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Bibliometric analysis of the 50 most cited articles on artificial intelligence for lung cancer imaging

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ABSTRACT

Aim: The use of machine learning has now become widespread in lung cancer. However, the research trend is still unclear. This study aimed to analyze the most influential publications on artificial intelligence (AI) for lung cancer.

Material and Method: A comprehensive PubMed and SCImago Journal and Country Rank (SJR) search was performed. The 50 most cited articles were recorded according to the citation numbers, the country and institute of articles, the name and metrics of the publishing journal, the year of publication, and the content of the articles.

Results: The citation numbers ranged from 24 to 628. Annual citations per article was between 1.47 and 104.6. The USA was the country with the most publications (n=22) followed by The Netherlands (n=9) and Peoples R China (n=5). The journal and institution that highly contributed to the 50 most cited articles were Radiology (n=5) and Harvard Medical School (n=5), respectively.

Conclusion: The importance of deep learning and AI in lung cancer imaging is increasing day by day. In this study, a detailed bibliometric analysis of the literature on AI in lung cancer imaging was performed. In addition, this bibliometric analysis informs researchers about current influential papers in this field, the characteristics of these studies, and potential future trends in the rapidly evolving field of AI in lung cancer screening.

Keywords: Artificial intelligence, bibliometric analysis, lung cancer

INTRODUCTION

Lung cancer is the most common type of cancer for decades and still causes more deaths worldwide in both sexes than any other type of cancer (1). As stated in Cancer Statistics 2020, the rate of 5-year survival in lung cancer is 19% (2). Most early-stage lung cancers have no obvious symptoms, and the patient is advanced when symptoms appear, resulting in a low overall rate of 5-year survival for advanced lung cancer (3). Because of the aggressive nature of lung cancer, early detection and intervention is vital. Thin section computed tomography (CT) is an efficient modality to screen high-risk groups. Computer-assisted diagnosis, invasive biomarkers, video-assisted thoracic surgery and fluorine-18 fluorodeoxyglucose positron emission tomography-CT (18F-FDG PET-CT) scanning are making important contributions to the prevention, early diagnosis and also treatment of lung cancer (4). Due to the widespread use of health and thin-section CT examinations in recent years, early diagnosis rate of lung cancer has increased (5). Early diagnosis is an important procedure to reduce deaths from lung cancer (6). To increase diagnostic efficiency, a computer-aided diagnosis (CAD) system was developed to assist physicians in interpreting medical imaging data (7,8), which has been cited as a useful second opinion for physicians (9). Standardizing the nodule follow-up in thorax CT scanning programs performed in high risk groups for lung cancer helps clinicians and radiologists in the early diagnosis of nodules with high cancer probability.

The traditional feature-based CAD task can be divided into three steps: nodule segmentation, feature extraction and selection, and clinical judgment inference (classification). For estimation of malignancy risk, measurements include the size, type, location, number and margin of nodule and emphysema finding on CT scans, and there are clinical variables such as patient's age, gender, timing of sampling, family history of lung cancer, and exposure to smoking. However, these features, although mostly subjective, often fail to

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provide a complete and quantitative description of the malignant nodule (6). The development of deep learning algorithms, especially convolutional neural networks, has led to further work to apply deep learning-based models to the CAD system to improve accuracy and reduce false positive rate and implementation time during lung tumor diagnosis (10,11).

Artificial intelligence (AI) also provides a different perspective in lung cancer-related research and allows exploration of the application of decision support mechanisms to facilitate precision oncology (6). In the context of oncology, AI is increasingly being researched and used for several different purposes (12). In recent years, the use of AI in cancer diagnosis has become widespread with the contributions of different fields such as medicine, computer science, mathematics and engineering, which is not limited to clinical practice (13).

Bibliometric analysis is an analysis based on evaluating the literature published on a particular subject (14). Citation frequency is used to determine how often a publication is cited by other researchers (15). It involves collating data to identify the most influential publications on this topic, identify trends in specific research areas, and identify potential gaps where further research is needed (14). The citation count of an article is an important objective indicator of how much credibility and attention it receives in the academic world (16).

The aim of this study was to analyze a list of the most cited publications on the use of AI in lung cancer imaging for clinicians and researchers. It also presents a detailed analysis of the evolution and change of trends in this area.

