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Artificial intelligence in healthcare: A bibliometric analysis

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A R T I C L E I N F O

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A B S T R A C T

Background: The implementation of artificial intelligence technology in health care improves disease prediction, classification, and diagnosis, benefiting both patients and healthcare providers. a surge in artificial intelligence popularity, owing largely to an enormous increase in computational capabilities and an even greater increase in data generation. The study's purpose was to conduct a bibliometric analysis on healthcare-related artificial intelligence research from the years 2000 to 2021.

Methods: The Scopus dataset has been used to find and retrieve all existing and referenced healthcare-related artificial intelligence research published in English. Based on bibliometric indicators, the rate of publication growth, the subject area, and the top active countries, institutions, journals, and funding sponsors were analyzed.

Results: The search identified non-duplicated 5,019 papers. During the years 2000 to 2009, there were fewer publications, but they increased in the subsequent years. Moreover, research released after 2012 constitutes 88.88% of the total publications. Overall, 96.85% of the included studies have been published in 9 countries. About 41.84% of the studies included were from the US. The technology keywords that appeared most were "Machine Learning", "Electronic health records", and "Natural language processing". Furthermore, Covid-19, Diabetes, Mental Health, Asthma, Dementia, and Cancer are some of the disease-related keywords that appeared frequently in healthcare-related artificial intelligence research.

Conclusions: The study carried out a thorough bibliometric study on healthcare-related artificial intelligence research, which will help researchers, legislators, and practitioners understand the field's growth and the prerequisites for responsible use of artificial intelligence technology within the healthcare system.

Introduction

Artificial Intelligence (AI) is a subdomain of computing science engaged in the creation of intelligent computer systems. This Intelligent System is a system that is comparable to human behavioral intelligence. Using AI, it is possible to develop systems with human-like reasoning abilities. Its applications include robotics, expert systems, automatic translation programs, speech recognition, natural language statement production, audio analyzers, simulators, and problem-solving theorems [1].

Although the importance of AI is undeniable, there is no widely accepted definition of the term itself. The phrase broadly refers to computing methods that mimic the human cognitive ability-related processes such as thinking, acquiring knowledge and adaptation, sensory ability to comprehend, and engagement. Artificial intelligence technology had quite a great influence on human life in the last decade and also has applications in various fields like engineering, communications, manufacturing, and healthcare [2,3].

AI is mainly driven by massive increases in computing capability and even greater increases in data generation. By combining improved algorithms that allow deep neural network training, many high-tech companies have been able to perform tasks that are close to or even beyond human performance: Playing chess, image processing, speech recognition, and self-driving vehicles are among these examples. The healthcare sector is expected to be the next to undergo a radical change due to artificial intelligence [4–7].

AI-based healthcare system improves disease prediction, diagnosis, and therapies, benefiting both patients and healthcare providers [8]. Applying AI in health care can benefit physicians, patients, and healthcare providers in four ways: i. by estimating the chances of treatment success and analyzing disease onset before treatment initiation; ii. by preventing or managing complications; iii. actively supporting patient care during diagnosis and/or treatment, and iv. by identifying the pathology of the disease, and also the best treatment [9].

The promise of increased diagnosis and treatment accuracy is amongst the most exciting applications of AI in healthcare. It can help healthcare providers diagnose symptoms more quickly than most healthcare experts [10]. By assessing patients' electronic health records horizontally and vertically in a short time, AI can improve diagnosis accuracy by mimicking the predicting capability of human physicians [11]. AI can also assist patients to be aware of complex symptoms, enhance their quality of life, as well as encourage adherence to treatment [12].

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A Study of randomized clinical trials, for example, discovered that an AI system increased medication adherence in stroke patients receiving anticoagulation treatment by 50% [13].

As AI is used more widely in healthcare services, relevant studies are processed more quickly. The existing literature is proliferating. As a result, healthcare-related AI research is steadily growing in current publications. Despite the increased interest in healthcare-related AI studies, just a few bibliometric analyses focus on AI applications in specific types of medical problems, such as depression [14], The COVID-19 Pandemic [15]. Analyzing a bibliometric on healthcare-related AI studies can yield an outline that can allow the researchers to understand better the expansion of AI research in healthcare and the future direction of trends and changes. Keeping up with the rapidly expanding body of AI research in healthcare helps practitioners and policymakers to seize the opportunities for using AI interventions to promote the well-being of patients and caregivers [16].

