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Evolutionary impacts of artificial intelligence in healthcare managerial literature. A ten-year bibliometric and topic modeling review

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A R T I C L E I N F O

Keywords:
Healthcare
Artificial intelligence
Bibliometric review
Topic modeling

A B S T R A C T

Background: In the last five years, there has been an accelerated growth in the scientific production about Artificial Intelligence and Healthcare by Scholars of the most diverse disciplines. Recently, the scientific corpus has been enriched with considerable literature reviews ranging from the overview of large collections of scientific documents to the recognition of the state of knowledge on specific aspects (e.g., in the medical field, ophthalmology, cardiology, nephrology, etc.).
Methods: The methodological approaches belong to the scientific fields of bibliometrics and topic modeling. Following a bibliometric analysis of the literature on the subject, conducted on a vast collection of scientific contributions, we also searched for the "latent" themes in the semantic structures of these documents, identified the relationships between them and recognized the most likely to be investigated in the future.
Results: Results show 24 topics about future trends in literature review connecting the field of AI and Healthcare.
Conclusions: This bibliometric review of the literature on artificial intelligence and healthcare allows identifying of some privileged areas of attention by scholars of different disciplines. However, it also reveals the limits of hard clustering techniques, as demonstrated by the presence of some keywords in several groups. The numerous existing reviews must be integrated by reviews based on Topic Modeling techniques, which make it possible to identify topics, historical trends (classical and emerging topics), associations between the documents and to predict, on a probabilistic basis, which scientific fields will be most likely to see development in the future.

1. Background

The complex set of concepts and technologies generally identified as "Artificial Intelligence" (AI) finds one of the most relevant and dynamic fields of application within the healthcare sector. Artificial intelligence and health evoke two areas in impetuous evolution whose boundaries are widening with at a pace that could accurately be described as daily. The combination of these two worlds, which, at first glance, may seem to be far removed from each other, has grown increasingly synergistic and intuitive. This convergence has led to the emergence of a novel domain, referred to as "Health AI" [1,2].

In the spiral of reciprocal interdependencies between the growth in demand for collective and individual health - further intensified by recent pandemic events - and the swift digitalization of socio-economic activities, the entire world of healthcare is taking on new and rapidly evolving physiognomies; so much so that Topol [3], in the subtitle of his book dedicated to Deep Medicine, introduces the reader to how "Artificial Intelligence can make healthcare human again". The applications of computer systems capable of carrying out tasks typically requiring human intelligence in healthcare are many. Both the Web and scientific literature offer basic taxonomies of such applications, for some of which it is possible to refer to Wang et al. [4], Bohr & Memarzadeh [5], Boonstra & Laven [6].

In recent years, the convergence of AI advancements with the surge in health data availability and enhanced processing capabilities has given rise to a new class of AI solutions that have a significant impact on every facet of healthcare ([7–9]; Bertalan [10]).

These solutions leverage cutting-edge Machine Learning and Deep Learning techniques, Natural Language Processing, and Computer Vision to analyze and interpret large datasets (big data). Their development can trace its ideological roots back to the 1950s, specifically to Turing's seminal question, "Can machines think?" (1950) [11], explored

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Table 1
Some previous bibliometric reviews about AI and Healthcare.

