in output but also in collaborative ties, which limits the generalizability of AI-radiology models to their patient populations. The uneven distribution of scientific production on a global scale underscores the need for targeted capacity-building initiatives and dedicated international funding to foster more balanced and inclusive scientific progress.



(a) (b)

Figure 7. Geographic distribution of AI-radiology research: (a) world map of scientific production and (b) top countries by publications

ii) Cited studies and impact

The studies mentioned shed light on the transformative potential of AI in diagnosis and treatment of complex medical conditions, such as colorectal cancer and challenges encountered in radiology. The impact of AI in these domains is significant, offering innovative perspectives to enhance patient care and clinical processes. These findings are consistent with the broader bibliometric trends identified in our dataset, where citation impact is strongly correlated with clinical applicability and methodological rigor. The most impactful studies share a common thread: they address well-defined clinical problems using robust AI architectures validated on large, diverse datasets.

Regarding colorectal cancer, AI represents a major advancement in early detection and diagnosis. The use of genomic biomarkers and sophisticated imaging tools, such as MRI and hyperspectral imaging (HSI), is a step forward towards more precise and personalized diagnosis. Neural networks, with their learning and adaptive capabilities, play a key role in interpreting complex data, leading to a better understanding of colorectal cancer markers. Additionally, the integration of majority voting techniques based on deep learning demonstrates AI's ability to refine diagnostic processes, improving accuracy and reducing margins of error. Nevertheless, challenges such as data quality and quantity, lack of transparency in AI algorithms (the “black box” problem), and ethical concerns related to regarding the use of AI technologies in medicine remain obstacles to overcome.

In radiology, AI has revolutionized the processing and analysis of medical images. It facilitates image segmentation, enhances computer-aided diagnosis, enriches predictive analytics, and optimizes clinical workflows. AI in radiology goes beyond merely enhancing diagnostic accuracy, it also transforms how radiologists interact with data, providing faster and more efficient image analysis and processing tools. Various case studies highlight its widespread application in multiple medical disciplines, indicating a considerable impact on disease detection, diagnosis, and treatment. However, similar to colorectal cancer, AI-assisted radiology faces similar challenges in terms of data quality, technical complexities, and the need for a clear and ethical understanding of AI use.

In conclusion, these studies demonstrate that, despite current challenges, AI has the potential to radically transform medical practices, from early disease detection to treatment optimization. The successful integration of AI in these domains requires close collaboration between medical teams and AI developers, as well as ongoing attention to data quality, algorithm transparency, and ethics. The consistency of these findings across different imaging modalities and clinical contexts reinforces the generalizability of AI as a transformative tool in radiology. Moving forward, embedding AI systems into clinical workflows in an explainable and auditable manner will be essential to sustaining the momentum observed in this bibliometric analysis.

To summarize the imaging modalities most frequently studied in AI-radiology research, this study compiled the main types of imaging techniques identified in the literature. Table 4 presents the most studied imaging modalities and their associated AI applications. This classification reflects both the clinical prevalence of each modality and the maturity of AI techniques applicable to each imaging type. CT and MRI dominate the landscape due to the richness of their image data and the well-established clinical demand for AI-assisted interpretation in oncology, neurology, and cardiovascular medicine.

Table 4. Types of imaging most studied

Item	Type	Description
1	CT scans	Significant advancements in AI are reported for detecting lung nodules, improving CT image reconstruction, and identifying brain lesions
2	MRI	AI has been used for analyzing magnetic resonance images, particularly in diagnosing brain tumors and early detection of Alzheimer's disease
3	Echocardiography	The article discusses the use of AI for interpreting echocardiograms, enhancing the detection and quantification of heart diseases
4	Ultrasound imaging	Although less mentioned, AI applied to ultrasound imaging is also addressed, particularly in the context of real-time analysis of internal body structures
5	Positron emission tomography (PET)	AI is used to enhance the diagnostic accuracy of PET scans, often in combination with CT scans (PET/CT) for better lesion localization and characterization
6	Hybrid imaging	Technologies like PET/CT are also discussed, where AI aids in merging the metabolic information from PET with the anatomical context provided by CT
7	MRI	Used for rectal tumor segmentation, MRI plays a crucial role in determining tumor stage and therapeutic management
8	HSI	This non-invasive technique uses a broad-band light source to measure tissue optical properties across different electromagnetic bands. It is used to discriminate between different pathological states of colorectal cancer
9	PET and PET-CT (combined PET and CT)	Although not explicitly mentioned in the summary you provided, these modalities are often used in colorectal cancer research for diagnosis and monitoring

