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Artificial Intelligence as Applied to Leukemia Research: A Dual Approach of Literature Review and Bibliometric Exploration

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Abstract

Objective: The application of artificial intelligence (AI) in leukemia management is rapidly expanding, with components such as machine learning (ML), deep learning (DL), and neural networks (NNs) offering innovative solutions for diagnosis and treatment. This study aims to analyze the global impact of AI in leukemia research through bibliometric analysis, highlighting trends in scientific production, institutional contributions, and keyword evolution.

Materials and Methods: A systematic literature review was conducted using Scopus and Web of Science (WoS) databases. Inclusion criteria focused on AI applications in leukemia, incorporating research articles and conference papers while excluding reviews and non-related studies. Data were analyzed using VosViewer (Version 1.6.20) and Bibliometrix-Biblioshiny to map publication trends, co-authorship networks, and keyword co-occurrence.

Results: A total of 248 documents from Scopus and 472 from WoS were analyzed. Machine learning emerged as the most frequently studied AI tool, followed by NNs and DL. A significant increase in AI-related leukemia research has been observed since 2017. The United States and China were the most active contributors. Studies primarily focused on acute leukemia, while chronic leukemia subtypes received comparatively less attention. Institutions and journals have increasingly prioritized AI in leukemia research, indicating growing academic and clinical interest.

Conclusion: The integration of AI into leukemia research is accelerating, with ML leading the way. However, more studies are needed to explore chronic leukemia subtypes and translate AI-driven advancements into clinical practice. The increasing global interest in AI applications suggests that these technologies will play a crucial role in future leukemia management.

Keywords: Artificial intelligence, bibliometric analysis, deep learning, leukemia, machine learning, neural networks

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INTRODUCTION

Hematologic neoplasms (HNs) arise from abnormal hematopoiesis, a process involving the differentiation of hematopoietic stem cells (HSCs) into either myeloid or lymphoid progenitors, followed by further proliferation and accumulation of immune or blood cells. Each type has distinct clinical characteristics and specific classification criteria (1-3). According to the World Health Organization (WHO) (3) and an international consensus article (4), blood cancers are classified based on their immunophenotypes, morphological features, clinical presentations, and cytogenetic/molecular alterations which widened the classification of all types of HNs (5). As a part of HNs, leukemia is clustered into different subtypes based on the pace of disease progression as acute and chronic leukemia and based on the type of cell they originated lymphoid or myeloid cells (6). Leukemia ranks as the 13th most common cancer and the 11th leading cause of cancer-related deaths with a global incidence of over 400,000 and a prevalence of more than 1.3 million, according to the GLOBOCAN 2020 report. In the United States, it is estimated that around 60,000 individuals will receive a diagnosis of leukemia in 2023 (7). This includes cases of acute myeloid leukemia (AML), chronic lymphocytic leukemia (CLL), chronic myeloid leukemia (CML), acute lymphocytic leukemia (ALL), and other subtypes, respectively in cases (8). The treatment modalities for leukemia include a range of chemical therapeutic agents like chemotherapy, targeted therapy, immunotherapy, and gene or cell therapy such as Chimeric antigen receptor T-cell (CAR-T), radiotherapy as well as hematopoietic stem cell transplantation (1). Current diagnostic tools for leukemia include physical exams, complete blood count, peripheral blood smears, immunophenotyping, bone marrow examinations (aspiration and biopsy), cytogenetics, immunohistochemistry, and imaging (9, 10). Early diagnosis and determining the subtype of disease are critical, and the tests that play a significant role in achieving this. However, certain challenges need to be addressed. For instance, the evaluation of these tests has inter-evaluator variation, and deviations can occur due to conducting experiments in different laboratory conditions and by different individuals. Sample processing and approval processes are also time-consuming, and clinical interventions such as bone marrow aspiration can be difficult. Therefore, it has become vital to integrate technology into the clinic, develop new methods, and reach a consensus in test evaluation (11, 12). In addition, integrating technology into clinical practice can aid treatment. This includes computer-based drug design for the disease's biological targets, monitoring technologies for dosages and remissions based on the patient's pathological history, software that integrates data from genetic, histological, microbiological, and routine tests, user-free evaluation methods by processing patient sample images, programs to aid patient-physician communication and symptom monitoring, and reducing patient hospitalization time. All these benefits pave the way for new developments that create new visions and missions both in healthcare and leukemia management. These developments will enable the effective provision of health services to meet the increasing demand for leukemia treatment (12-14). To achieve these goals, first, healthcare professionals should integrate data management tools to make the data meaningful, validated, standardized, and subjective (15).

The recent growth in humanity's cumulative knowledge has resulted in the integration of technological advancements in data management and contextualization. This includes stages such as collection, identification, classification, processing, exploration, analysis, and interpretation of large-scale data from different sources. These processes help in identifying current or prospective issues and finding solutions to them (16). However, data management enables us to better handle complex tasks, it is difficult to accomplish through human intelligence (HI) or natural intelligence (NI) alone due to the detailed nature of data and the requirement of time and effort. For these reasons, using artificial intelligence (AI) tools has extensive benefits as they offer valuable insights and even foresight, and recently gained attention from researchers or institutes globally (17). As historical background, Alan Turing proposed the Turing test to determine "if machines can think like humans". After that, the term "artificial intelligence" was first mentioned by John McCarty as a discipline that investigates the functions of machines and their integration with HI as performing or simulating cognitive activities akin to humans (18, 19). As we strive towards achieving zero-touch simulation of HI, the field of AI has expanded and evolved into six distinct yet interrelated subcategories, namely machine learning (ML), deep learning (DL), NNs (NN), natural language processing (NLP), computer vision (CV), and robotics (in this article NLP, CV, and robotics were excluded) (20). With the advancements in ML, AI has reached a level where it can perform tasks that previously required HI. It is also capable of processing large amounts of data on its own, without requiring any explicit instructions on how to carry out the tasks. Furthermore, it can generate solutions to complex problems when presented with more intricate data (21). Deep learning is another subset of AI that uses data combinations to derive meaningful results. The process involves combining data in various ways and summarizing the outcomes. These combinations are then added back to the data set as separate elements and the process repeats. In essence, this structure mimics the neural network similar to neurons in the human brain, simulating the recall of memories and making connections between phenomena (22). Although NNs form the basis of DL, the primary difference between them is the number of connections that have been made during data processing, with DL having more complex connection patterns as its name implies (23).