Bibliometrics is a quantifiable informatic technique for analyzing emerging trends in knowledge structure in a particular field, to obtain measurable, accurate, and detailed information [12]. The bibliometric analysis enables researchers and other stakeholders to acquire a thorough understanding of the subject matter while also enhancing the multidisciplinary approach [17]. The study used bibliometric data to identify research patterns in the healthcare application of artificial intelligence. It is a valuable source for researchers, eager to know about the field and conduct research. In addition, it is a good source for those curious about how an intelligent system can be applied to healthcare services but are unfamiliar with the field.

The study was intended to provide a bibliometric analysis of healthcare-related artificial intelligence research publications from the years 2000 to 2021. And answers the following questions:

1 How are the studies distributed by year?
2 What is the number of studies and citation rankings of the journals?
3 Which countries and institutions are leading and promoting the development of health-related artificial intelligence research?
4 What is the distribution of the studies by subject areas of publications, and funding sponsors?
5 What is the frequency of occurrence of the author-keywords?

Literature review

Over the past few decades, artificial intelligence has been developed and introduced to every area of medicine, from primary care to rare diseases, emergency medicine to biomedical research to aspects related to public health management. According to Forbes, the most important areas for AI will be robotic surgery, virtual nursing assistants, aiding clinical judgment and diagnosis, image analysis, workflow, and administrative tasks [18].

AI-assisted robotic surgery

AI-assisted robotic surgery has been available since 1985 [19]. These include cardiac surgery, thoracic surgery, gastrointestinal surgery, gynecology, orthopedic surgery, spine surgery, transplant surgery, urology, and general surgery [20–23]. Traditionally, surgeons were limited to operating on what could be seen with their eyes, and in general, the only way to see inside a patient is to operate by open surgery. Robotic surgery powered by AI allows surgeons to perform procedures with exceptional precision by inserting cameras and tools through small incisions. Its goal is to reduce postoperative complications and accelerate patient recovery times. With AI-assisted robotic surgery, it is also possible to capture all data and details such as video recording of the surgery, all movements and cutting and sewing actions of ongoing surgery, and use this collected data for further analysis in order to improve and lean the surgery process [24].

When examining the clinical effectiveness of robotic surgery technology, a systematic review of 95 studies published in Canada in 2011 found that AI-assisted robotic surgery in prostatectomy, hysterectomy, nephrectomy, and cardiac surgery has many advantages in clinical outcomes, including shorter hospital stays, lower blood loss and transfusion rates, and fewer complications [25]. Some AI-assisted robotic surgery procedures have reduced operation times, like laparoscopic prostatectomy, while others have increased them, like open prostatectomy and open hysterectomy. The economic evidence for prostatectomy, cardiac surgery, nephrectomy, and hysterectomy was also evaluated in the same review. A cost analysis revealed that shortening the lengths of stay after robotic radical prostatectomy resulted in lower hospitalization costs when compared to laparoscopic and open surgery. [24].

A systematic review was made in 2017 to evaluate patient benefits, cost, and surgeon conditions when using AI-assisted robotic surgery in gynecological oncology. Using AI-assisted robotic surgery as part of treatment for cervical cancer, endometrial cancer, and ovarian cancer was studied by reviewing a total of 76 references. The results indicated that safety in oncological surgery was comparable to earlier surgical techniques, however, AI-assisted robotic surgery will also increase overall costs because of the high costs associated with applying, purchasing, and maintaining the equipment [26]..

Virtual nursing assistants

Modern digitalization has allowed healthcare organizations and actors in healthcare processes to use virtual assistants which are already widely used in other sectors. Using virtual nurse assistants, hospitals can reduce sudden hospital visits and reduce healthcare professionals' workloads. These applications can listen, talk, and provide advice/recommendations. Your.MD is one of the most widely used platforms that meet European Medical Device Directives. The virtual health assistant uses artificial intelligence (AI) and machine learning to provide personalized pre-primary care based on data from the United Kingdom National Health Service (NHS). Patients will access pre-primary care before they access primary care. Using Your.MD, patients can diagnose themselves at home using a mobile app or website. Harvard University and the Royal College of General Practitioners have verified Your.MD benchmark tests to be 85% accurate for the 20 most common medical conditions [27].