Article reference	Publication year	Years considered	Publications considered	Keywords searched	Bibliometric software(s) used	Database(s) used
Sohn, Noh, Lee, & Kwon [21]	2018	2012–2017	7324	precision medicine & al.	KnowledgeMatrix Plus, Gephi and VOSviewer	WoS
Gu, Li, Wang, Li, et al. [22]	2019	2000–2017	4820	AI & chronic diseases	HistCite, CiteSpace, MS Excel	WoS
Gu, Li, Wang, Yang, & Yu [23]	2019	1992–2017	3085	IT and Health	HistCite, CiteSpace, NetDraw, and NEViewer, SATI	WoS
Gupta & Katarya [24]	2020	2010–2018	1240	social media-based surveillance systems that predict the disease in real-time	Systematic SLR	(IEEE, ACM Digital Library, ScienceDirect, PubMed) f
Hussien, Yasin, Udzir, Ninggal, & Salman, [25]	2021	2016–2020	941	blockchain technology in the healthcare industry	R	WoS e Scopus
Islam et al. [26]	2021	2020–2021	1697	AI applications in Covid-19	VOSviewer, R	WoS
Saheb, Saheb, & Carpenter [27]	2021	any period	585	ethics of artificial intelligence in healthcare	VOSviewer	Scopus
Secinaro et al. [15]	2021		288	"Artificial Intelligence" OR "AI" AND "Healthcare" with a focus on "Business, Management, and Accounting", "Decision Sciences", and "Health professions".	Systematic SLR	Scopus
Wang et al. [4]	2021	Up to 2020	8444	digital/healthcare/covid	VOSviewer and CiteSpace	Scopus
Ahsan, & Siddique [28]	2022	Up to 2021	346 (47)	Health & Industry 4.0	VOSviewer	Scopus and WoS
Stoumpos, Kitsios and Talias [29]	2023	2008 to 2021	5847 (321)	"digital transformation", "digitalisation", "Ehealth or e-health", "mhealth or m-health", "healthcare" and "health economics"	VOSviewer	Scopus, Science Direct and PubMed
Ali, Abdelbaki, Shrestha, … Alryalat, Dwivedi [30]	2023	2010–2021	180	"artificial intelligence OR "machine learning" OR "data processing" AND "healthcare" OR "medical centre" AND "benefit" OR "advantage" OR "feature" AND "challenge" OR "issue" AND "methodologies" AND "functionality"	Systematic	EEE, Emerald, IS Web of Knowledge, and Scopus

Source: Authors' elaboration.

in some aspects in the following years [such as Samuel's [12] demonstration of a machine that could outperform its programmer in checkers, Quinlan's [13] work on decision-making machines, and many others]. In healthcare, big data from diverse sources—Electronic Health Records (EHRs), wearable devices, and patient-generated data—aid healthcare professionals and decision-makers in several domains [14]. These include precision medicine, risk prediction and prevention, drug discovery and development, and Robotic Process Automation for administrative and managerial tasks.

The healthcare sector stands out as one of the most data-rich yet, at the same time, one of the least digitalized sectors [15,16]. In recent years, however, there has been a growing interest in the use of AI solutions in healthcare, mainly driven by 3 factors:

- the exponential increase in data availability due to the growth of EHRs (Electronic Health Records) and other digital health initiatives;
- the swift advancement of AI technologies, especially in the area of Deep Learning;
- the pressing need to tackle some of the healthcare sector's foremost challenges, including escalating costs, chronic disease management, and the acceleration of drug development.

Precision medicine represents one of the most promising applications of AI in healthcare [17–20]. AI technologies can be used to analyze vast amounts of data —including genomic information, patient medical records, and clinical trial outcomes— to identify patterns and correlations that can help develop highly personalized treatment strategies for each patient. In the past, precision medicine was constrained by the scarcity of data and the insufficient computational power. However, with the recent advancements in AI and machine learning, it's now feasible to process and analyze large datasets swiftly and with a high degree of accuracy. Consequently, precision medicine is increasingly being employed to craft tailored treatment plans for patients, marking a significant leap forward in personalized healthcare.

AI can also be used to forecast a patient's likelihood of developing specific diseases and to detect early indicators of illness. This insight can be used to develop preventative strategies and to design more effective treatments, taking into account a variety of factors such as the patient's medical history, genetic data, and lifestyle information.

AI is also playing an increasingly important role in the field of drug discovery and development, areas known for their lengthy and costly processes that can extend over a decade to introduce a new drug to the market. AI can be used to rapidly screen extensive collections of chemicals and biological compounds, identifying those with the highest likelihood of success. Furthermore, AI can streamline the clinical trial phase by identifying patients who are most likely to benefit from a specific treatment, thereby accelerating the development timeline.