Throughout its evolution, AI has played a crucial role in integrating knowledge and experience in medicine and other fields it impacts. It has greatly lightened the burden of healthcare in numerous branches and aspects, both physically and virtually with all of its constituents (24). To reveal the potential of AI tools, bibliometric studies can be applied. Bibliometric studies reveal the development and accumulation of knowledge and facilitate qualitative and quantitative literature analysis to understand authors' perspectives and orientations toward topics. By virtue of these studies, the amount of scientific output that has been made in a specific discipline and information gaps can be assessed, then these assessments pave the way for future studies and for designing innovative ideas (25). Literature analysis using a literature database involves filtering data sets based on keywords and specific inclusion or exclusion criteria. This helps to define the research scope and ensure that the conclusions drawn fall within a spectrum between objective and subjective which can be thought-provoking for the researchers (26).

Accepting AI tools as current and future orchestrators in leukemia management, we aimed to describe the current state of AI, ML, DL, and NN tools applied in leukemia and its subtypes using literature, bibliometric, network, and descriptive analysis, worldwide.

MATERIALS AND METHODS

A comprehensive manual review of the literature was conducted utilizing the Scopus and Web of Science (WoS) databases separately to extract knowledge from articles and conference proceedings on the correlation between leukemia and AI tools such as ML, DL, and NNs. To ensure a detailed analysis, the keywords were divided into discrete groups, including leukemia and AI tools, all AI tools and leukemia, with each group designed with queries that do not interfere with other queries to understand the terms of AI tools and their applications in leukemia and its subtypes by using Boolean operators "AND" and "AND NOT". The conceptualization of queries is referred to in Appendix 1 (see Supplementary Materials). The publication year was not indicated in the queries; instead, the oldest publication year was confirmed as the beginning and the final published document as the end. For the Scopus database query search, publication years of documents were between 1989-2023 while for WoS, it was 1994-2023. Only research articles and conference papers that deal with the application of AI tools in leukemia were included. In contrast, research on other types of cancer or diseases, reviews, and opinions on this topic were excluded. The information contained in the exported CSV files (taken from Scopus) and plain text files (taken from WoS) were counted and checked for duplication. The final number of documents is indicated (Tables 1-2). All groups separated by keywords were combined in each Scopus and WoS results, and co-occurrence with keywords and co-authorship within countries were determined using VOSviewer (Version 1.6.20). All the keywords and countries are scaled in the time interval of 2013-2023 to show trends in the usage of keywords and current attention taken by countries in the last decade. The bibliometric analysis by using manually collected files was done by the Biblioshiny platform which is supported by R programming and within the scope of the data taken from Scopus and WoS are categorized as annual scientific publications, affiliation production over time, and the number of publications by journals in timeline.

RESULT

Overview- Scopus

We found a total of 248 distinct documents *via* a manual Scopus database search as chasing the relevance of AI tools and leukemia within the total of 3312 documents that were counted with unfiltered query search. We excluded the documents that a) do not have available abstract or comma-separated values (CSV) files, b) other document types rather than articles and conference papers, and c) studies that have not been specified in the context of leukemia and its subtypes. Out of the 248 documents analyzed, most of them (135 documents, or 54.4%) were focused on using ML algorithms to study leukemia. Following ML, AI (n=50, 20.2%), NNs (n=34, 13.7%), DL (n=19, 7.7%) and all AI tools combined (n=10, 4%) are on the list respectively (Table 1).

Overview – Web of Science

We searched the WoS database and manually screened 472 documents (selected from a total of 1952 documents that were retrieved by unfiltered query search) related to leukemia research. We excluded documents that either didn't have an abstract or plain text file, were not articles or conference proceedings or were not relevant to leukemia research. Out of the 472 documents, 249 (52.8%) were related to ML, followed by NNs (110, 23.3%), DL (57, 12%), and AI (53, 11.2%). All AI tools combined accounted for only 3 (0.7%) of the documents (Table 2).

TABLE 1. The process of studying AI tools and their application in leukemia management involved several steps, including identification, screening, exclusion, and inclusion. Scopus queries (separated as 5 identical keyword combinations – row 1) were entered to retrieve relevant documents, and the number of documents for each step was shown along with the exclusion criteria. After manually reviewing the literature, 248 reports were identified as appropriate for further bibliometric analysis.

	Identification of Studies via SCOPUS				
Identification	"Leukemia" and "Artificial Intelligence"	"Leukemia" and "Machine Learning"	"Leukemia" and "Neural Networks"	"Leukemia" and "Deep Learning"	"Leukemia" and "Artificial Intelligence" and "Machine Learning" and "Deep Learning" and "Neural Networks"
Screening	Total documents in the interval of years 1989-2023 **(n=559)**	Total documents in the interval of years 1998-2023 **(n=1265)**	Total documents in the interval of years 1992-2023 **(n=935)**	Total documents in the interval of years 2013-2023 **(n=512)**	Total documents in the interval of years 2017-2023 **(n=41)**
	Document Type: Article and Conference Paper **(n=392)**	Publication stage at Final **(n=1250)**	Document type: Article and Conference Paper **(n=799)**	Document type: Article and Conference Paper **(n=403)**	Document Type: Article and Conference Paper **(n=23)**
	Written in English **(n=386)**	Document type: Article and Conference Paper **(n=1011)**	Publication stage: Final **(n=784)**	Publication stage: Final **(n=398)**	Publication stage: Final **(n=23)**
	Publication Stage at Final **(n=380)**	Written in English **(n=1000)**	Written in English **(n=776)**	Written in English **(n=395)**	Written in English **(n=23)**
	Exclusion by "**AND NOT**" Boolean Operator ("deep learning" and "leukemia") – ("artificial intelligence and leukemia") – ("neural network and leukemia) – ("artificial intelligence" and "machine learning" and "deep learning" and "neural network" and "leukemia") **(n=82)**	Exclusion by "**AND NOT**" Boolean Operator ("deep learning" and "leukemia") – ("artificial intelligence and leukemia") – ("neural network and leukemia) – ("artificial intelligence" and "machine learning" and "deep learning" and "neural network" and "leukemia") **(n=312)**	Exclusion by "**AND NOT**" Boolean Operator ("deep learning" and "leukemia") – ("artificial intelligence and leukemia") – ("machine learning and leukemia) – ("artificial intelligence" and "machine learning" and "deep learning" and "neural network" and "leukemia") **(n=116)**	Exclusion by "**AND NOT**" Boolean Operator ("machine learning" and "leukemia") – ("artificial intelligence and leukemia") – ("neural network and leukemia) – ("artificial intelligence" and "machine learning" and "deep learning" and "neural network" and "leukemia") **(n=32)**	Not excluded by Boolean Operator to see all of the results and at least 2 AI tools usage in the paper are included **(n=23)**
Excluded	Excluded documents from 82 documents **(n=32)**	Excluded documents from 312 documents **(n=177)**	Excluded documents from 116 documents **(n=82)**	Excluded documents from 32 documents **(n=13)**	Excluded documents from 23 documents **(n=13)**
Included	**n=50**	**n=135**	**n=34**	**n=19**	**n=10**
Result	Total dataset as checking duplicates **(n= 248)**				