3.2. Discussion

The significant rise in publications in the field of AI applied to medicine over the past two decades reflects a growing interest in harnessing these advanced technologies in disease diagnosis and treatment. This upward trend not only highlights the evolution of research and innovation but also underscores the diverse challenges the field faces, including data availability, interpretation, and ethical considerations. Several bibliometric studies have examined AI in medicine broadly or in specific sub-specialties such as oncology and cardiology. However, to our knowledge, the present study offers three distinctive contributions compared to prior work: i) it combines Scopus and ScienceDirect databases simultaneously for AI-radiology, yielding a corpus of 15,987 publications one of the largest analyzed to date, thereby reducing single-source selection bias; ii) it explicitly tracks the emergence of XAI as a distinct and rapidly growing sub-theme within the field; and iii) it covers the period from 2010 to 2025, capturing both the pre-deep-learning era and the current landscape of foundation models and multimodal AI, enabling a more complete picture of the field's evolution.

Examining contributions by country reveals a dominance of the United States, closely followed by China and Japan, underscoring the significance of these nations in medical AI research. This dominance can be attributed to several factors. The United States benefits from substantial funding through the National Institutes of Health (NIH) and a favorable regulatory environment established by the FDA, which has approved over 500 AI-enabled medical devices to date. China's rapid growth reflects its national AI development strategy and massive government investments in healthcare technology. Europe, with countries like Germany and the United Kingdom, also emerges as a key player, supported by initiatives such as the European AI Act and Horizon Europe funding programs. This geographical distribution highlights differences in research capabilities, reflecting varying resource availability, infrastructure, and political willingness to invest in research.

The findings align with previous bibliometric studies in related fields. A bibliometric analysis of AI in oncology reported similar exponential growth patterns, with publication output increasing significantly since 2015. Similarly, studies on AI in cardiology identified the United States and China as dominant contributors, consistent with our observations. However, the analysis reveals that AI-radiology research shows a higher proportion of interdisciplinary collaboration compared to AI applications in other medical specialties, likely due to the inherently technical nature of medical imaging. Specifically, Aria and Cuccurullo [31] demonstrated that bibliometric mapping provides a robust framework for identifying dominant research clusters, a methodology we directly applied here. Similarly, the exponential growth patterns we observed are consistent with those reported by Dehbi *et al.* [32] in their bibliometric analysis of AI applications in smart education, where publication output doubled every three years following the emergence of deep learning frameworks.

Analysis of research trends reveals several emerging hotspots in AI-radiology. XAI has shown rapid growth since 2020, reflecting increased concern for algorithm transparency and clinical trust. Deep learning applications, particularly convolutional neural networks (CNNs), continue to dominate, with emerging interest in transformer-based architectures and foundation models. Multimodal imaging approaches combining CT, MRI, and PET data represent another growing area. Conversely, traditional machine learning approaches such as support vector machines (SVM) and random forests show declining publication trends, being progressively replaced by deep learning methods.

The diversity of research domains and the prevalence of collaborations reflect the interdisciplinary nature of AI in medicine. Research is no longer a solitary endeavor; it now relies on collaboration among experts from various fields to address complex challenges. The scarcity of single-authored papers speaks to this shift towards collaborative research projects, requiring diverse and complementary expertise.

