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Harnessing multi-source data for AI-Driven oncology insights: Productivity, trend, and sentiment analysis

Abstract

This study aims to provide an overall view of the current status of AI publications in the entire field of oncology, encompassing productivity, emerging trends, and researchers' sentiments. A total of 1,296 papers published between January 2019 and January 2024, were selected using the PRISMA framework. Citespace software and the R package "Biblioshiny" were utilized for bibliographic analysis. China has been the leading contributor to global production with over 2,596 publications, followed by Europe. Among 8339 authors, Kather JN was the third most prolific author and held a central position in the co-authorship network. The most prominent article emphasized the Explainability of AI methods (XAI) with a profound discussion of their potential implications and privacy in data fusion contexts. Current trends involve the utilization of supervised learning methods such as CNN, Bayesian networks, and extreme learning machines for various cancers, particularly breast, lung, brain, and skin cancer. Late image-omics fusion was the focus of various studies during 2023. Recent advancements include the use of "conductive hydrogels" and "carbon nanotubes" for flexible electronic sensors. Ninety and a half percent of the researchers viewed these advancements positively. To our knowledge, this study is the first in the field to utilize merged databases from WoS, Scopus, and PubMed. Supervised ML methods, Multimodal DL, chatbots, and intelligent wearable devices have garnered significant interest from the scientific community. However, issues related to data-sharing and the generalizability of AI algorithms are still prevalent.

1. INTRODUCTION

Recent years have witnessed an enormous evolution of P4 medicine personalized, preventive, predictive, and participatory healthcare (Hood & Friend, 2011). Driven by new technological advancements such as Artificial Intelligence (AI), big data (BD), and the Internet of Things (IoT) P4 offers a great opportunity to impact oncology related complexity problems. Complexity is undeniably the greatest challenge faced by numerous scientific and engineering disciplines (Tian et al., 2012). In this context, Oncology - a multifaceted discipline that focuses on diagnosing, treating, and preventing cancer prevails (Hajdu, 2016).

Patients undergo a cautious physical examination alongside imaging studies and biopsies to confirm a diagnosis. Early cancer diagnosis remains a priority for organizations like the WHO and the International Alliance for Cancer Early Detection. While screening is considered promising, public buy-in, financial considerations, and other factors limit its effectiveness in covering all at-risk populations (Ahnen et al., 2014). After diagnosis, staging guides treatment, which may involve surgical resection, radiation therapy, hormone therapy, and immunotherapy. Clinicians review trial criteria and baseline characteristics to infer clinical evidence when treating specific patients. Yet subpopulations are often defined by one or two characteristics, and any patient may fit into several subgroups with heterogeneous treatment effects (McAlister et al., 2000).

Decision-making remains a challenge, as patients and clinicians assess treatment options differently (Reyna et al., 2015). Patients often struggle to interpret risk figures and probabilities (Redelmeier et al., 1993; Mazur & Hickam, 1993). For instance, breast cancer patients weigh treatment costs and benefits related to symptom-free survival, daily life quality, relapse time, and functional status (Lee et al., 2010).

Once treatment is done, regular monitoring and follow-up care are paramount to detect recurrence. Remote patient monitoring (RPM) assists doctors in monitoring chronically ill people and elderly patients at home, using wearable devices or sensors. A standout case is the COVID-19 pandemic, which posed challenges in managing outpatient cancer patients who were COVID-19-positive but did not require hospitalization. Remote patient monitoring programs have reported high patient engagement rates. The oncology landscape is undergoing a big data revolution, incorporating complex data from pathology, laboratory tests, radiology, molecular profiling, wearable devices, and mobile health applications (Farina et al., 2022; Seyhan & Carini, 2019). Despite the best efforts of medical professionals, the human brain has limitations when processing extensive datasets quickly and accurately.

The accuracy of AI a convergence of mathematics, computer science, and engineering has been demonstrated to surpass expert diagnoses in various medical fields. Machine learning (ML) and deep learning (DL) methods are particularly effective at analyzing large datasets, especially for identifying complex correlations and addressing nonlinear and non-stationary problems (Younis, 2024). For instance, predicting epilepsy seizures using Long Short-Term Memory (LSTM) networks and deep feedforward networks (DFN) trained on electroencephalography (EEG) signals captures subtle patterns within dynamic data (Sidaoui, 2024). Radial Basis Function (RBF) networks and Support Vector Machines (SVM) manage nonlinear relationships and high-dimensional data, excelling at modeling local dependencies and complex datasets (Karpiński et al., 2023). Advanced signal decomposition techniques, such as Ensemble Empirical Mode Decomposition (EEMD) combined with Detrended Fluctuation Analysis (DFA), extract meaningful features from non-stationary signals (Machrowska et al., 2024). These innovations demonstrate AI's potential to revolutionize patient care by providing real-time insights into health, enabling timely interventions. Nonetheless, conventional DL models, such as Convolutional Neural Networks (CNNs), mainly operate on single-modal data, limiting their capability to understand intricate relationships within complex datasets. This can be addressed through multimodal AI methods, which fusion various data types to identify correlations across modalities and improve diagnostic accuracy, particularly in cancer research (Boehm et al., 2022). Combined with Large Language Models (LLMs), Multimodal interfaces present interesting opportunities for enhanced access (Cuadra et al., 2024).