Aid clinical judgment or diagnosis

The diagnostic disciplines where AI algorithms have received the most attention are pathology and radiology, but they have also been used to support diagnostic procedures in a variety of other fields, such as dermatology, ophthalmology, gastrointestinal, and cardiology. Recent assessments undertaken by the cardiologist and medical futurist Eric Topol have described some of these uses [28]. The majority of these technologies have only been utilized in research contexts; they have not yet been implemented in standard clinical practice. The U.S. Food and Drug Administration has recently authorized a few applications for usage in therapeutic settings, though [29]. These include the "Idx-DR. system" for detecting diabetic retinopathy and stroke software for CT scans "Viz.AI".

Beyond these well-known instances, several auxiliary settings that affect clinical care already employ AI algorithms. To analyze bacterial growth on agar plates digitally, several microbiology laboratories, for instance, have integrated AI-powered picture recognition software [30]. Similarly, hematology laboratories are increasingly using digital image recognition software that makes use of neural networks to automate activities that were formerly carried out manually by laboratory technologists, such as blood cell differential and morphological analysis [31].

Image analysis

Much research is being done on applying artificial intelligence (AI) in diagnostic medical imaging. AI promises to improve tissue-based detection and characterization and has demonstrated outstanding accuracy and sensitivity in identifying imaging abnormalities [32]. Currently, many AI imaging investigations calculate sensitivity and specificity to determine diagnostic accuracy, whereas others evaluate clinically significant outcomes [33,34]. Imaging pattern alterations that are difficult for humans to identify may be recognized by AI. For instance, employing machine learning to analyze brain MRI data may be more sensitive than a human reader at detecting tissue changes indicative of an early ischemic stroke within a constrained time window following the onset of symptoms [35,36].

Despite the promise of early diagnosis through machine learning, it is unclear whether very subtle alterations detected by AI are associated with gross neurological outcomes. Examples include small evolving infarcts or non-ischaemic processes detected by AI. There is a need to determine whether AI-defined cerebral changes suggestive of early ischemia correlate with a different profile of neurologic disability or benefit from thrombolysis. Furthermore, difficult circumstances might arise in which a recommendation for treatment might be given without a well-defined abnormality detected by routine imaging [36].

Workflow, and administrative tasks

Healthcare systems are characterized by heavy administrative workloads involving multiple actors and organizations: patients (e.g. billing management), health professionals, healthcare facilities, labs, pharmacies, payers, and regulators. There are several possible areas of concern in this highly administrative environment, according to a report done in a primary care setting. These include the time spent pursuing financial compensation, entering information into numerous siloed practice-based information systems, processing data from hospitals and other outside sources, and guiding patients through a disjointed healthcare system. According to the study's findings, bureaucracy accounted for more than 50% of practice time, the majority of which could have been avoided [37].

AI can perform these routine tasks more efficiently, accurately, and unbiased manner. One argument in favor of using artificial intelligence in administrative practices is that errors in these activities are less serious than errors in clinical settings. However, the threat of hacking, a lack of privacy, and a lack of security remain [38,39]. AI applications can be extremely useful in organizing patient flow. Lack of bed availability, for example, is a major cause of surgical cancellations [40], but it is an ovoidable administrative error in patient flow. This problem occurs frequently and is linked to discharge delays in the clinical ward [41].

Methods

The Scopus dataset was used for the search. Because it covers a variety of research fields. Due to the limitations of downloading completed data greater than 2000 papers, the author downloaded papers by dividing the years.

Inclusion criteria

The author conducted a structured search of peer-reviewed journal articles using search terms associated with Artificial Intelligence technologies and Table 1 Healthcare.

Exclusion criteria

gray literature, conference proceedings, and books/book chapters were excluded from the study. Articles published in languages other than English were also not included.

Bibliometric indicators

The retrieved documents were analyzed, and the following bibliometric indicators were obtained: the rate of publications growth, the subject area, and the top active countries, institutions, journals, and funding sponsors. Scopus examines the affiliation of countries as well as institutes in the retrieved documents and counts the number of documents that have the affiliation of a specific country or institution. As a result, the top Nine active countries were determined based on the presence of the country name in the affiliation of the authors, regardless of the author's role in that country. Each country's research output is the aggregate of documents published through international research collaboration (inter-country collaboration) and documents published through intra-country research collaboration.