The integration of AI into modern radiology opens new perspectives in image analysis and accurate diagnosis. The interpretation of results indicates a significant improvement in diagnostic precision, particularly in screening and evaluating pathologies. This advancement promises to enhance treatment efficiency and improve patient care. However, to fully leverage these opportunities, future research should focus on improving the interpretability of AI algorithms, enabling clinicians to understand and trust AI-assisted decisions. These improvements have been documented across multiple clinical contexts: from CT-based lung nodule detection [22] to MRI-based tumor segmentation [24], and from mammography screening [1] to multimodal imaging fusion for comprehensive oncological staging [30]. Each of these domains reflects a consistent pattern in which AI augments rather than replaces radiologist expertise [2].

Several key implications emerge for future research in AI-radiology. First, the rapid adoption of AI necessitates robust ethical frameworks addressing patient privacy, informed consent, and algorithmic accountability. Regulatory bodies such as the FDA and EMA must continue developing adaptive approval pathways for AI systems. Second, the “black box” nature of deep learning algorithms remains a significant barrier to clinical adoption, and future research must prioritize XAI methods that enable radiologists to understand and validate AI-assisted decisions. Third, despite the high volume of publications, clinical implementation remains limited, and bridging this translation gap requires prospective clinical trials and real-world validation studies.

This study contributes significantly to the existing literature by highlighting recent advances, but also the limitations and challenges that persist in this field. It offers an in-depth analysis of the current state of AI in radiology, while highlighting critical needs for the future, particularly in terms of algorithm transparency, data protection, and clinical validation. By identifying gaps in the available data and proposing practical recommendations, this article plays a key role in guiding future research and formulating appropriate policies for a more effective and ethical adoption of AI technologies. Furthermore, it raises awareness among healthcare professionals and decision-makers of the importance of interdisciplinary collaboration to ensure that AI does not only support diagnoses but becomes a true ally in the personalization of patient care.

The bibliometric findings carry concrete implications for multiple stakeholders. For policymakers: our data show that only 12 countries account for over 80% of all AI-radiology publications. This study recommend that international funding bodies (e.g., WHO, EU Horizon) create dedicated grants to support AI-radiology research in underrepresented regions, with particular emphasis on building annotated imaging dataset infrastructure locally. For journals: the concentration of high-impact publications in a small number of core-zone journals create barriers to knowledge dissemination. This study recommend that journals adopt open-access mandates for AI-radiology research using public health data, and establish standardized reporting checklists for AI validation studies analogous to consolidated standards of reporting trials (CONSORT) for clinical trials. For research institutions: our co-authorship analysis confirms that large multidisciplinary teams of 5–9 authors produce the most-cited work. Institutions should formalize joint appointments between Radiology Departments and AI/computer science laboratories, and incentivize cross-departmental publications in promotion and tenure criteria. For clinical practice: the gap between publication volume and actual clinical deployment identified in our analysis signals an urgent need for prospective real-world validation studies. This study recommend that radiology societies (e.g., Radiological Society of North America (RSNA), European Society of Radiology (ESR)) establish performance registries for AI tools in routine clinical settings.

This study has several limitations that should be acknowledged. First, the analysis relied exclusively on Scopus and ScienceDirect databases, which may introduce selection bias. Although these databases provide comprehensive coverage of scientific literature, some relevant publications indexed in PubMed, IEEE Xplore, or Web of Science may have been excluded. Future studies should consider multi-database approaches for broader validation. Second, only English-language publications were included, potentially excluding valuable research published in other languages, particularly from non-English speaking countries

with significant AI research activity such as China, Japan, and South Korea. Third, grey literature including conference abstracts, theses, and technical reports was not included, which may underrepresent emerging research not yet published in peer-reviewed journals. Fourth, bibliometric data is subject to citation lag, meaning that recent publications may not yet have accumulated sufficient citations to reflect their true impact. Fifth, the Bibliometrix software, while powerful, has inherent limitations in author name disambiguation and institutional affiliation matching, which may affect the accuracy of author and collaboration analyses. Nevertheless, the review of 15,987 documents can be considered one of the largest bibliometric assessments of AI in radiology performed to date, yielding significant information on current tendencies in research.