As AI continues to revolutionize medical practices, it is timely to determine the current status of AI publications in the entire field of oncology, to provide an overall view of the topic, to help gain insights into future trends, and to gauge the sentiment of the medical community. This will be achieved through a comprehensive bibliometric analysis over the past five years. In line with the study's purpose, the following research questions are posed:

RQ1: How was productivity distributed in this field between 2019 and 2024?

RQ2: Which nations, affiliations, journals, and authors were mostly prominent?

RQ3: What are the current trends and frontiers?

RQ4: How do researchers feel regarding the application of AI in oncology?

RQ5: How do chatbots, multimodal models, and wearable devices align with the objectives of P4 medicine?

2. LITERATURE REVIEW

Bibliometric analysis is a popular and diligent method for exploring and analyzing large amounts of scientific data. It involves applying quantitative techniques, including mathematical and statistical approaches. Early discussions on bibliometrics started in the 1950s. Over the last years, AI has awoken the interest of academics and medical researchers; For instance, a Google Scholar search shows about 3460 reviews on AI in oncology. A significant proportion of the literature, 27.03% (935 papers), is dedicated to breast cancer. Similarly, lung cancer receives notable focus (19.62%). Prostate cancer research follows, accounting for 13.21% (457 papers). Studies on colon and rectal cancer make up 4.97% (172 papers), while pancreatic cancer is less frequently addressed, with only 0.75% (26 papers). Skin cancer is the interest of 6.33% (219 papers), brain cancer of 1.85% (64 papers), and cervical cancer of 5.87% (203 papers). While the remaining proportion covers various other cancer types, only a few bibliometrics generally analyze AI's application in oncology. Some of these studies are cited in Table 1. Academics often rely on multidiscipline databases like Web of Science (WoS) and Scopus to access a wide range of scholarly articles and citation information. Yet, there is a need to develop methods and indicators encompassing scientific output from various databases (Mongeon & Paul-Hus, 2016). In response to this call, this study contributes to the existing literature by merging data from Scopus, WoS, and PubMed.

Tab. 1. Bibliometric studies in oncology: Overview

Ref	Bibliometric aspects				
	Source	**Period**	**Analysis approach**	**AI techniques**	**Tools used**
(Karger & Kureljusic, 2023)	Scopus	1986-2022	Quantitative	ML, DL	Biblioshiny
(Wu et al., 2022)	WoSCC	2012-2022	Quantitative & Qualitative	ML, DL	VOSviewer, CiteSpace
(Musa, 2021)	WoS	1988-2021	Quantitative	ML	Biblioshiny
(Koçak & Akçalı, 2024)	WoS& InCites	1992-2022	Quantitative	DL, radiomics	Biblioshiny,VOS viewer, Litmaps
Our study	WoS& Scopus & PubMed	2019 -2023	Quantitative & Qualitative	ML, DL, Chatbots, Multimodal, Intelligent wearables.	Biblioshiny, Citespace

3. MATERIAL AND METHODS

3.1. Data acquisition and search strategy

In this study, the search terms, described in Table 2, were employed to retrieve data from Scopus, WoS, and PubMed; The selection of keywords was guided by the challenges identified in the oncology process, particularly concerning the integration of AI methods for improving diagnosis, treatment, and patient monitoring. The additional keywords were chosen based on their potential to address these challenges as outlined in the introduction. The time interval was set for 2019-2024. Only articles, reviews, and proceeding papers, written in English, were included. Abstracts, authors, article titles, journal names, keywords, and affiliations were collected and saved as plain text from WoS and as CSV from Scopus. PubMed data integration involved the direct execution of the identical query in PubMed, the extraction of the corresponding list of PMIDs, and its subsequent use for obtaining the equivalent plain text in WoS. This allowed for a representation of PubMed-indexed articles in WoS format. Ethical approval was not required since the data were directly downloaded from the databases.

Tab. 2. Search strategy

Search	Review component	Query structure
1	Population	("cancer" OR "tumor" OR "malignancy" OR "neoplasm" OR "oncology")
2	Technologies	("artificial intelligence" OR "AI" OR "machine learning " OR "deep learning")
3	Additional Keywords	("chatbot" OR "ChatGPT" OR "LLM" OR "data fusion" OR "multimodal data integration" OR "multimodal model" OR "wearable devices" OR "virtual assistance" OR "wearable sensors")
Total	-	1 & 2 & 3