TABLE 2. The process of studying AI tools and their application in leukemia management involved several steps, including identification, screening, exclusion, and inclusion. Web of Science (WoS) queries (separated as 5 identical keyword combinations – row 1) were entered to retrieve relevant documents, and the number of documents for each step was shown along with the exclusion criteria. After manually reviewing the literature, 473 reports were identified as appropriate for further bibliometric analysis.

	Identification of Studies via WoS				
Identification	"Leukemia" and "Artificial Intelligence"	"Leukemia" and "Machine Learning"	"Leukemia" and "Neural Networks"	"Leukemia" and "Deep Learning"	"Leukemia" and "Artificial Intelligence" and "Machine Learning" and "Deep Learning" and "Neural Networks"
Screening	Total documents in the interval of years 1993-2023 **(n=467)**	Total documents in the interval of years 1998-2023 **(n=762)**	Total documents in the interval of years 1992-2023 **(n=435)**	Total documents in the interval of years 2013-2023 **(n=280)**	Total documents in the interval of years 2020-2023 **(n=7)**
	Document Type: Article and Proceeding Paper **(n=363)**	Document type: Article and Proceeding Paper **(n=636)**	Document type: Article and Conference Paper **(n=411)**	Document type: Article and Conference Paper **(n=255)**	Document Type: Article and Conference Paper **(n=4)**
	Written in English **(n=362)**	Written in English **(n=634)**	Written in English **(n=410)**	Written in English **(n=254)**	Written in English **(n=4)**
	Exclusion by **"AND NOT"** Boolean Operator ("deep learning" and "leukemia") – ("machine learning" and "leukemia") – ("neural network and leukemia) – ("artificial intelligence" and "machine learning" and "deep learning" and "neural network" and "leukemia") **(n=223)**	Exclusion by **"AND NOT"** Boolean Operator ("deep learning" and "leukemia") – ("artificial intelligence and leukemia") – ("neural network and leukemia) – ("artificial intelligence" and "machine learning" and "deep learning" and "neural network" and "leukemia") **(n=452)**	Exclusion by **"AND NOT"** Boolean Operator ("deep learning" and "leukemia") – ("artificial intelligence and leukemia") – ("machine learning and leukemia) – ("artificial intelligence" and "machine learning" and "deep learning" and "neural network" and "leukemia") **(n=212)**	Exclusion by **"AND NOT"** Boolean Operator ("machine learning" and "leukemia") – ("artificial intelligence and leukemia") – ("neural network and leukemia) – ("artificial intelligence" and "machine learning" and "deep learning" and "neural network" and "leukemia") **(n=97)**	Not excluded by Boolean Operator to see all of the results and at least 2 AI tools usage in the paper are included
Excluded	Excluded documents from 223 documents **(n=170)**	Excluded documents from documents **(n=203)**	Excluded documents from documents **(n=102)**	Excluded documents from documents **(n=40)**	Excluded documents from documents **(n=1)**
Included	**n=53**	**n=249**	**n=110**	**n=57**	**n=3**
Result	The total dataset is checking duplicates from a total of 473 documents **n= 473**				

Analysis of Publications that were Manually Selected *via* Scopus and WoS Databases

Artificial Intelligence Is Becoming a General Term

The definition of artificial intelligence, as a concept, has significantly evolved. Its expanded structure now includes various subheadings such as ML, NNs, and DL, respectively, which have contributed to a broader definition. The term is no longer characterized by strictly defined boundaries, but rather by its flexibility to encompass multiple subheadings. In academic settings, researchers often employ specific subheadings to describe their studies, rather than using the term “artificial intelligence”. An analysis of the past 10 years also reveals that the use of the term “artificial intelligence” has been replaced by the more specific phrases “machine learning” and “neural networks”. Such linguistic precision reflects the growing sophistication of research in this field and highlights the importance of staying up-to-date with the latest terminology (Figure 1 and Figure 3)

Machine Learning Is the Most Common AI Tool in Leukemia Management

According to a VOSviewer analysis of Scopus and WoS databases, researchers have been utilizing terms like ML, NNs, and DL, instead of the broader term artificial intelligence. Machine learning, in particular, has been the most frequently mentioned and recently used AI tool. This shift in terminology could be attributed to the fact that AI is comprised of overlapping subsets that are sequentially related, and the number of published documents follows this pattern and decreases as one moves to another subset. Therefore, researchers tend to begin with the general concept of AI and progress to more specific areas, such as ML, NNs, and DL. This suggests that as re-