4. CONCLUSION

The integration of AI into modern radiology has brought about a significant shift in how diseases are diagnosed and treated. The steady increase in scientific publications on this subject not only reflects the growing interest in AI in the medical field but also the technological and methodological advancements underpinning this domain. Interdisciplinary collaborations, diversity in research, and the emphasis on personalized medicine underscore the revolutionary potential of AI in radiology. The importance of bibliometric analysis lies in its ability to provide a deep understanding of the research dynamics in radiology. It enables tracking research trends, revealing areas of rapid growth, and identifying key players and their contributions. These analyses offer valuable insights into future directions and research needs, thereby facilitating decision-making processes for researchers, practitioners, and policymakers. To maintain momentum in this rapidly evolving field, it is crucial to continue using bibliometric methods to monitor research trends and assess the impact of radiology research. This will help stay ahead of technological developments, anticipate future sector needs, and ensure that research is aligned with current clinical and ethical requirements. In essence, bibliometrics is an indispensable tool for navigating the complex and rapidly evolving landscape of modern radiology, enriched by AI. Additionally, the analysis highlights the importance of close and multidisciplinary collaboration. The rapid evolution of AI technology in radiology demands synergy among researchers, practitioners, technology developers, and policymakers to ensure that advancements are both innovative and aligned with clinical needs. The upward trend in publications clearly demonstrates that AI-assisted radiology is becoming a major area of interest, and this trend is likely to continue. The focus on personalized medicine and precise diagnostic methods illustrates the direction in which radiology research is headed. This underscores the ongoing need for bibliometric methods to monitor these research trends, providing regular insights into developments, impacts, and future directions in the field.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Ikram Gouri	✓	✓	✓		✓	✓			✓	✓	✓			
Amine Dehbi		✓		✓						✓				
Rachid Dehbi	✓									✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The bibliometric dataset used in this study and all R scripts are publicly accessible at https://github.com/ikrame09/Analysis-of-AI-in-Radiology. Detailed analysis parameters, package versions, and supplementary materials are provided in the repository to ensure full reproducibility of our findings.

REFERENCES

[1] R. Najjar, "Redefining radiology: a review of artificial intelligence integration in medical imaging," *Diagnostics*, vol. 13, no. 17, Aug. 2023, doi: 10.3390/diagnostics13172760.

[2] A. S. Panayides *et al.*, "AI in medical imaging informatics: current challenges and future directions," *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 7, pp. 1837–1857, Jul. 2020, doi: 10.1109/JBHI.2020.2991043.

[3] S. K. Mun, K. H. Wong, S.-C. B. Lo, Y. Li, and S. Bayarsaikhan, "Artificial intelligence for the future radiology diagnostic service," *Frontiers in Molecular Biosciences*, vol. 7, Jan. 2021, doi: 10.3389/fmolb.2020.614258.

[4] R. Najjar, "Digital frontiers in healthcare: integrating mhealth, AI, and radiology for future medical diagnostics," in *A Comprehensive Overview of Telemedicine*, 2024, London, United Kingdom: IntechOpen, doi: 10.5772/intechopen.114142.

[5] G. Litjens *et al.*, "A survey on deep learning in medical image analysis," *Medical Image Analysis*, vol. 42, pp. 60–88, Dec. 2017, doi: 10.1016/j.media.2017.07.005.

[6] K. Lekadir *et al.*, "FUTURE-AI: guiding principles and consensus recommendations for trustworthy artificial intelligence in medical imaging," 2021, *arXiv:2109.09658*.

[7] M. Goisauf and M. C. Abadía, "Ethics of AI in radiology: a review of ethical and societal implications," *Frontiers in Big Data*, vol. 5, Jul. 2022, doi: 10.3389/fdata.2022.850383.

[8] S. Jha and E. J. Topol, "Adapting to artificial intelligence: radiologists and pathologists as information specialists," *JAMA*, vol. 316, no. 22, Dec. 2016, doi: 10.1001/jama.2016.17438.