3.2. Data integration framework

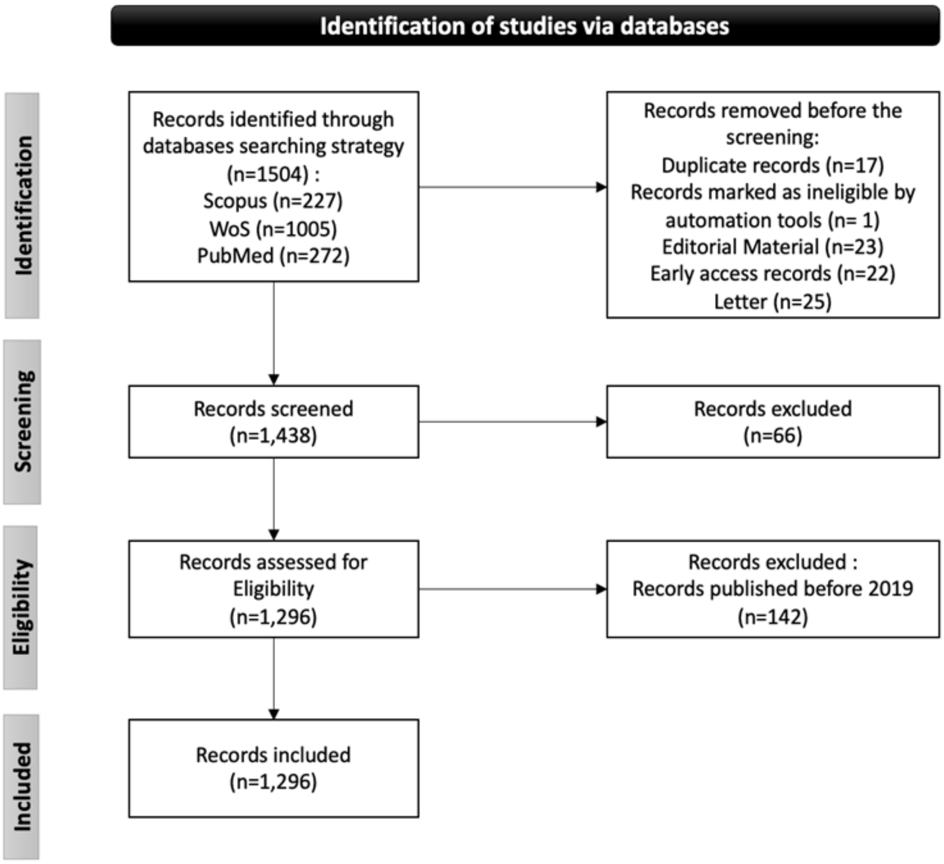

Fig. 1. Prisma Flowchart for Data selection

The collected documents from Scopus, WOS, and PubMed were combined using the PRISMA method. As illustrated in Figure 1, this method streamlined the process of identifying pertinent studies with a concise four-step approach: identifying studies, screening them, determining their eligibility, and including them in the analysis. When merging the three datasets, a primary challenge arose due to discrepancies in their tagging systems. For example, the tag field for the author in Scopus is denoted as “Author”, whereas, in WoS format, it is referred to as “AU”. CiteSpace a science mapping tool working principally with data in WoS format- addressed this issue and effectively removed duplicates. After the cleansing process, 1296 research papers were included in this bibliometric analysis.

3.3. Data analysis approach

The included bibliographic information allowed two types of analysis to be performed: quantitative, aiming to produce a general overview of the research quality and productivity over time, i.e., dynamics of literature production (e.g., authors, affiliations, countries, documents, and journals), and qualitative, intending to identify at first the literature hotspots, then to analyze the community sentiment toward the use of AI in Oncology.

4. RESULTS AND DISCUSSION

4.1. Research quality and productivity analysis:

Within 5 years, the field experienced an exponential increase in scientific publications, as illustrated in Figure 2.A. Starting with 191 papers published in 2019-2020, the number rose to 235 in 2020-2021, showing a growth rate of approximately 23.04%. This upward trend continued into 2021-2022, marking a growth rate of 21.70%.The most pronounced increase was observed between 2022-2023, where the growth rate surged to 101.05% suggesting a significant expansion in research output.

4.1.1. Authors

Overall, 8339 authors were analyzed. Figure 2.B illustrates Lotka's law distribution (a dashed line), where the x-axis represents the number of articles, and the y-axis represents the percentage of authors. The resulting long-tailed distribution indicates that a mere 0.6% of the authors have authored 5 articles each. In contrast, 83.5% of the researchers have only one publication to their name. The 10 most prolific authors are listed in Table 3. WANG Y has the most publications (17 articles), followed by WANG J (16 articles), and KATHER JN (15 articles). The top authors for betweenness centrality were ZHANG J (0.18), WANG Y (0.13), and LIU Y (0.09).