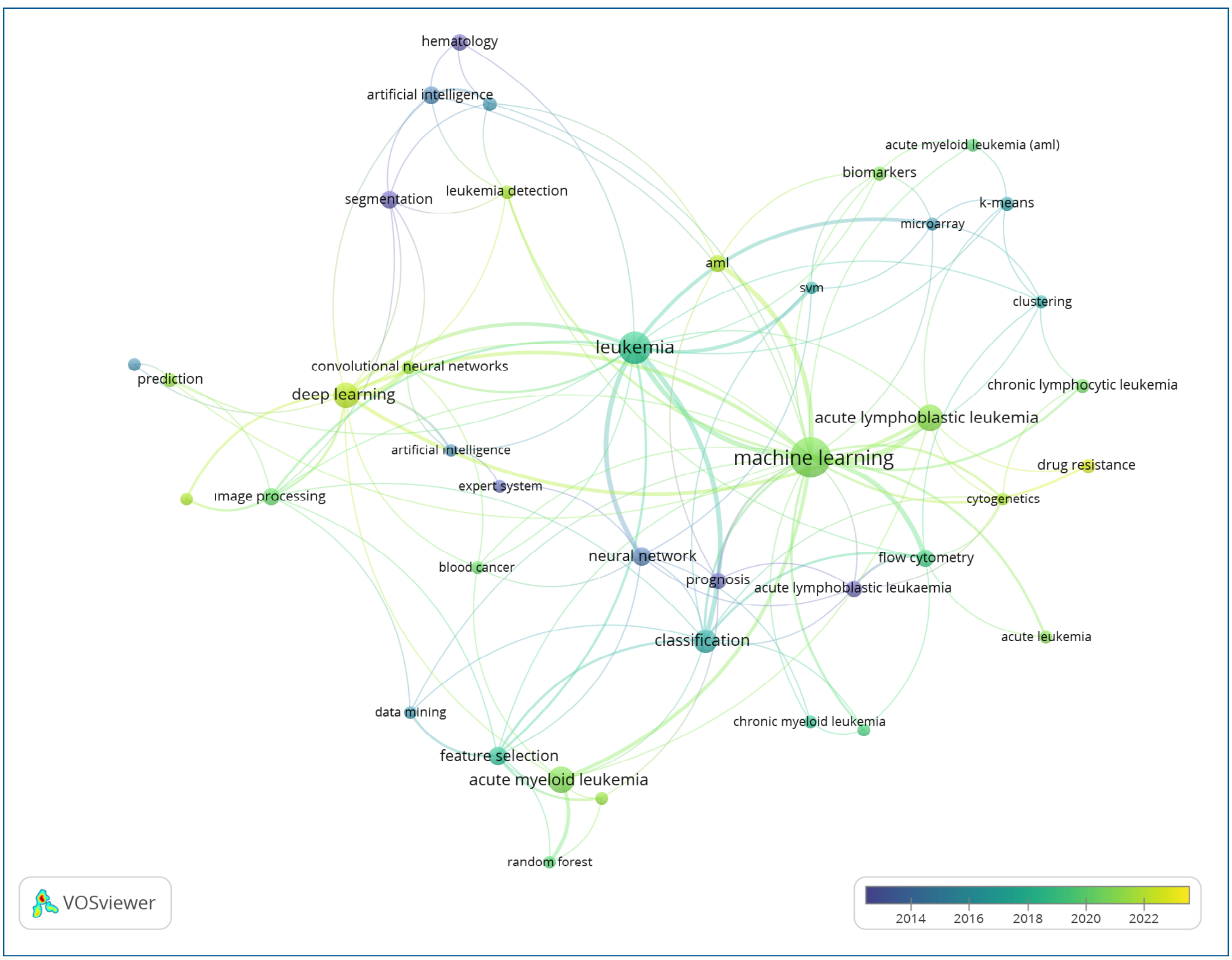

FIGURE 1. Co-occurrence analysis of author keywords from the documents that were manually selected via utilizing the Scopus database. For the colored presentation, the VOSviewer platform was used. The minimum number of occurrences of a keyword was arranged as 3 times in a total of 248 documents. Of the 671 keywords, 42 keywords met the threshold. Corresponding results were colored as in the time of last 10 years and the spectrum varies from dark purple to light yellow. This color-coded representation indicates the trend of keyword usage from 2013 to 2023 by the authors. (Keywords: “artificial intelligence” and “machine learning” and “deep learning” and “neural network” and “leukemia”)