MATERIAL AND METHOD

This study was carried out as a retrospective bibliometric analysis and did not include human or animal subjects. So, ethical approval was not required for this bibliometric study.

The literature search of 50 most cited articles was performed using PubMed® database (search at: https://pubmed.ncbi.nlm.nih.gov/) (17), SCImago Journal and Country Rank (SJR) based on Scopus® data (Elsevier BV Company, GA, USA; search at https://www.scimagojr.com/) (18) and 2021 Journal Citation Reports® (search at: https://jcr.clarivate.com/jcr/home) (19). MeSH terms that was used for search included "Lung cancer, imaging" and "artificial intelligence".

The search was restricted to human study and English in article language. Research and review articles were included in the study. No publication year restrictions were made in the search. The research started on March 20, 2023. Publications whose full text was not available, were excluded. Articles that included at least one imaging modality (e.g., x-ray, CT, magnetic resonance imaging, ultrasound) were included in the study. Finally, 1563 articles were reached. The articles that did not meet the inclusion criteria, was excluded. 875 articles remained including research and review articles in English language (**Figure 1**). Articles were noted in order of citation numbers from highest to lowest in PubMed® database (17). Citation per year was calculated by dividing the total number of citations by the time elapsed until the year the article was published (20). Article type, publication year, author and article information, journal metrics, country and author institution information were recorded in an excel file. The institutions were provided by affiliations of first authors. The countries were noted according to the address stated by the first author. The impact factors were taken from the 2021 Journal Citation Reports® (19) and journals' h-index and SJR values were obtained from SCImago based on Scopus® data (Elsevier BV Company, GA,USA; search at https://www.scimagojr.com/) (18).

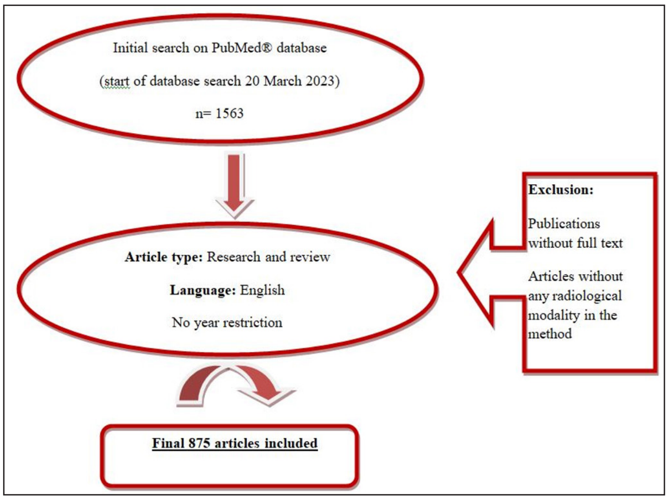

Figure 1. Literature search strategy - inclusion and exclusion criteria

For the data analysis, descriptive statistics were performed. No statistical tests were performed. In this study, the distribution of the literature on the use of AI in lung cancer by different years, countries, institutions and authors were evaluated. Therefore, numbers were used in statistical analysis without comparison between groups.

RESULTS

The information of the 50 most cited articles on AI for lung cancer were given in **Table 1**. The citation numbers ranged from 24 to 628 (mean: 71.56). Annual citations per article was between 1.47 and 104.6 (mean:12.62).

Table 1. The 50 most cited articles about artificial intelligence on lung cancer imaging