Collaborative relationships among authors based on joint publications were investigated through the Co-authorship Analysis network presented in Figure 3.A. Usually, pair nodes are formed when two authors collaborate. Central nodes indicate authors who have a high degree of collaboration. 2020 saw intensified cooperation among authors such as Heij, Lara R., Brenner, Hoffmeister, and Tom, within Pan-cancer image-based detection of clinically actionable genetic alterations (Kather et al., 2020). Hence, in our study, Kather and Jakob Nikolas's collaboration (Kather et al., 2020) occupied the central node with over 12 citations. This node was linked directly to a pair node involving (Truhn, Daniel), suggesting shared scholarly contributions to the utilization of generative pre-trained transformer 4 (GPT-4) in extracting structured information from unstructured histopathology reports (Truhn et al., 2024). Further analysis revealed (Kather JN, Jakob Nikolas)'s involvement in a cluster of active collaborations during 2022, with a common interest in analyzing Pan-cancer integrative histology-genomic via multimodal deep learning (R. J. Chen et al., 2022). Lastly, author Kather JN emerges prominently as the third most prolific contributor, occupying a pivotal position within the central node of the COA, highlighting both their substantial scholarly output and influential role in fostering collaborative networks.

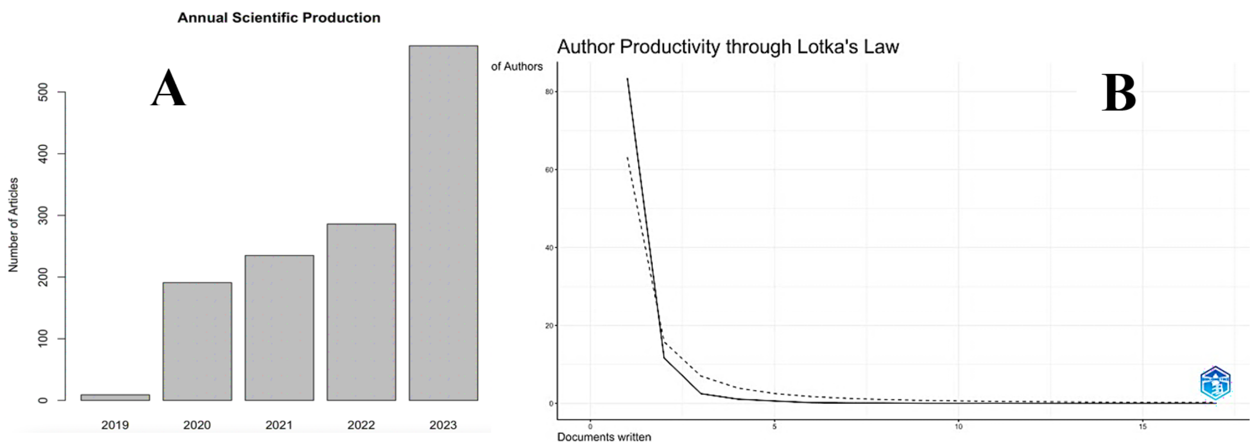

Fig. 2. Analysis of scientific productivity from 2019 to 2024:
A) Annual production Bar plot, B) Lotka's Law distribution from Biblioshiny

Tab. 3. Top 10 productive authors over time

Authors	Production over Time (N of articles)					Centrality
	2019	2020	2021	2022	2023	
WANG Y	1	5	-	5	6	0.13
WANG J	-	4	1	4	7	0.02
KATHER JN	-	2	2	5	6	0.00
LI J	-	1	2	4	6	0.00
WANG ZL	-	4	1	5	2	0.00
ZHANG Y	-	2	1	3	6	0.01
KAHN MA	-	2	3	3	3	-
LI X	-	1	-	1	9	0.01
WANG L	1	2	2	1	5	0.01
ZHANG J	-	2	1	3	5	0.18

4.1.2. Countries

On a global scale, Asia, primarily led by China, was the most prolific continent with a cumulative production frequency of 2,596. Europe followed with a significant frequency of 1,891. North America also demonstrated a strong production capacity (1,647), heavenly influenced by the USA's contribution. Oceania, represented mainly by Australia and New Zealand, registered a moderate total frequency of 169. On the other hand, despite its vast natural resources and potential for industrial growth, Africa showed a low total frequency 74. South America's status as an industrial region emerged with a total frequency of 31. These statistics could be explained through the network of collaboration among countries presented in Figure 3.B. In this network map, China, the USA, and England had larger node sizes, representing higher accumulated citations. Italy, France, India, Spain, and Turkey were central countries. The main common collaborators were England, Netherlands, South Korea, Saudi Arabia, Morocco, Australia, Qatar, Vietnam, Denmark, the Philippines, Portugal, and Poland. In addition, with a centrality of 0.27, ITALY maintained close ties with the USA, Pakistan, Finland, Sweden, Belgium, Norway, Ireland, Romania, South Africa, Chile, Kuwait, Libya, Bangladesh, Hungary, Serbia, Slovenia, and Nepal. While India worked closely with Palestine, Ethiopia, Yemen, Russia, Macao, and Kazakhstan, France has expanded its scientific production scope by collaborating with Japan, Oman, Canada, Greece, Egypt, and Switzerland. Turkey also worked alongside Brazil, Austria, and Lithuania.