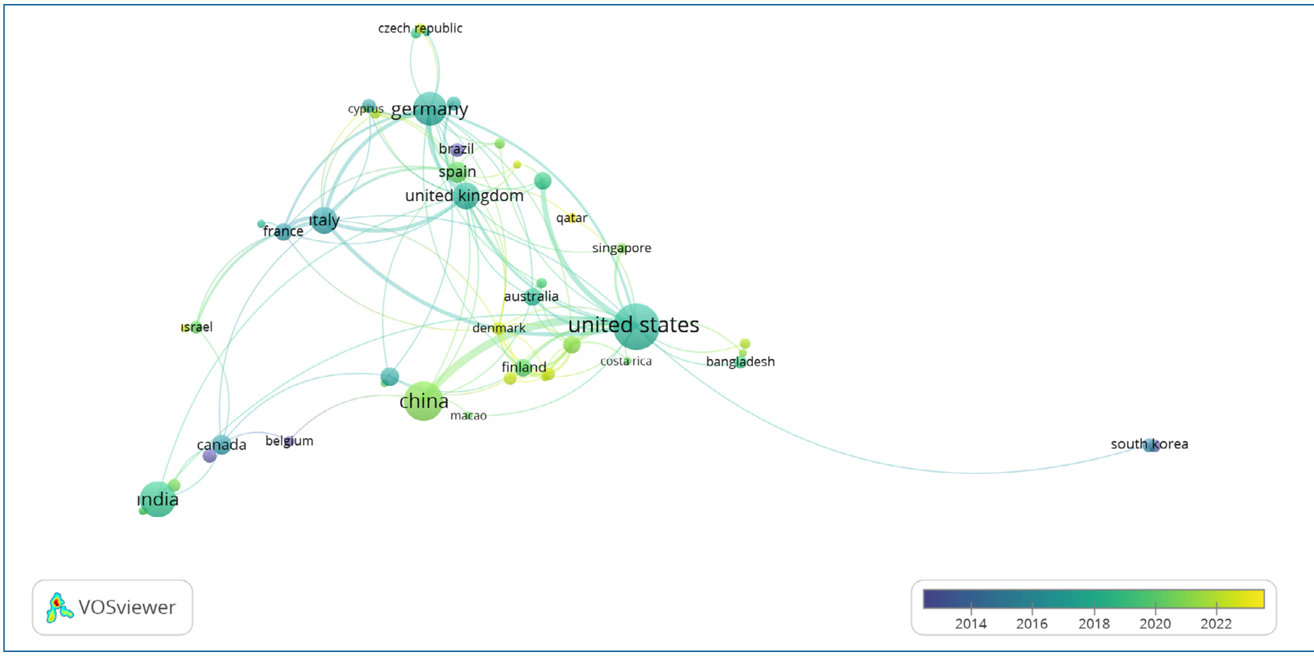

FIGURE 2. Co-authorship analysis of countries via VOSviewer, corresponding data taken by Scopus query search, and 248 documents scanned after filtering. Minimum number of documents of a country was determined as 1. Out of the 60 countries, 47 countries were found to be connected. Corresponding results were colored as in the time of last 10 years and the spectrum varies from dark purple to light yellow. This color-coded representation indicates the trend (color spectrum) country contribution (size of points) and country-based co-authorship (connected lines) between 2013 and 2023. (Keywords: "artificial intelligence" and "machine learning" and "deep learning" and "neural network" and "leukemia")

searchers gain a better understanding of the supergroup, they begin to incorporate the subgroups into their research (Table 1 – Table 2).

Limited Number of Research to Cope with Leukemia in The Era of Technology but Progress Is Promising

Our literature research was conducted by analyzing articles and conference proceedings to catch up on recent applications of AI tools in the field of leukemia management. Even though the oldest document was published in 1989 for the Scopus database in 1994 for WoS, the studies conducted in the following years were not consistent. It was only after 2017 that a steady increase was observed in the number of documents published (determined by Scopus query search) (Figure 5A). Moreover, according to WoS query search, the number of documents published has increased approximately 16-fold since 2012, with a significant increase observed in 2022 (Figure 6A).

Researchers tend to Study Leukemia with Unspecified Subtypes

In the realm of leukemia research, investigators have historically conducted studies on experimental groups with a mix of hematological cancers without any specific focus on leukemia itself. To tackle this issue, researchers have employed the use of AI and its constituents to differentiate between healthy and patient groups and to develop a precise diagnostic tool for leukemia. Initially, the study of microscopic slides of peripheral blood smears was the primary method for researchers. However, with the advent of microarrays and flow cytometry, researchers can now identify genetic landscape and immunophenotypic features, and as such, have shifted their approach to focus more on leukemia, especially AML and acute lymphocytic leukemia.

What Are the Countries' Attitudes Toward the Application of AI Tools in the Case of Leukemia?

One factor that influences the scope of topics in scientific publications is how authors approach a subject recently, and the policies followed by the countries to which they are affiliated. In this context, collaborating with authors from other countries emerges as a phenomenon that influences and enhances the research environment. The way authors from different countries collaborate and work together affects the diversity and richness of the research landscape. In our VOSviewer co-authorship analysis conducted by using Scopus and Wos databases to understand the role of countries in studies that combine leukemia and AI components, we observe that research originating from the United States and China is quite prevalent with comparable to the contribution to the field and as following the trends (Figure 2 and Figure 4). Whether they are located on different continents or