	Article type	Year	Citation number	Citation per year	First Author	Title	Journal
1	research	2017	628	104.6	van Griethuysen JJM	Computational Radiomics System to Decode the Radiographic Phenotype.	Cancer Res.
2	research	2015	379	47.3	Parmar C	Machine Learning methods for Quantitative Radiomic Biomarkers.	Sci Rep.
3	research	2019	184	46	Ardila D	End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography.	Nat Med.
4	review	2019	154	38.5	Bi WL	Artificial intelligence in cancer imaging: Clinical challenges and applications.	CA Cancer J Clin.
5	research	2017	144	24	Rios Velazquez E	Somatic Mutations Drive Distinct Imaging Phenotypes in Lung Cancer.	Cancer Res.
6	research	2018	140	28	Rajpurkar P	Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists.	PLoS Med.
7	research	2019	131	32.75	Nam JG	Development and Validation of Deep Learning-based Automatic Detection Algorithm for Malignant Pulmonary Nodules on Chest Radiographs.	Radiology.
8	research	2019	130	32.5	Xu Y	Deep Learning Predicts Lung Cancer Treatment Response from Serial Medical Imaging.	Clin Cancer Res.
9	research	2016	111	15.8	Setio AA	Pulmonary Nodule Detection in CT Images: False Positive Reduction Using Multi-View Convolutional Networks.	IEEE Trans Med Imaging.
10	research	2019	78	19.5	Trebeschi S	Predicting response to cancer immunotherapy using noninvasive radiomic biomarkers.	Ann Oncol.
11	research	2007	66	4.125	van Baardwijk A	PET-CT-based auto-contouring in non-small-cell lung cancer correlates with pathology and reduces interobserver variability in the delineation of the primary tumor and involved nodal volumes.	Int J Radiat Oncol Biol Phys.
12	research	2002	64	3.04	Hripcsak G	Use of natural language processing to translate clinical information from a database of 889,921 chest radiographic reports	Radiology.
13	research	2019	60	15	Beig N	Perinodular and Intranodular Radiomic Features on Lung CT Images Distinguish Adenocarcinomas from Granulomas.	Radiology.
14	research	2018	57	11.4	Lustberg T	Clinical evaluation of atlas and deep learning based automatic contouring for lung cancer.	Radiother Oncol.
15	research	2018	54	10.8	Hosny A	Deep learning for lung cancer prognostication: A retrospective multi-cohort radiomics study.	PLoS Med.
16	review	2020	52	17.3	Avanzo M	Radiomics and deep learning in lung cancer.	Strahlenther Onkol.
17	research	2017	50	8.33	Dou Q	Multilevel Contextual 3-D CNNs for False Positive Reduction in Pulmonary Nodule Detection.	IEEE Trans Biomed Eng.
18	research	2017	44	7.33	Wang S	Central focused convolutional neural networks: Developing a data-driven model for lung nodule segmentation.	Med Image Anal.
19	research	2019	43	10.75	Lou B	An image-based deep learning framework for individualizing radiotherapy dose.	Lancet Digit Health.
20	research	2006	43	2.52	Kuhnigk JM	Morphological segmentation and partial volume analysis for volumetry of solid pulmonary lesions in thoracic CT scans.	IEEE Trans Med Imaging.
21	research	2018	42	8.4	Nishio M	Computer-aided diagnosis of lung nodule classification between benign nodule, primary lung cancer, and metastatic lung cancer at different image size using deep convolutional neural network with transfer learning.	PLoS One.
22	research	2007	42	2.625	McNitt-Gray MF	The Lung Image Database Consortium (LIDC) data collection process for nodule detection and annotation.	Acad Radiol.
23	research	2010	41	3.15	Messay T	A new computationally efficient CAD system for pulmonary nodule detection in CT imagery.	Med Image Anal.
24	research	2017	41	6.83	Ciompi F	Towards automatic pulmonary nodule management in lung cancer screening with deep learning.	Sci Rep.
25	research	2011	41	3.42	Tan M	A novel computer-aided lung nodule detection system for CT images.	Med Phys.

Table 1. The 50 most cited articles about artificial intelligence on lung cancer imaging