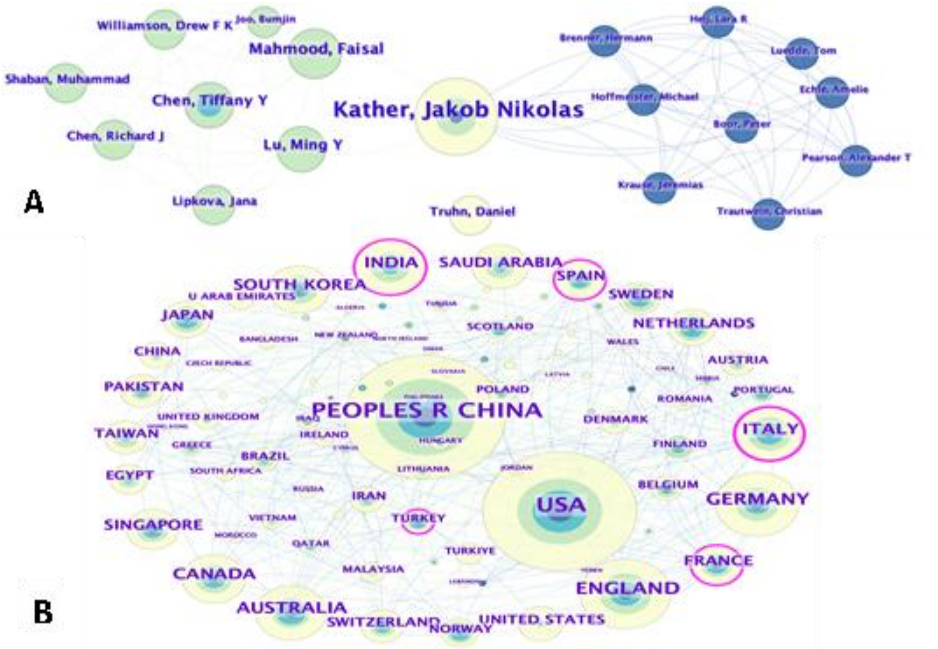

Fig. 3. Citespace collaboration networks uses the g-index measure with a scale factor of 25 and log-likelihood ratio for the labels, showing A) the two largest clusters of authors and B) countries, with central nodes represented by pink circles

4.1.3. Journals and institutions

This research field was covered by 712 academic journals, with the majority being from the UK as shown in Table 4. Among 6832 institutions, the analysis of the top 10 identified five in the USA, three in China, and one each in Germany and the UK. Although HARVARD UNIVERSITY was the most productive institution with over 128 papers, it ranked second regarding its accumulative citations. Collaboration patterns demonstrated that the central institutions were the Indian Institute of Technology System, King Abdulaziz University, Assistance Publique Hospitaux Paris (APHP), and the University of Copenhagen moreover, NAT MED, AM. HEART J and NAT COMMUN were the central journals.

Tab. 4. Citespace output highlights the top 10 institutions based on the citation count and the top 10 journals by betweenness centrality

Rank	Institution	Citations count	Rank	Journal	Centrality
1	Chinese Academy of Sciences (CHINA)	81	1	NAT MED (UK)	0.21
2	Harvard University (USA)	57	2	AM. HEART J (USA)	0.19
3	Harvard Medical School (USA)	43	3	NAT COMMUN (UK)	0.18
4	University of California System (USA)	36	4	NANOSCALE (UK)	0.17
5	Stanford University (USA)	36	5	LANCET (UK)	0.15
6	Helmholtz Association (GERMANY)	35	6	BIOINFORMATICS (UK)	0.09
7	University of Chinese Academy of Sciences (CHINA)	35	7	SCI REP-UK (UK)	0.09
8	University of London (UK)	34	8	PLOS ONE (USA)	0.08
9	University of Texas System (USA)	33	9	CELL (USA)	0.08
10	Sun Yat Sen University (CHINA)	30	10	NATURE (UK)	0.07

4.1.4. Articles

Table 5 illustrates the most cited articles, corresponding authors, and total citation counts. Globally, the leading article focused on concepts related to the explainability of AI methods (XAI) with a profound discussion on its potential implications and privacy in data fusion contexts. MCKINNEY SM's paper, which presents an AI system capable of surpassing human experts in breast cancer prediction, was locally cited more than 40 times.