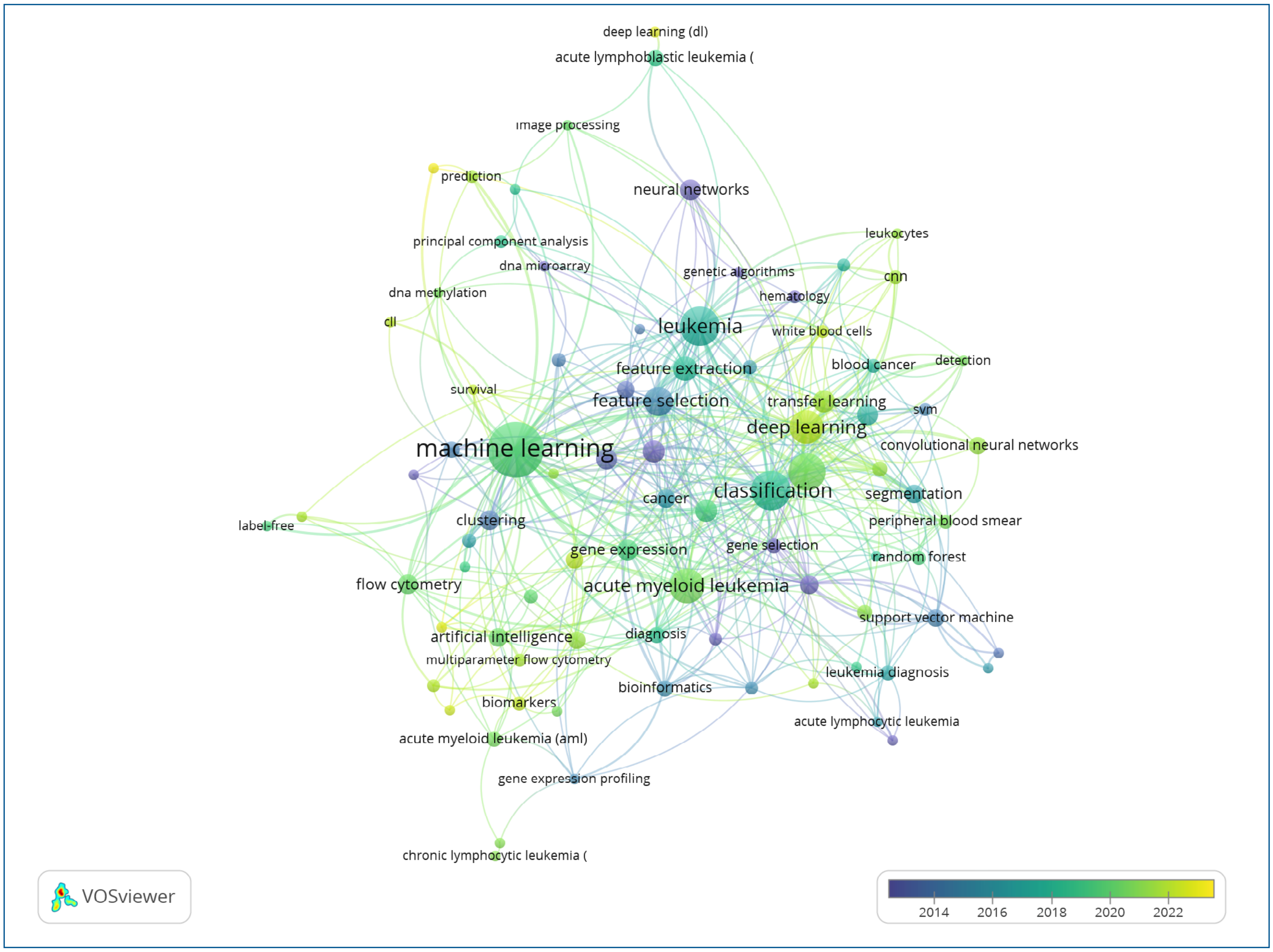

FIGURE 3. Co-occurrence analysis of author keywords from the documents that were manually selected via utilizing the Web of Science database. For the colored presentation, the VOSviewer platform was used. The minimum number of occurrences of a keyword was arranged as 3 times in a total of 473 documents. Of the 1124 keywords, 84 keywords met the threshold. Corresponding results were colored as in the time of last 10 years and the spectrum varies from dark purple to light yellow. This color-coded representation indicates the trend of keyword usage from 2013 to 2023 by the authors. (Keywords: "artificial intelligence" and "machine learning" and "deep learning" and "neural network" and "leukemia")

not, researchers are making collaborations in the way of using AI tools in the case of leukemia.

Publishers and Institutes Are Giving Attention to Study in This Field

Sharing scientific findings through journals or other scientific resources provides numerous advantages as it shapes the current and future direction of a field. Publishing has many benefits that promote scientific progress by bringing together the characteristics of scientific knowledge such as verifiability, reproducibility and sustainability and then presenting these results to the readers. We can also emphasize the importance of the author's working environment, from the production stage to the publication process, as it provides research infrastructure and collaborations. In our research, we found an increase in the number of documents published in peer-reviewed journals on the leukemia-AI tools axis (Figure 5B – Figure 6B) and an increase in the contributions of institutions across the globe which indicates that attention was drawn to this field recently (Figure 5C – Figure 6C).

DISCUSSION

This study examines the use of AI and its components—ML, NNs, and DL —in leukemia research. A search query with inclusion and exclusion criteria was designed to analyze AI applications separately. The literature review utilized Scopus and WoS databases, along with bibliometric analysis tools to identify trends based on keywords, countries, affiliations, and sources. While databases like Google Scholar and PubMed could have ex-

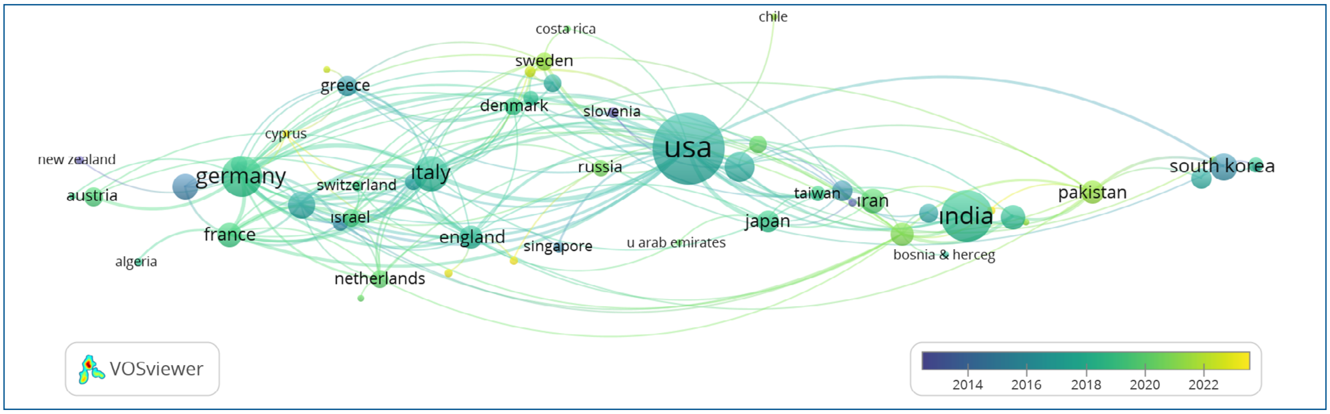

FIGURE 4. Co-authorship analysis of countries via VOSviewer, corresponding data taken by Web of Science query search, and 473 documents scanned after filtering. Minimum number of documents of a country is determined as 1. Out of the 66 countries, 60 met the threshold and 54 countries are found to be connected. Corresponding results were colored as in the time of last 10 years and the spectrum varies from dark purple to light yellow. This color-coded representation indicates the trend (color spectrum) country contribution (size of points) and country-based co-authorship (connected lines) between 2013 and 2023. (Keywords: “artificial intelligence” and “machine learning” and “deep learning” and “neural network” and “leukemia”)

panded the dataset, Scopus and WoS provided the most relevant documents. The study found that ML is widely used for classifying genetic, histological, and morphological characteristics of leukemia, with a focus on myeloid and lymphocytic subtypes. However, research on chronic leukemia subgroups remains limited.

Despite differences in their advantages and the number of documents retrieved, we found no significant differences in the inferences drawn from Scopus and WoS. The country of a researcher’s affiliation significantly affects research scope. Developed countries such as the United States and China play a pioneering role in AI applications for leukemia. AI is expected to be widely utilized in healthcare, but collaboration among physicians, patients, and AI developers is necessary for successful integration. Hematologists need to gain AI literacy to ensure better clinical care and decision-making.

AI’s integration into hematology remains in its early stages. While AI has shown promise in diagnostic precision and efficiency, several challenges persist, including clinical validation, standardization and regulatory approvals (27, 28). AI-based models have demonstrated their ability to classify acute and chronic leukemias based on genetic and morphological patterns, yet their implementation requires physician competency in AI-driven decision-making. AI’s ability to analyze high-dimensional biological data, such as next-generation sequencing (NGS) and transcriptomics, is a significant contribution to leukemia research (8). Machine learning-based classification models have enhanced early detection and risk stratification (29). However, most AI models focus on myeloid and lymphoid leukemias, while chronic leukemia subgroups remain underrepresented. Future research should emphasize AI applications for chronic leukemia progression and treatment response prediction (30).