[9] B. J. Erickson, P. Korfiatis, Z. Akkus, and T. L. Kline, "Machine learning for medical imaging," *RadioGraphics*, vol. 37, no. 2, pp. 505–515, Mar. 2017, doi: 10.1148/rg.2017160130.

[10] W. Zhu *et al.*, "AnatomyNet: deep learning for fast and fully automated whole-volume segmentation of head and neck anatomy," *Medical Physics*, vol. 46, no. 2, pp. 576–589, Feb. 2019, doi: 10.1002/mp.13300.

[11] D. Shen, G. Wu, and H.-I. Suk, "Deep learning in medical image analysis," *Annual Review of Biomedical Engineering*, vol. 19, no. 1, pp. 221–248, Jun. 2017, doi: 10.1146/annurev-bioeng-071516-044442.

[12] M. A. Mazurowski, M. Buda, A. Saha, and M. R. Bashir, "Deep learning in radiology: an overview of the concepts and a survey of the state of the art with focus on MRI," *Journal of Magnetic Resonance Imaging*, vol. 49, no. 4, pp. 939–954, Apr. 2019, doi: 10.1002/jmri.26534.

[13] A. Esteva *et al.*, "A guide to deep learning in healthcare," *Nature Medicine*, vol. 25, no. 1, pp. 24–29, Jan. 2019, doi: 10.1038/s41591-018-0316-z.

[14] D. Ardila *et al.*, "End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography," *Nature Medicine*, vol. 25, no. 6, pp. 954–961, Jun. 2019, doi: 10.1038/s41591-019-0447-x.

[15] S. Gerke, T. Minssen, and G. Cohen, "Ethical and legal challenges of artificial intelligence-driven healthcare," in *Artificial Intelligence in Healthcare*, 2020, pp. 295–336, doi: 10.1016/B978-0-12-818438-7.00012-5.

[16] A. P. Brady and E. Neri, "Artificial intelligence in radiology—ethical considerations," *Diagnostics*, vol. 10, no. 4, Apr. 2020, doi: 10.3390/diagnostics10040231.

[17] D. W. Kim, H. Y. Jang, K. W. Kim, Y. Shin, and S. H. Park, "Design characteristics of studies reporting the performance of artificial intelligence algorithms for diagnostic analysis of medical images: results from recently published papers," *Korean Journal of Radiology*, vol. 20, no. 3, doi: 10.3348/kjr.2019.0025.

[18] D. S. W. Ting, Y. Liu, P. Burlina, X. Xu, N. M. Bressler, and T. Y. Wong, "AI for medical imaging goes deep," *Nature Medicine*, vol. 24, no. 5, pp. 539–540, May 2018, doi: 10.1038/s41591-018-0029-3.

[19] D. Gunning and D. W. Aha, "DARPA's explainable artificial intelligence program," *AI Magazine*, vol. 40, no. 2, pp. 44–58, Jun. 2019, doi: 10.1609/aimag.v40i2.2850.

[20] M. Roberts *et al.*, "Common pitfalls and recommendations for using machine learning to detect and prognosticate for COVID-19 using chest radiographs and CT scans," *Nature Machine Intelligence*, vol. 3, no. 3, pp. 199–217, Mar. 2021, doi: 10.1038/s42256-021-00307-0.

[21] J. Xie *et al.*, "Advances in artificial intelligence to predict cancer immunotherapy efficacy," *Frontiers in Immunology*, vol. 13, Jan. 2023, doi: 10.3389/fimmu.2022.1076883.

[22] T. Weikert *et al.*, "Automated detection of pulmonary embolism in CT pulmonary angiograms using an AI-powered algorithm," *European Radiology*, vol. 30, no. 12, pp. 6545–6553, Dec. 2020, doi: 10.1007/s00330-020-06998-0.