Visualization

VOSviewer software (version 1.6.17) was used to analyze and visualize author keywords. "Links attribute" and "Total link strength attribute" were used as standard weight attributes. [42].

Result

Publications growth rate

Fig. 1, illustrates the annual frequency distribution of publications. On average, the growth rate of scientific papers on healthcare-related AI research between the years 2000 and 2021 was 37.88%. The year 2020 is ranked first, with 926 published records (18.45%), followed by 2021 with 850 (16.94%) and 2019 with 718 (14.31%) of the total 5019 records collected respectively.

Publications by country

Table 2, depicts 96.85 percent (4861/5019) of the articles included were published in 9 countries. The United States accounted for approximately 41.84% (2100/5019) of the included studies. China came in second (738/5019, 14.70%), subsequently, the United Kingdom (634/5019, 12.63%). It is observed that most of the countries on the list are highly economically developed countries.

Source of publications

Table 3, presents the top 9 journals which published articles on the field of AI in healthcare. The Journal Of The American Medical Informatics Association published the most papers (1099/5019, 21.89%), followed by IEEE Access (652/5019, 12.99%), Journal Of Biomedical Informatics (628/5019, 12.51%), and Journal Of Medical Internet Research (512/5019, 10.20%) respectively.

Documents citation

Table 4, displays the list of 10 most cited documents in the domain of AI in health care including the authors, sources, the respective number of citations, and the citation per year. Data has been accessed from the Scopus dataset search window for the required details. Six of the top ten mentioned papers have been published in one journal, the "American Medical Informatics Association (JAMIA)". The article "Mayo clinical Text Analysis and Knowledge Extraction System (cTAKES): Architecture, component evaluation, and applications" is having high total citation score of 1121, and 93.4 citations per year. Followed by the publication "Personal health records: Definitions, benefits, and strategies for overcoming barriers to adoption" is in 2nd position with 1005 citations and with 62.8 citations per year respectively. Based on the citation per year (CPY), the top 2 papers were recent, Li, S., Wang, et.al (2020) with 372, and Chen, M., Hao,.et.al. (2017) with 101.6.

Table 1
Search query terms.

Construct	Search key terms
AI-related terms	("artificial intelligence") OR ("computational intelligence") OR ("machine learning") OR ("deep learning") OR ("decision trees") OR ("decision forest") OR ("expert system*") OR ("fuzzy logic") OR ("automatic programming") OR ("autonomous robot*") OR ("intelligent agent*") OR ("neural net*") OR ("voice recognition") OR ("text mining") OR ("electronic health record* ").
Health-related terms	(health) OR ("healthcare") OR ("medicine")
Document types	Articles
Language	English
Period	2000–2021

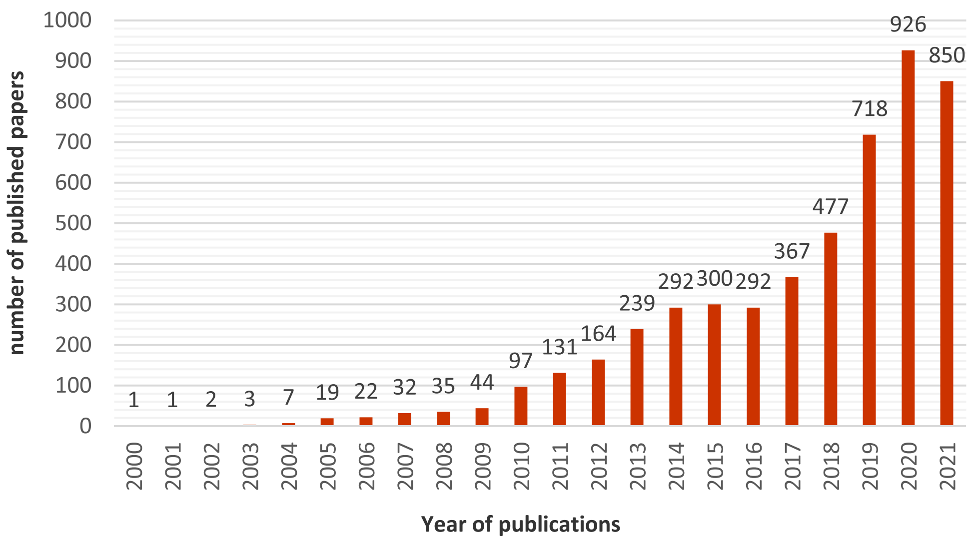

Fig. 1. Publication counts by Years.