Tab. 5. Most globally and locally cited documents

Rank	Most Global Cited Documents (citations count)	Most Local Cited Documents (citations count)
1	ARRIETA AB, 2020, INFORM FUSION (2817)	MCKINNEY SM, 2020, NATURE (40)
2	ALZUBAIDI L, 2021, J BIG DATA-GER (1852)	KATHER JN, 2020, NAT CANCER (19)
3	MCKINNEY SM, 2020, NATURE (1148)	ARRIETA AB, 2020, INFORM FUSION (17)

4.2. Research hotspots analysis

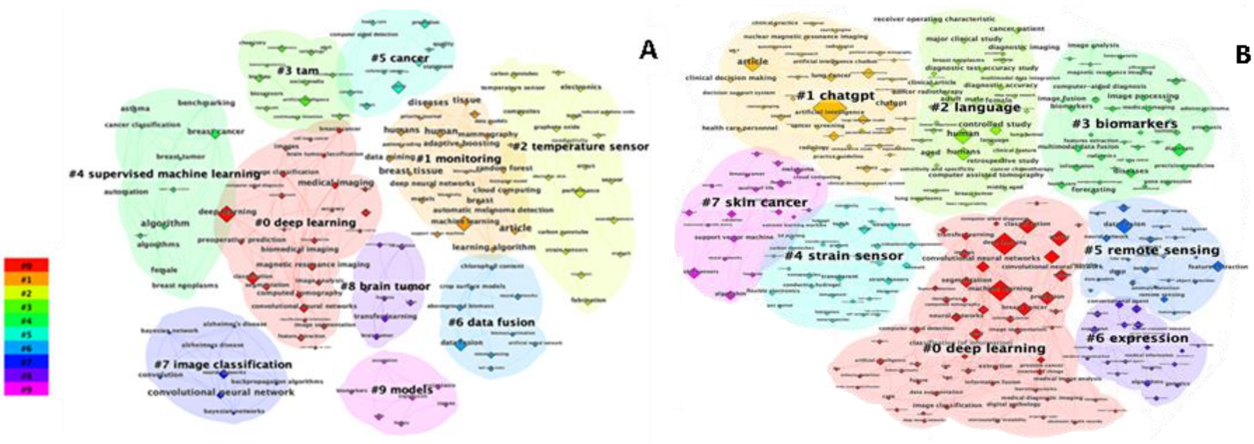

Fig. 5. Citespace keywords co-occurrence networks, illustrating A) the 2019-2021 network and B) the 2022-2024 network

The intellectual foundation of AI application to oncology was analyzed through keyword co-occurrence analysis to identify trending themes and trajectories. This study examined two networks: one for 2019-2021, with ten clusters, and another for 2022-2024 with eight clusters.

4.2.1. Supervised machine learning

The presence of clusters #0, #4, #5, #7, #8, and #9 from the 2019-2021 period, along with cluster #0 from 2022-2024, underscored the prominence of supervised machine learning. This theme initially delved into classical methods for detecting breast cancer. For instance, after eliminating insignificant features by applying the gain ratio feature selection method, Extreme Learning Machine (ELM) was employed in a cloud computing-based system for remote breast cancer diagnosis (Lahoura et al., 2021). Furthermore, simple crow-search algorithms (ICS-ELM) were utilized to optimize customized methods of integrating the ELM with deep learning. One class of DL, namely convolutional neural networks (CNN), has proven exceptionally effective for image recognition and classification tasks and is therefore commonly utilized for analyzing medical images; In addition to breast cancer, Magnetic resonance imaging (MRI) has been the focus of much research in brain cancer. The features of the brain MRI images were extracted using a pre-trained CNN, i.e., GoogLeNet, and then classified using classifiers such as Softmax, Support Vector Machine (SVM), and K-nearest neighbor (K-NN) (Sekhar et al., 2022). Segmentation algorithms aided in feature extraction for classifying lung nodes (Murugesan et al., 2022), ultimately enhancing the AUC-ROC performance metric. Starting in 2023, CNN's application has significantly expanded to include various types of cancer, such as prostate cancer. To tackle the issues of speed and accuracy, a recent study demonstrated that by combining stimulated Raman scattering microscopy with a convolutional neural network, it became possible to quickly analyze histopathology and automatically determine Gleason scores on fresh prostate biopsies, without the need for complex processing (Ao et al., 2023). Generalizability also emerged as a critical focus, as demonstrated by a study leveraging ResUNet++ for colorectal cancer detection (Jha et al., 2021). By integrating Conditional Random Fields (CRF) and Test-Time Augmentation (TTA), the model achieved improved cross-dataset performance, addressing a key challenge in translating supervised learning models into clinical practice. Similarly, federated learning (FL) has been proposed to enhance multi-institutional training without centralizing patient data. FL demonstrated superior performance and generalizability compared to single-institution models, achieving robust results while preserving data privacy (Sarma et al., 2021).