AI implementation in healthcare raises regulatory and ethical concerns. AI models require extensive patient data, leading to issues regarding informed consent, data ownership, and cybersecurity risks. Regulatory bodies such as the U.S. Food and Drug Administration (FDA) and the European Medicines Agency (EMA) emphasize transparency and explainability in AI-driven decisions. Ensuring that AI models are unbiased and validated across diverse patient populations is critical to preventing disparities in leukemia diagnosis and treatment.

CONCLUSION

In some respects, our research has limitations as the results primarily based on the findings gathered from Scopus and WoS, while these databases are comprehensive, including sources like PubMed or Google Scholar might have provided a more extensive dataset. Furthermore, the study is based on bibliometric analysis and literature review rather than direct experimental or clinical validation of AI applications in leukemia. This limits the ability to assess real-world effectiveness. While AI’s potential in leukemia management is acknowledged, challenges related to data privacy, model transparency, and regulatory approvals are not deeply explored. Also, the study highlights the increasing use of AI in leukemia but does not critically compare the performance of different AI models or algorithms across studies. Additionally, the study primarily focuses on ML, DL, and NN, while other AI subfields like NLP and robotics were excluded.

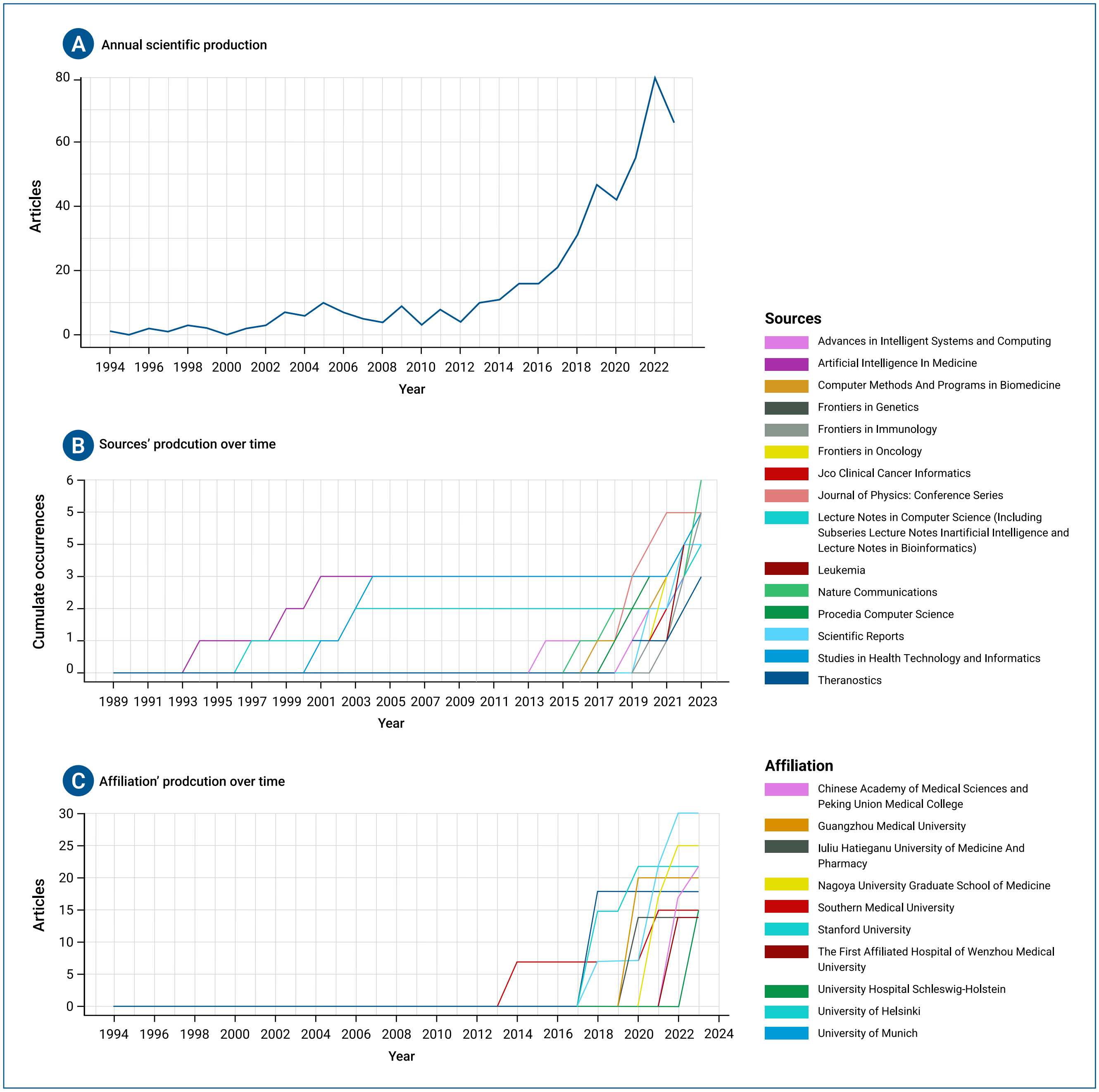

FIGURE 5A. Number of documents taken into account for the bibliometric analysis after utilizing Scopus query search and manual selection of documents. 248 documents are listed in the time interval of 1989-2023. This graph is created via the Bibliometrix-Biblioshiny platform. (Keywords: "artificial intelligence" and "machine learning" and "deep learning" and "neural network" and "leukemia")

FIGURE 5B. Scientific journals that published articles and conference proceedings on AI in leukemia between the years 1989-2023. 248 published documents were categorized according to their corresponding publisher. This graph is created via the Bibliometrix-Biblioshiny Platform. Data were taken from a Scopus query search. (Keywords: "artificial intelligence" and "machine learning" and "deep learning" and "neural network" and "leukemia")