Table 2
. Publications distribution by top 9 countries.

Rank	Countries	Output(N = 5019)
1st	United States	2100 (41.84%)
2nd	China	738 (14.70%)
3rd	United Kingdom	634 (12.63%)
4th	Canada	286 (5.69%)
5th	South Korea	273(5.44%)
6th	Australia	267 (5.32%)
7th	Spain	223 (4.44%)
8th	Netherlands	172 (3.43%)
9th	Germany	168 (3.35%)

Subject areas publications

The Scopus subject categories were used to specify the research domains of the included articles, as revealed in Table 5. It is found that the maximum contribution on the topic of healthcare-related artificial intelligence research was done by the field of Medicine 2226 (44.35%), followed by Computer Science 947(18.87%) respectively. Whereas, some articles are published by Engineering, Material Science, and other mentioned domains.

Publications by affiliations

Publications are affiliated with corporate, government, medical, and other institutions. To ascertain the affiliation, documents were analyzed in the study. Based on the number of scholarly publications recorded in the Scopus database. The top 9 most productive institutions are from the US. Fig. 2 indicates that Harvard Medical School considered the most productive academic institution which is the majority of publications (328 publications) are at the top of the list, followed by the Brigham and Women's Hospital (223 publications), University of Texas Health Science Center at Houston (148 publications), Columbia University (146 publications), and Mayo Clinic (143 publications). respectively.

Funding sponsor

The study identified the most productive and prominent institutions that had funded the development of healthcare-related AI research.

Table 3
Publications distribution by top 9 journals.

Journals	Output(N = 5019)	Citations(N = 114,194)
Journal of the American Med. Inform. Association	1099 (21.89%)	41,806 (36.61%)
IEEE Access	652 (12.99%)	12,856 (11.26%)
Journal of Biomedical Informatics	628 (12.51%)	16,709 (14.63%)
Journal Of Medical Internet Research	512 (10.20%)	10,620 (9.29%)
BMC Medical Informatics And Decision Making	510 (10.16%)	9457 (8.28%)
BMJ Open	413 (8.23%)	4925 (4.31%)
Applied Clinical Informatics	410 (8.17%)	3959 (3.47%)
International Journal Of Environmental Research And Public Health	400 (7.97%)	4297 (3.76%)
Plos One	395 (7.87%)	9565 (8.38%)

Table 4
Top 10 Highly Cited articles.

Document Title	Authors	Year	Source	TC	CPY
Mayo clinical Text Analysis and Knowledge Extraction System (cTAKES): Architecture, component evaluation, and applications.	Savova, G.K., Masanz, J.J., et.al	2010	Journal of the American Medical Informatics Association. 17(5), pp. 507–513	1121	93.4
Personal health records: Definitions, benefits, and strategies for overcoming barriers to adoption.	Tang, P.C., Ash, J.S.,et.al	2006	Journal of the American Medical Informatics Association. 13(2), pp. 121–126	1005	62.8
The impact of covid-19 epidemic declaration on psychological consequences: A study on active weibo users.	Li, S., Wang, Y., Xue, J., Zhao, N., Zhu, T.	2020	International Journal of Environmental Research and Public Health 17(6),2032	744	372
2010 i2b2/VA challenge on concepts, assertions, and relations in clinical text.	Uzuner, Ö.,.,et.al	2011	Journal of the American Medical Informatics Association. 18(5), pp. 552–556	625	56.82
The impact of electronic health records on time efficiency of physicians and nurses: A systematic review.	Poissant, L., Pereira, J., et al.	2005	Journal of the American Medical Informatics Association. 12(5), pp. 505–516	604	35.53
Bio2RDF: Towards a mashup to build bioinformatics knowledge systems.	Belleau, F., A., et. al	2008	Journal of Biomedical Informatics. 41(5), pp. 706–716	557	39.78
Methods and dimensions of electronic health record data quality assessment: enabling reuse for clinical research.	Weiskopf, N.G., Weng, C.	2013	Journal of the American Medical Informatics Association. 20(1), pp. 144–151	550	61.11
Disease Prediction by Machine Learning over Big Data from Healthcare Communities	Chen, M., Hao, Y., Hwang, K., Wang, L., Wang, L.	2017	IEEE Access 5,7,912,315, pp. 8869–8879	508	101.6
Harnessing context sensing to develop a mobile intervention for depression.	Burns, M.N., et.al.	2011	Journal of Medical Internet Research. 13(3), pp. e55	389	35.36
Next-generation phenotyping of electronic health records.	Hripcsak, G., Albers, D.J.	2013	Journal of the American Medical Informatics Association. 20(1), pp. 117–121	366	40.67

Note: TC=Total Citation CPY= Citation Per Year.