4.2.2. Multimodal learning

The identified topic included keywords from cluster #6 (2019-2021), such as "data fusion" and "neural network", and keywords from cluster #3 (2022-2024), specifically "image fusion" and "multimodal data fusion”. In oncology, it is increasingly important to develop effective multimodal fusion approaches, as a single modality may not be enough to capture the complexity of cancer to improve personalized medical care. Multi-omics data fusion integrated various data types including gene expression, copy number alteration, and clinical data. For instance, to predict survival in breast cancer patients, a Multimodal Affinity Fusion Network (MAFN) has demonstrated significant advantages over single-data approaches, by utilizing a stack-based shallow self-attention network to amplify tiny lesion regions, followed by an affinity fusion module that maps structured patient information to multimodal data (Guo et al., 2021). Recently, there has been a significant trend in developing joint image-omics prognostic models. According to the literature, three fusion techniques are frequently utilized: early fusion which combines modalities into a single feature vector pre-training, joint fusion which merges intermediate neural network features with other modalities, and late fusion, which integrates predictions from multiple models (S.-C. Huang et al., 2020). The latter proved its effectiveness in jointly analyzing pathology whole-side images (WSIs) and molecular data for 14 cancer types (R. J. Chen et al., 2022). In addition, a novel multimodal data fusion based on residual learning architecture and two multilayer perceptron with attention mechanisms illustrated the feasibility of incorporating computed tomography (CT) images and clinical variables (H. Huang et al., 2022). MDFNet similarly fused clinical skin images and patient clinical data and effectively solved the problems of feature paucity and insufficient feature richness that only use single-mode data (Q. Chen et al., 2023). A significant multimodal approach in oncology involves upper gastrointestinal (UGI) cancer screening, where researchers combined gastrointestinal image recognition with textual medical record analysis. Using a semantic-level cancer screening network (SCNET), this study achieved a 4.01% improvement in screening accuracy compared to existing methods (Ding et al., 2021). These results highlight how integrating diverse data sources can enhance UGI cancer detection and improve patient care. Along similar lines, (Du et al., 2024) examined clinical data, mammography, and multimodal MRI images from 132 patients to develop a deep-learning model capable of distinguishing between benign and malignant breast lesions. By utilizing ResNet34-based models within a voting framework, their multimodal approach achieved an AUC of 0.943, substantially outperforming individual imaging methods like mammography (AUC 0.645) and T2WI (AUC 0.595). To conclude, multimodal learning has proven to be a key factor in advancing oncology by combining various data types to improve diagnostic precision and foster personalized treatment approaches.

4.2.3. Large language models (LLMs)

This topic represented 16.05% of the bibliographic data analyzed. The initial clusters, labeled “ChatGPT” and “Language,” which covered the years 2022-2024, were primarily examined in the context of clinical decision-making and the support of patient information. For instance, a study found that 70% of recommendations generated by ChatGPT-3.5 were consistent with the decisions made by a breast cancer tumor board (Davis et al., 2024). However, pathologists assessed its performance in histopathology tasks as suboptimal, emphasizing its dependency on provided prompts, which limited its diagnostic accuracy (Oon et al., 2023). In another study, two experienced surgeons found that 86.4% of ChatGPT’s responses to 154 head and neck cancer-related questions were accurate and comprehensive, while 11% were partially correct, and 2.6% were mixed, with no entirely incorrect responses (Kuşcu et al., 2023). A cross-sectional analysis further highlighted the challenges associated with large language models, such as ChatGPT-4, ChatGPT-3.5, and Google Bard, revealing issues of inaccuracy and incompleteness in their responses, even though these models show promise as tools in immuno-oncology (Iannantuono et al., 2024). In contrast, ChatDoctor an adaptation of the large language model meta-AI (LLaMA) using 100,000 anonymized patient-doctor dialogues, integrating a self-directed information retrieval mechanism from sources like Wikipedia and medical databases demonstrated significant improvements in understanding patient needs and providing accurate medical advice (Li et al., 2023). ChatGPT-4, known for its multimodal capabilities, showed a 50% accuracy rate in neuroradiology cases by combining medical history with imaging findings (Horiuchi et al., 2024). Similarly, a recent evaluation of ChatGPT-4’s performance in ophthalmology indicated that it could interpret ophthalmic images with a 70% accuracy rate across 136 cases (Mihalache et al., 2024). The chatbot performed better on non-image-based questions (82%) compared to those requiring image interpretation (65%), with a significant difference ($\chi^2 = 12.2$, $P < .001$). It excelled in retinal cases (77%) but showed lower accuracy in neuro-ophthalmology (58%), highlighting both the potential and current limitations of multimodal AI in clinical image interpretation. This demonstrates both the prospective capabilities and existing limitations of multimodal chatbots in clinical decision-making, particularly when dealing with complicated image datasets.

4.2.4. Wearable devices and sensors

Over the past five years, there has been noteworthy advancement and diversification in wearable devices and sensors. In particular, temperature sensors, biosensors, strain sensors, and chemical sensors have found widespread application in the field of oncology. Their utilization has contributed to the enhancement of real-time monitoring capabilities and the development of personalized treatment strategies. As an illustration, the electronic tongue a simple, portable, and affordable analytical instrument demonstrated a good promise for distinguishing between people with bladder cancer and healthy people, via a potentiometric multisensory system and ML algorithms such as SVM and voting classifier (Belugina et al., 2021). Thanks to their exceptional mechanical properties, conductivity, and high resemblance to human tissue, “conductive hydrogels” and “carbon nanotubes” made flexible electronic sensors suitable for monitoring human health. A dual-function hydrogel sensor that can measure temperature and strain simultaneously has shown significant potential in this regard (Pang et al., 2022). Recent advancements in wearable continuous glucose monitoring (CGM) systems have sparked interest in extending this technology to monitor therapeutic drugs in bodily fluids (Teymourian et al., 2020). This allowed for personalized dosing and tracking changes in drug behavior while ensuring patient adherence to medication. Within this framework, the fifth cluster, spanning 2019-2021 and labeled "Technology Acceptance Model (TAM)", highlighted the significant role of social media in users' intention to continue using and engaging with digital health solutions.