FIGURE 5C. Number of documents retrieved from Scopus query search as indicating the affiliation's production over time (between 1994-2023). (Keywords: "artificial intelligence" and "machine learning" and "deep learning" and "neural network" and "leukemia")

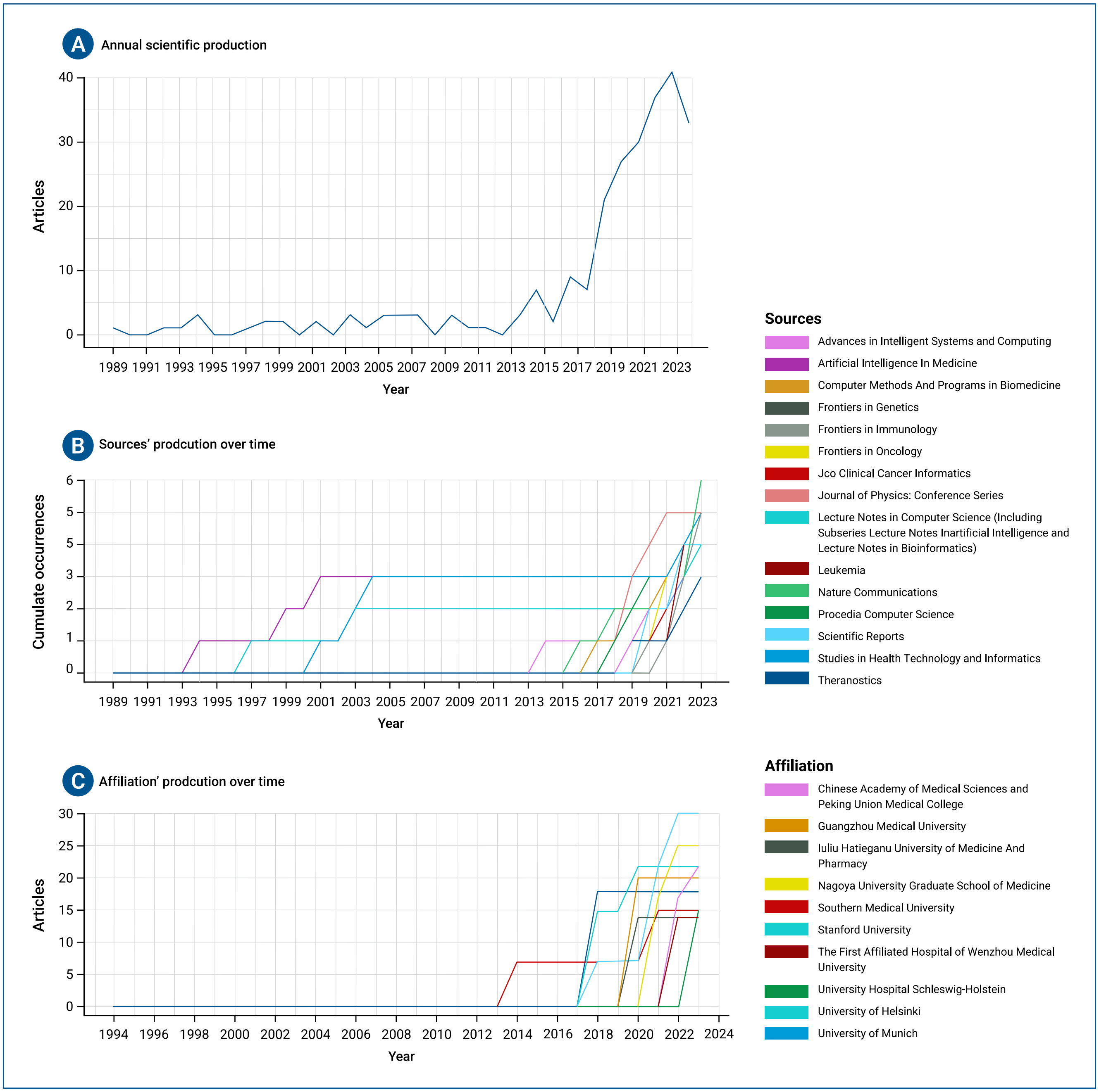

FIGURE 6A. Number of documents taken into account for the bibliometric analysis after utilizing Web of Science query search and manual selection of documents. 248 documents are listed in the time interval of 1994-2023. This graph is created via the Bibliometrix-Biblioshiny platform. (Keywords: "artificial intelligence" and "machine learning" and "deep learning" and "neural network" and "leukemia")

FIGURE 6B. Scientific journals that published articles and conference proceedings on AI in leukemia between the years 1994-2023. 248 published documents were categorized according to their corresponding publisher. This graph is created via the Bibliometrix-Biblioshiny Platform. Data were taken by Web of Science query search. (Keywords: "artificial intelligence" and "machine learning" and "deep learning" and "neural network" and "leukemia")

FIGURE 6C. Number of documents retrieved from Web of Science query search as indicating the affiliation's production over time (between 1994-2023). (Keywords: "artificial intelligence" and "machine learning" and "deep learning" and "neural network" and "leukemia")

The integration of AI in leukemia research and management has significant potential in enhancing diagnosis, treatment, and disease monitoring. Bibliometric analysis highlights the growing impact of AI—particularly ML, DL, and NN—in leukemia research. While AI applications in leukemia have gained momentum since 2017, most studies focus on acute leukemia subtypes, with relatively limited exploration of chronic leukemia.

Machine learning remains the most frequently utilized AI tool, particularly for diagnostic classification and pattern recognition. The increasing number of publications and institutional contributions demonstrates a global interest in AI-driven leukemia research, with the United States and China emerging as key contributors. Despite these advancements, challenges such as data standardization, clinical validation, and ethical considerations must be addressed to ensure AI's effective integration into routine clinical practice.

Future research should focus on expanding AI applications to chronic leukemia subtypes and improving AI-driven predictive models for personalized treatment strategies. Strengthening collaborations between clinicians, data scientists, and AI developers will be crucial in bridging the gap between AI research and real-world clinical applications. As AI continues to evolve, its potential to revolutionize leukemia management remains promising, paving the way for more precise, efficient, and personalized approaches to patient care.

Ethics Committee Approval: N.A

Informed Consent: N.A

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