Table 5
Publications distribution by top 9 research domains.

Rank	Research domains	Output(N = 5019)
1st	Medicine	2226(44.35%)
2nd	Computer Science	947(18.87%)
3rd	Engineering	366(7.29%)
4th	Material Science	365(7.27%)
5th	Health Professions	230(4.58%)
6th	Environmental Science	224(4.46%)
7th	Agricultural and Biological Sciences	222(4.42%)
8th	Biochemistry, Genetics, and Molecular Biology	221(4.40%)
9th	Multidisciplinary	218(4.34%)

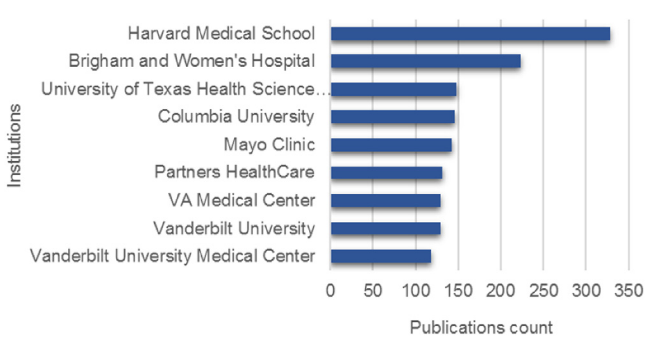

Fig. 2. The number of publications by the top 9 Affiliations.

Fig. 3, shows the top 9 funding institutions and the corresponding number of publications. The "National Institutes of Health" was the leading institution with 641 publications. Followed by the "U.S. National Library of Medicine" with 554 publications. The "National Natural Science Foundation of China" with 372 publications, the National Center

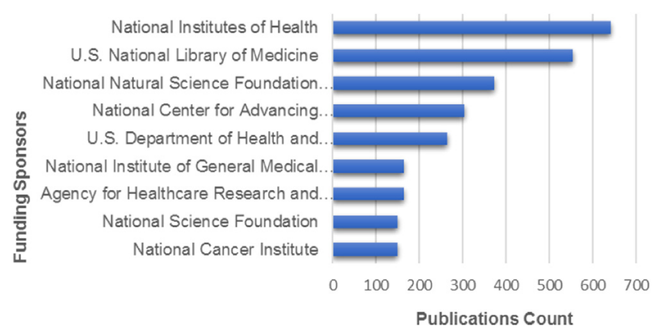

Fig. 3. The number of publications by the top 9 funding sponsors.

for Advancing Translational Sciences with 303 publications, and others were mentioned.

Visualization of authors' keywords

Fig. 4 shows the co-occurrence of the authors' keywords using the full count method., which means that each occurrence of a keyword in a document is counted. Out of a total of 9063 keywords, the network visualization selected where the keywords appeared at least 10 times, resulting in 256 keywords grouped in 8 clusters displayed on the network diagram. The diagram shows several colored and differently sized circle fields, which are connected at a shorter or longer distance. Color is part of a group or a cluster. This group mapping identifies topics with highly interconnected aspects. The size of the circle is determined by the frequency of use. The more often a keyword is used in the document, the larger its circle. Distances between keywords represent connections, shorter distances mean stronger associations between keywords, and the connection of terms in studies is symbolized by lines.