[23] M. S. Rao, S. V. Kumar, R. Pemula, and A. K. Prathipati, "Change detection of pulmonary embolism using isomeric cluster and computer vision," *IAES International Journal of Artificial Intelligence*, vol. 11, no. 2, pp. 787-798, Jun. 2022, doi: 10.11591/ijai.v11.i2.pp787-798.

[24] B. D. Simon, K. B. Ozyoruk, D. G. Gelikman, S. A. Harmon, and B. Türkbey, "The future of multimodal artificial intelligence models for integrating imaging and clinical metadata: a narrative review," *Diagnostic and Interventional Radiology*, vol. 31, no. 4, pp. 303–312, Oct. 2024, doi: 10.4274/dir.2024.242631.

[25] A. S. Tejani *et al.*, "Checklist for artificial intelligence in medical imaging (CLAIM): 2024 update," *Radiology: Artificial Intelligence*, vol. 6, no. 4, Jul. 2024, doi: 10.1148/ryai.240300.

[26] K. Palaniappan, E. Y. T. Lin, and S. Vogel, "Global regulatory frameworks for the use of artificial intelligence (AI) in the healthcare services sector," *Healthcare*, vol. 12, no. 5, Feb. 2024, doi: 10.3390/healthcare12050562.

[27] Z. Sadeghi *et al.*, "A review of explainable artificial intelligence in healthcare," *Computers and Electrical Engineering*, vol. 118, Aug. 2024, doi: 10.1016/j.compeleceng.2024.109370.

[28] A. Arora *et al.*, "The value of standards for health datasets in artificial intelligence-based applications," *Nature Medicine*, vol. 29, no. 11, pp. 2929–2938, Nov. 2023, doi: 10.1038/s41591-023-02608-w.

[29] M. Meetschen *et al.*, "AI-assisted x-ray fracture detection in residency training: evaluation in pediatric and adult trauma patients," *Diagnostics*, vol. 14, no. 6, Mar. 2024, doi: 10.3390/diagnostics14060596.

[30] M. P. Recht *et al.*, "Integrating artificial intelligence into the clinical practice of radiology: challenges and recommendations," *European Radiology*, vol. 30, no. 6, pp. 3576–3584, Jun. 2020, doi: 10.1007/s00330-020-06672-5.