4.3. Researchers sentiment analysis

Sentiment analysis involves various tasks such as sentiment extraction, classification, subjectivity detection, opinion summary, and opinion spam detection. This research focused on categorizing 307 reviews as positive or negative. SciBERT, a variant of BERT (Bidirectional Encoder Representations from Transformers) specifically trained on scientific text, was chosen for its potential to effectively perform sentiment analysis within the biomedical domain, surpassing the capabilities of BioBert (Beltagy et al., 2019). Initially, abstracts were retrieved and parsed alongside their associated document types to filter for reviews (e.g., 'DT'='Review'). Each review's abstract was then tokenized and converted into tensors suitable for input into the model. Predictions were made based on the Softmax output of the model's logits to ensure binary classification. In this process, the logits represent unnormalized confidence scores for the sentiment labels (positive or negative). These logits were passed through a Softmax function, which converted them into probabilities. The label with the highest probability was selected as the final sentiment classification. For example, if the probability for the positive label is higher (e.g., 0.85 for positive vs. 0.15 for negative), the abstract is classified as positive. Conversely, if the probability for the negative label is higher (e.g., 0.70 for negative vs. 0.30 for positive), the abstract is classified as negative. The majority of reviews (91.5%) were classified as positive due to the focus on AI advancements in healthcare. For instance, (Schukow et al., 2024) highlight AI tools like ChatGPT, which can quickly summarize vast data to aid diagnostic pathology, reflecting a positive outlook on AI's potential. However, negative sentiments were identified in abstracts discussing AI challenges. (Lou et al., 2020) discuss the slow pace of wearable health monitoring systems' commercialization, citing obstacles such as limitations in current semiconductor technologies and design methodologies. Despite these setbacks, the study acknowledges progress in materials science and manufacturing methods, emphasizing the need for continued development to advance flexible electronics and human health monitoring devices. It is noteworthy that while SciBERT's specialized "scivocab" enriches its capacity to navigate scientific discourse with precision, its foundation on a general scientific corpus introduces subtle biases such as a tendency to overfit to prevalent scientific jargon and difficulty in capturing the intricate nuances of a domain-specific language, particularly in highly specialized fields like oncology (Nair et al., 2024).

4.4. Limitations and future perspectives

This study has several limitations that need to be considered. Firstly, the focus on databases such as Scopus, WoS, and PubMed, while excluding others like Google Scholar and Lens, may have narrowed the scope of our data. Although the selected keywords were relevant to AI in oncology, terms like "data fusion," "LLM," and "wearable devices" may have left out other important aspects of the field, potentially creating gaps. Additionally, differences in database tagging across Scopus, WoS, and PubMed may have affected the consistency and accuracy of the data. While CiteSpace was used to address some of these discrepancies, variations in tagging practices across platforms could still have influenced the results. Regarding sentiment analysis, SciBERT was applied; however, it may not fully capture the nuanced sentiments specific to oncology research. Looking ahead, future work should aim to refine the selection of keywords, enhance consistency in database tagging, and provide further qualitative discussion to better understand the scientific implications of the emerging technologies in the field. Importantly, we have multiple follow-up studies planned, one of which will explore community sentiments around the ethics of AI in oncology. This work will compare several pre-trained language models across different sentiment categories positive, negative, and neutral using precision, recall, and F1-score metrics. These efforts are designed to contribute to a more nuanced understanding of the ethical dimensions of AI applications in oncology.

5. CONCLUSIONS

Drawing on data from multiple sources, this study aims to identify, assess, and illustrate the research productivity, trends, and the sentiment of the scientific community regarding AI applications across the entire spectrum of cancer research. Over the past five years, there has been a significant increase in scientific publications in this field, indicating a growing interest in its clinical implementation. Diagnostic imaging, prediction of clinical parameters, continuous mentoring, decision-making support, and risk stratification were the most reported AI applications. Breast, lung, brain, and skin cancer were the most extensively researched cancer types. The current trending topics revealed by this analysis were supervised learning methods (e.g., CNN, Bayesian networks, and extreme learning machines), multimodal deep learning models (e.g., late image-omics fusion), large language models, and sensors (e.g., conductive hydrogel wearables). According to sentiment analysis, 91.5% of the researchers viewed these advancements positively. While China and the USA led global production efforts, research efforts should not be confined to specific geographical areas to harness a larger pool of data, maximize research impact, and resolve the generalizability of AI algorithms-related problems. Despite its comprehensive scope, the selection of keywords could have influenced the results obtained, suggesting that future studies could benefit from including alternative keywords to enhance the depth of analysis.

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