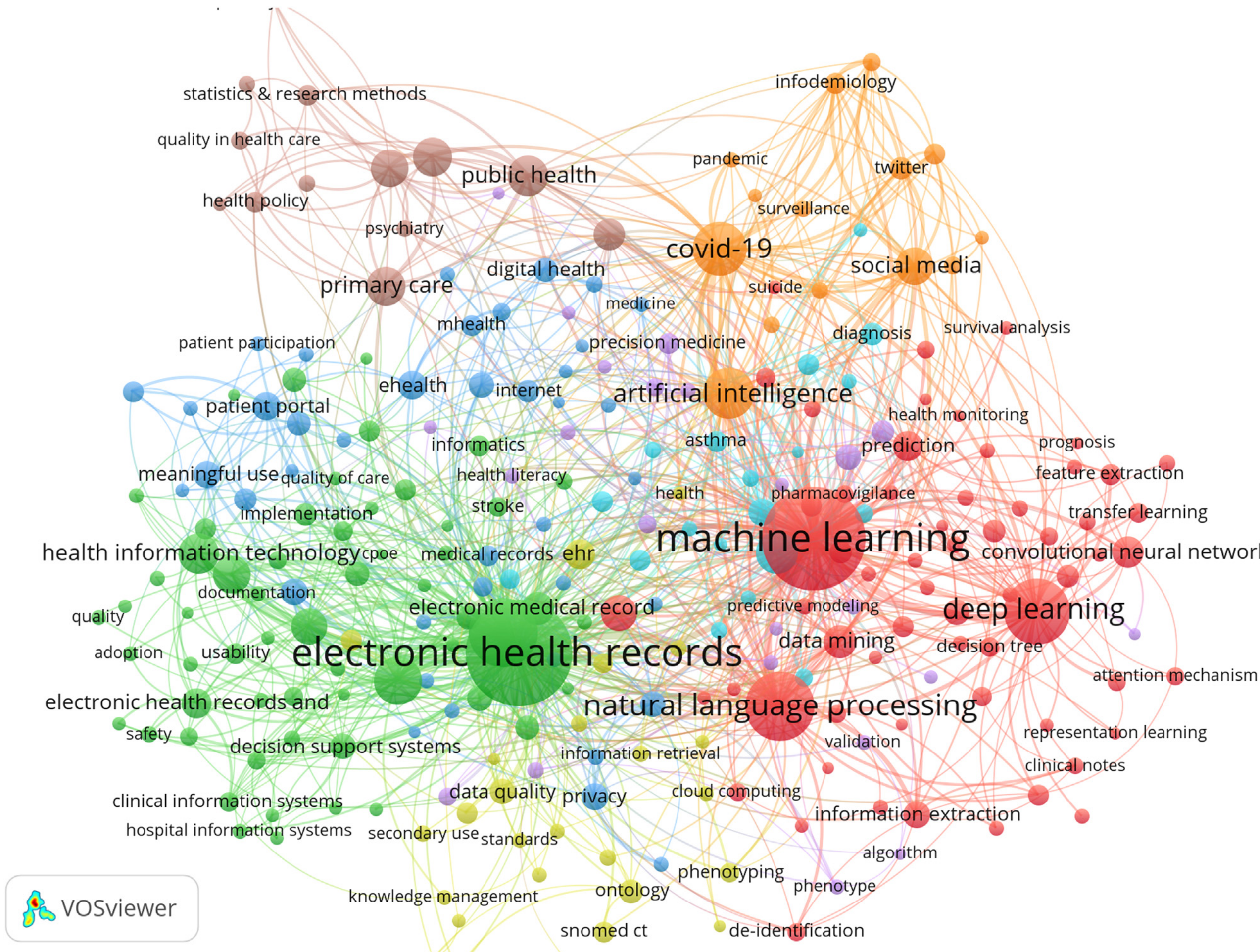

Fig. 4. Co-occurrence of Author's keywords.

As illustrated in the diagram, "Machine learning", "Natural language processing", and "Deep learning" are some of the most common Artificial intelligence approaches that frequently used keywords. "Electronic health records" also demonstrated their importance for patient safety in the digital health systems, in the area of clinical decision support systems. Generally, "learning", "machine", "artificial", "data", "intelligence", "deep", "health information system", and "clinical decision support system" were the most popular topics. This reflects the advances achieved in AI-based healthcare systems.

Discussion

The current study considered bibliometric data to analyze published scientific works in the healthcare application of artificial intelligence. The findings are discussed below.

Out of the 5019 documents retrieved, all of them were journal articles. The number of articles published between 2000 and 2009 was low, but there was an increase in the later years. Moreover, papers produced after 2012 constitute 88.88% of the total publications. This shows further research was conducted in the formative years to understand how AI technology could be involved in applications for our day-to-day medicine and healthcare activities. That means the rise of automated systems, speech synthesis, neural nets, and deep learning opened up previously unimagined possibilities for disease prediction, diagnosis, treatment, and management [43,44].