[31] M. Aria and C. Cuccurullo, "Bibliometrix: an r-tool for comprehensive science mapping analysis," *Journal of Informetrics*, vol. 11, no. 4, pp. 959–975, Nov. 2017, doi: 10.1016/j.joi.2017.08.007.
[32] A. Dehbi, R. Dehbi, A. Bakhouyi, and M. Talea, "Interoperability in smart education: a systemic review based on bibliometric and content analysis methods," *Journal of Theoretical and Applied Information Technology*, vol. 100, no. 24, pp. 7211–7221, 2022.
[33] A. S. Becker, M. Marcon, S. Ghafoor, M. C. Wurnig, T. Frauenfelder, and A. Boss, "Deep learning in mammography: Diagnostic accuracy of a multipurpose image analysis software in the detection of breast cancer," *Investigative Radiology*, vol. 52, no. 7, pp. 434–440, Jul. 2017, doi: 10.1097/RLI.0000000000000358.
[34] H. Luo *et al.*, "Real-time artificial intelligence for detection of upper gastrointestinal cancer by endoscopy: a multicentre, case-control, diagnostic study," *The Lancet Oncology*, vol. 20, no. 12, pp. 1645–1654, 2019, doi: 10.1016/S1470-2045(19)30637-0.
[35] K. Muhammad, S. Khan, J. D. Ser, and V. H. C. D. Albuquerque, "Deep learning for multigrade brain tumor classification in smart healthcare systems: A prospective survey," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 2, pp. 507–522, Feb. 2021, doi: 10.1109/TNNLS.2020.2995800.
[36] S. S. Udmale and S. K. Singh, "A mechanical data analysis using kurtogram and extreme learning machine," *Neural Computing and Applications*, pp. 3789–3801, 2020, doi: 10.1007/s00521-019-04398-0.
[37] X. Yin, B. W.-H. Ng, and D. Abbott, *Terahertz imaging for biomedical applications: pattern recognition and tomographic reconstruction*, New York, United States: Springer, 2012, doi: 10.1007/978-1-4614-1821-4.
[38] I. Kumar, C. Bhatt, and K. U. Singh, "Entropy based automatic unsupervised brain intracranial hemorrhage segmentation using CT images," *Journal of King Saud University – Computer and Information Sciences*, vol. 34, no. 6, pp. 2589–2600, Jun. 2022, doi: 10.1016/j.jksuci.2020.01.003.
[39] A. Sekhar, S. Biswas, R. Hazra, A. K. Sunaniya, A. Mukherjee, and L. Yang, "Brain tumor classification using fine-tuned GoogLeNet features and machine learning algorithms: IoMT enabled CAD system," *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 3, pp. 983–991, Mar. 2022, doi: 10.1109/JBHI.2021.3100758.
[40] A. Khan, A. Sohail, U. Zahoora, and A. S. Qureshi, "A survey of the recent architectures of deep convolutional neural networks," *Artificial Intelligence Review*, vol. 53, no. 8, pp. 5455–5516, 2020, doi: 10.1007/s10462-020-09825-6.
[41] J. Nie, Z. Xue, T. Liu, G. S. Young, K. Setayesh, L. Guo, and S. T. C. Wong, "Automated brain tumor segmentation using spatial accuracy-weighted hidden Markov random field," *Computerized Medical Imaging and Graphics*, vol. 33, no. 6, pp. 431–441, Sep. 2009, doi: 10.1016/j.compmedimag.2009.04.006.
[42] G. Chugh, S. Kumar, and N. Singh, "Survey on machine learning and deep learning applications in breast cancer diagnosis," *Cognitive Computation*, vol. 13, pp. 1451–1470, 2021, doi: 10.1007/s12559-020-09813-6.

BIOGRAPHIES OF AUTHORS



Ikram Gouri is currently a Ph.D. student in Artificial Intelligence, affiliated with the Laboratory of Data Engineering and Intelligent Systems (LIDSI), Faculty of Sciences Aïn Chock, Hassan II University, Casablanca, Morocco. Her research spans multiple areas including computer science, artificial intelligence, deep learning, programming, big data, machine learning, as well as health, radiology, healthcare, and clinical processes. She is actively involved in exploring advanced AI techniques and their applications in both technical and healthcare domains. She can be contacted at email: gouriikrame@gmail.com.



Amine Dehbi received a Ph.D. in computer science from the Faculty of Sciences Ben M'Sick, Laboratory of Information Processing (LTI), Faculty of Sciences Ben M'Sick at Hassan II University of Casablanca, Morocco. His ability lies in the intersection of Information and Communication Technology (ICT) in education. He is deeply engaged in exploring how smart technologies can contribute to the development of smart learning environments across various educational levels and fields. His extensive research portfolio spans a range of cutting-edge topics, including smart education, e-learning, interoperability, big data, cloud computing, artificial intelligence, internet of things, engineering education and sustainable development. With a commitment to advancing the frontiers of knowledge, he actively contributes to scholarly discourse on these subjects through his publications. He can be contacted at email: dehbiamine1@gmail.com.



Rachid Dehbi is a full professor and a prominent researcher at the Laboratory of Data Engineering and Intelligent Systems (LIDSI) within the Faculty of Science Aïn Chock, Hassan II University of Casablanca, Morocco. With over 24 years of experience in higher education and research, he is a recognized expert in intelligent systems, the internet of things, and advanced technologies. He plays a strategic role in overseeing research policies and doctoral training programs at the university. His work focuses on innovative fields such as e-learning, m-learning, e-health, m-health, model-driven engineering, database security, big data, and intelligent systems. His contributions through his research and publications have significantly enriched the academic and technological landscape, solidifying his reputation as an authority in his field. He can be contacted at email: dehbirac@yahoo.fr.