	Article type	Year	Citation number	Citation per year	First Author	Title	Journal
26	research	2005	39	2.16	Suzuki K	Computer-aided diagnostic scheme for distinction between benign and malignant nodules in thoracic low-dose CT by use of massive training artificial neural network.	IEEE Trans Med Imaging.
27	research	2009	38	2.71	Ye X	Shape-based computer-aided detection of lung nodules in thoracic CT images.	IEEE Trans Biomed Eng.
28	research	2003	38	1.9	Suzuki K	Massive training artificial neural network (MTANN) for reduction of false positives in computerized detection of lung nodules in low-dose computed tomography.	Med Phys.
29	research	2009	37	2.64	Murphy K	A large-scale evaluation of automatic pulmonary nodule detection in chest CT using local image features and k-nearest-neighbour classification.	Med Image Anal.
30	review	2020	36	12	Chassagnon G	Artificial intelligence applications for thoracic imaging.	Eur J Radiol.
31	research	2020	36	12	Sim Y	Deep Convolutional Neural Network-based Software Improves Radiologist Detection of Malignant Lung Nodules on Chest Radiographs.	Radiology.
32	research	2020	36	12	Mu W	Non-invasive decision support for NSCLC treatment using PET/CT radiomics.	Nat Commun.
33	research	2016	35	5	Teramoto A	Automated detection of pulmonary nodules in PET/CT images: Ensemble false-positive reduction using a convolutional neural network technique.	Med Phys.
34	research	2006	35	2.05	Reeves AP	On measuring the change in size of pulmonary nodules.	IEEE Trans Med Imaging.
35	research	2017	31	5.16	Nibali A	Pulmonary nodule classification with deep residual networks.	Int J Comput Assist Radiol Surg.
36	research	2008	31	2.06	Pu J	Adaptive border marching algorithm: automatic lung segmentation on chest CT images.	Comput Med Imaging Graph.
37	research	2019	29	7.25	Liao F	Evaluate the Malignancy of Pulmonary Nodules Using the 3-D Deep Leaky Noisy-OR Network.	IEEE Trans Neural Netw Learn Syst.
38	research	2015	29	3.625	Ciompi F	Automatic classification of pulmonary peri-fissural nodules in computed tomography using an ensemble of 2D views and a convolutional neural network out-of-the-box.	Med Image Anal.
39	research	2019	29	7.25	Zhao W	Toward automatic prediction of EGFR mutation status in pulmonary adenocarcinoma with 3D deep learning.	Cancer Med.
40	research	2019	27	6.75	Baek S	Deep segmentation networks predict survival of non-small cell lung cancer.	Sci Rep.
41	research	2020	27	9	Sibille L	18F-FDG PET/CT Uptake Classification in Lymphoma and Lung Cancer by Using Deep Convolutional Neural Networks.	Radiology.
42	review	2020	27	9	Rogers W	Radiomics: from qualitative to quantitative imaging.	Br J Radiol.
43	research	2019	26	6.5	Linning E	Radiomics for Classification of Lung Cancer Histological Subtypes Based on Nonenhanced Computed Tomography.	Acad Radiol.
44	research	2018	26	5.2	Chen CH	Radiomic features analysis in computed tomography images of lung nodule classification.	PLoS One.
45	research	2020	25	8.33	Baldwin DR	External validation of a convolutional neural network artificial intelligence tool to predict malignancy in pulmonary nodules.	Thorax.
46	research	2006	25	1.47	Meyer CR	Evaluation of lung MDCT nodule annotation across radiologists and methods.	Acad Radiol.
47	research	2007	25	1.56	Reeves AP	The Lung Image Database Consortium (LIDC): a comparison of different size metrics for pulmonary nodule measurements.	Acad Radiol.
48	review	2016	24	3.42	Valente IR	Automatic 3D pulmonary nodule detection in CT images: A survey.	Comput Methods Programs Biomed.
49	research	2020	24	8	Dercle L	Identification of Non-Small Cell Lung Cancer Sensitive to Systemic Cancer Therapies Using Radiomics.	Clin Cancer Res.
50	review	2011	24	2	Shiraishi J	Computer-aided diagnosis and artificial intelligence in clinical imaging.	Semin Nucl Med.

There were 28 journals in which the 50 most cited articles were published. Of these 50 articles, 6 (12%) were reviews and 44 (88%) were research articles. The 50 most cited articles were published between 2002 and 2020 with almost half of them published in the 4-year period between 2017 and 2020. With 11 articles, 2019 was the year with the most article publications (**Figure 2**). This was followed by 2020 with 8 articles. Radiology published most articles on AI for lung cancer (n=5), followed by Academic Radiology (n=4), Medical Image Analysis (n=4) and IEEE Transactions on Medical Imaging (n=4). The impact factor of the most cited journals ranged from 3.408 to 286.13. H-index and SJR values of the most cited journals were given in **Table 2**.