Research on the use of artificial intelligence in healthcare has drawn researchers from around the globe, but high-income countries dominate the field. The United States contributed about 41.84% of the studies in the field. The USA spends a high amount of money on Artificial Intelligence studies, which have evolved into leading edge, revolutionary life-enhancing innovations, rising technology industry, motivating workers, and boosting security interests. In comparison, this research field in non–high-income countries remains small because many low-income countries have limited healthcare resources, but their public health issues are growing dramatically as a result of rapid globalization and urbanization [45].

There are developed countries, for instance, the UK, that have launched federal AI healthcare policies that include guidance on the development and regulation of AI technology in healthcare, A typical example is the UK "Code of Conduct for Data-Driven Health and Care Technology" [46]. Consequently, most research outputs were generated in developed countries, even though 80% of the global population resides in developing countries. These disparities are caused by several factors, including funding, prioritization, research capacity, infrastructure, and language [47]. Artificial intelligence technologies are promising for progressing healthcare services in developing nations with scarce healthcare resources. Healthcare-related AI research is generally favored by large-scale journals related to healthcare. Various information technology and engineering advancements have paved the path for Artificial Intelligence to develop [16].

Among the top 9 sources based on the results, IEEE Access was the only journal that nearly reached 652 papers, researchers can see a dominance of medical journals and journals dealing with medical informatics. Moreover, no traditional journals from other fields, such as information systems, operations management, or operations research, were among the top eight. Besides that, the "American Medical Informatics Association" publishes six of the ten most highly cited publications on this subject, demonstrating the publisher's dominance in the field.

The research also considered authors' keywords, which represent the main research topics of the publications [48]. Fig. 4 shows the prominence of 256 Authors' keywords list which appear on the Scopus database in the search results. The technology keywords that appeared most were "Machine Learning", "Electronic health records", and "Natural language processing". Whereas some of the keywords that appeared frequently in the domains of disease in AI research were, Covid-19, Diabetes, Mental health, Asthma, Dementia, and Cancer. Healthcare-related Artificial intelligence research has primarily focused on diseases that are the leading causes of death. By 2030, chronic diseases will account for 80% of all human deaths, resulting in a serious global disease burden [49–51]. As a result, researchers are concentrating their aspirations and endeavors on early detection and condition management using advanced AI technology [52,53].

Artificial intelligence technology is increasingly popular in the areas of medical diagnosis, prediction, detection, classification, treatment, and disease survival prediction [54–56]. It has a key role in advancing healthcare quality within the health system [57]. Because of the benefits, AI can assist physicians in making a much better medical determination or even substitute human being decisions in certain responsive medical fields [58].

Conclusions

Artificial intelligence has been used for a variety of purposes. This concept is evolving and changing daily, and it has become widespread, particularly in the healthcare field, as investments in this technology have increased. This study examined the trends in healthcare-related artificial intelligence research that were indexed in the Scopus dataset. In recent decades, the rate of publication growth has accelerated. The main factor in increased publications productivity has been the increased adoption of artificial intelligence technology in healthcare, which has resulted in the transformation of healthcare services. This has been motivated by the fast dispersion of technology, which has resulted in an increased demand for improved healthcare quality as manifested in improved patient health. In this context, the study can be a source for state-of-the-art AI diffusion as reflected in publications data. Furthermore, it assists scholars, legislators, as well as practitioners in better understanding the evolution of healthcare-related artificial intelligence research and also, the prerequisites for responsible use of artificial intelligence in healthcare settings.

Limitations

limitations of the work: i. The author believes that the Scopus database is large enough to provide a diversity of publications necessary for this analysis; however, future studies will use other databases, such as WOS, to examine more papers. ii. The author did not include gray literature (i.e., books) or papers written in languages other than English. Due to this, relevant studies conducted in different formats and languages may be overlooked. Research in the future can increase the range of searches to incorporate more relevant research to enrich the literature.

Declarations

Competing interests

No competing interests.

Contributorship

Not applicable

Funding

None

Ethical approval information

Ethical approval did not require for this study because no persons' were included. The review analyses and investigates obstructions to the execution of EMR systems' previously published papers.

Data sharing statement

Not Applicable

Patient and public involvement

Not applicable

Declaration of Competing Interest

No Conflict of Interest

Acknowledgments

Not applicable

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