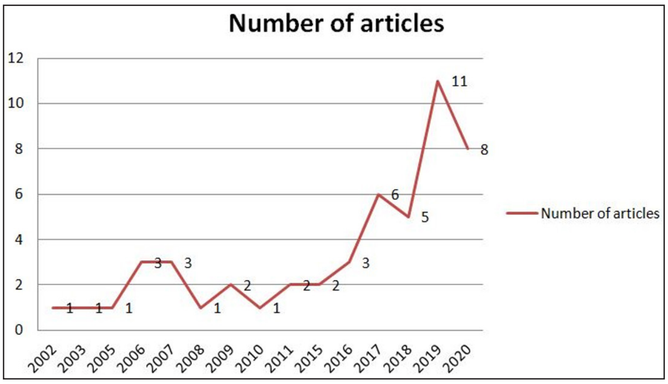

Figure 2. Number of articles by publication year

Table 2. The most cited journals with impact factor (IF), H index as provided by SCImago and SCImago Journal Rank (SJR) values

Journal	Number of articles	IF	H index	SJR
Radiology	5	29.146	307	4.59
Acad Radiol	4	5.482	100	1.02
Med Image Anal	4	13.828	143	4.17
IEEE Trans Med Imaging	4	11.037	233	4.05
Sci Rep	3	4.996	242	1.01
Med Phys	3	4.506	189	1.17
PLoS One	2	3.752	367	0.85
PLoS Med	2	11.613	242	4.18
IEEE Trans Biomed Eng	2	4.756	210	1.3
Clin Cancer Res	2	13.8	344	4.4
Cancer Res	2	13.312	466	3.08
Ann Oncol	1	51.77	258	8.59
Br J Radiol	1	3.629	110	0.8
CA Cancer J Clin	1	286.13	182	56.2
Cancer Med	1	4.711	65	1.14
Comput Med Imaging Graph	1	7.422	82	1.49
Comput Methods Programs Biomed	1	7.027	115	1.33
Eur J Radiol	1	4.531	119	1.01
IEEE Trans Neural Netw Learn Syst	1	14.255	221	4.22
Int J Comput Assist Radiol Surg	1	3.408	53	1
Lancet Digit Health	1	36.615	30	6.02
Nat Commun	1	17.7	410	4.85
Nat Med	1	87.241	576	24.16
Radiother Oncol	1	6.901	163	1.95
Semin Nucl Med	1	4.802	91	1.09
Strahlenther Onkol	1	4.033	72	0.92
Thorax	1	9.203	231	2.31
Int J Radiat Oncol Biol Phys	1	8.013	257	1.9

There were 13 different countries in the 50 most cited articles.The USA was the leading publication country (n=22), followed by The Netherlands (n=9) and Peoples R China (n=5) (**Figure 3**).

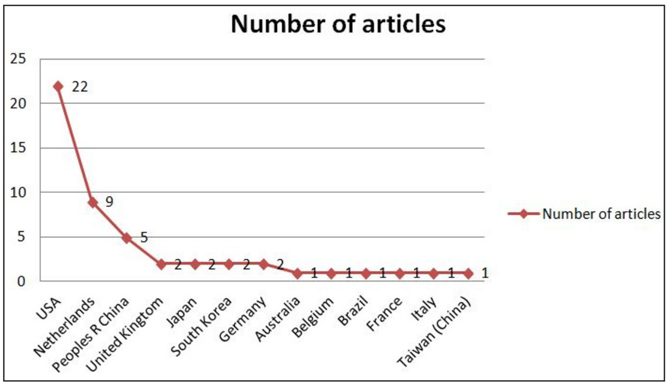

Figure 3. Number of articles by countries (according to address stated by the first author)

There were 36 different institutions in the 50 most cited article list. Harvard Medical School contributed the highest number of articles (n=5), followed by Maastricht University (n=4), Radboud University Medical Center (n=3), and the University of Chicago (n=3) (**Table 3**).

Table 3. The affiliations of the first authors by number of articles

Institution	Number of articles
Harvard Medical School	5
Maastricht University	4
Radboud University Medical Center	3
the University of Chicago	3
Columbia University	2
Cornell University	2
Stanford University	2
La Trobe University	1
Université Paris Descartes	1
University of Dayton	1
Case Western Reserve University	1
Centro di Riferimento Oncologico di Aviano (CRO) IRCCS	1
China Medical University Hospital	1
David Geffen School of Medicine at UCLA	1
Digital Technology and Innovation Division, Siemens Healthineers	1
Fujita Health University	1
Google AI	1
H. Lee Moffitt Cancer Center and Research Institute	1
Huadong Hospital Affiliated to Fudan University	1
Kyoto University	1
Medicsight PLC	1
MeVis-Center for Medical Visualization and Diagnostic Systems	1
Netherlands Cancer Institute	1
Nottingham University	1
Seoul National University Hospital and College of Medicine	1
Shanxi DAYI Hospital	1
The Chinese University of Hong Kong	1
Tsinghua University	1
Universidade Federal do Ceará	1
University Hospital Münster	1
University Medical Center, Utrecht	1
University of Chinese Academy of Sciences	1
University of Iowa	1
University of Michigan	1
Vrije Universiteit Brussel	1
Yonsei University College of Medicine	1

DISCUSSION

AI has become widespread in lung cancer imaging. Especially in last years, the number of related publications have increased. However, bibliometric analyzes aimed at assessing research trends regarding the role of AI in lung cancer imaging are still lacking in the literature. To the best of our knowledge, this bibliometric analysis is the first study on AI in lung cancer imaging.

In this bibliometric analysis, USA was the most productive country consistent with some studies on AI for cancer detection (13) and AI for radiotherapy in non-small cell lung cancer (21). In these two publications (13,21), the second most productive country was China. Differently, in this study, the Netherlands was the second most productive country. In a study conducted for the h-indexes of countries and using the Essential Science Indicators data (22), among the 40 countries evaluated, the USA had the highest h-index value of 749. This may be the result of the USA being able to allocate funds and resources to scientific research through its economic strength. It also gives information about the influence of developed countries in the conduct of scientific studies (23). Consistent with the result of this study, data from another study (24) showed that lung cancer radiomic research was predominantly concentrated in the USA, China, the Netherlands, and other countries. Some countries such as the USA and the Netherlands have undertaken many pioneering work based on theoretical and technological leadership. Some countries such as China, are generating abundant clinical data based on large numbers of cases, combined with advanced computer technology, contributing to important practical application outcomes. Therefore, current relevant research is relatively concentrated in the above-mentioned countries and research institutions, but collaborative research in this area is relatively extensive and many authors have participated in international collaboration (24).

In this study, the number of citations in 2019 and 2020 was higher than in other years. With the breakthroughs in AI technology, it is an expected result that the publication numbers will increase in the last few years depending on current trends. The fact that 2019 was the most productive year may be associated with the bibliometric analysis of the 50 most cited articles. The length of time elapsed since the publication of the article plays an important role in increasing citation numbers. Considering all the data in this study, the regular increase in the number of articles draws attention in recent years.

The fact that Radiology, Academic Radiology and Medical Image Analysis are the journals that highly contributed to 50 most cited articles is a result of radiology-based literature review.

Among the imaging modalities used in the studies, CT, PET-CT and radiomics were predominant. The increasing use of PET-CT for cancer staging, technological advances in PET-CT imaging and the discovery of new radiotracers, and clinical use of hybrid and molecular imaging modalities reflect the growing interest in PET-CT (25-28). In Liang et al.'s (24) literature analysis, radiomics were reported to be promising for lung cancer. In this study, articles using these imaging modalities were commonly encountered in the list of 50 most cited articles.

Yaxley et al. (28) stated it is not surprising that studies focusing on cancer detection and staging had the highest citation numbers, they also reported that it was interesting to notice the lack of studies on lung cancer imaging. Based on this lack in the literature, this study would be useful and contribute to the literature. However, there were some limitations of this study. It is an advantage of the study that it is not limited to a single database in the analysis of bibliometric data. However, being a single observer in the study is a limitation. A second limitation is that with the rapid development of AI technology, new publications are brought to the literature, so this study reflects the current data. As the third limitation, the publications that were not indexed in PubMed® could not be evaluated.

CONCLUSION

To the best of our knowledge, this is the first bibliometric analysis on AI in lung cancer imaging. This study will be a guide for future research. For researchers who want to work on this topic, it will be an important resource for a comprehensive literature review on research on AI in lung cancer imaging. Thus, the field of AI, which is developing day by day, will be able to develop with further studies.

ETHICAL DECLARATIONS

Ethics Committee Approval: This study was carried out as a retrospective bibliometric analysis and did not include human or animal subjects. So, ethical approval was not required for this bibliometric study.

Informed Consent: Not applicable.

Referee Evaluation Process: Externally peer reviewed.

Conflict of Interest Statement: The authors have no conflicts of interest to declare.

Financial Disclosure: The authors declared that this study has received no financial support.

Author Contributions: All the authors declare that they have all participated in the design, execution, and analysis of the paper, and that they have approved the final version.

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