Robotic process automation (RPA) is another domain where AI is

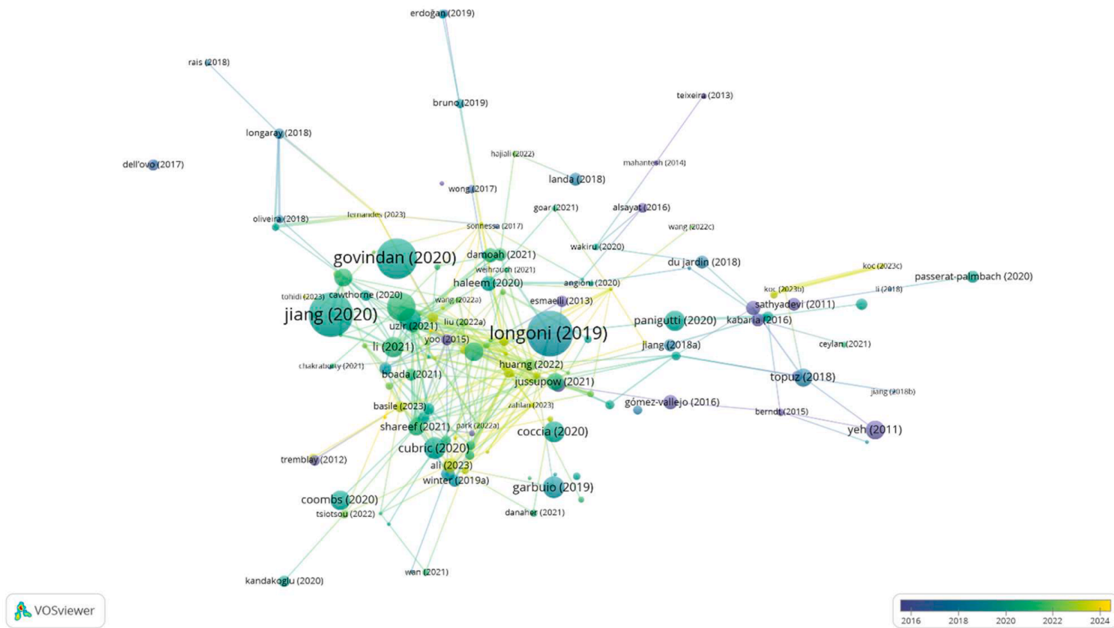


Fig. 1. . Bibliographic coupling of the documents.

starting to have an impact in healthcare. RPA is a form of artificial intelligence that can be used to automate mundane and repetitive tasks like data entry and claims processing. This automation can help free up clinicians' time to dedicate more time to activities that add greater value, such as patient care.

CHATBOTS, exemplified by the increasingly popular ChatGPT & Meta Sam, serve as pivotal AI applications within healthcare, simulating human conversation to effectively interact with patients. These sophisticated tools support patients by delivering treatment information, coordinating appointment schedules, and other services that enhance the patient experience. ChatGPT & Meta Sam, with their advanced conversational capabilities, can considerably reduce the communication overhead for healthcare providers by managing a significant volume of routine inquiries, thereby allowing medical professionals to allocate more time for patient care. In addition to streamlining workflows, these interactive chatbots play a crucial role in assisting patients with appointment reminders and medication adherence, leveraging their AI capabilities to personalize the interaction and ensure a higher level of patient engagement and health management.Numerous others potential applications of AI in healthcare exist, signaling that the health sector is at the beginning of an AI-driven transformation that will have a profound impact on the way care is provided and managed.

At the same time, in recent years, there's been a surge in interest in bibliometric reviews, which employ quantitative methods to evaluate the academic contributions of individuals, institutions, or entire fields of study. These reviews can provide valuable insights into patterns of research productivity, emerging trends, and areas of potential impact.

Despite their popularity, bibliometric reviews have been criticized for several reasons. First and foremost, their approach is commonly challenged for being overly simplistic and not taking into account significant elements such as publication bias. Second, their findings are frequently contested on the grounds that they are too broad and not precise enough to be useful to practitioners. Finally, how these evaluations are conducted is frequently criticized for being inefficient and time-consuming.

Despite these criticisms, bibliometric reviews can be a valuable tool for researchers and practitioners alike. When used correctly, they can provide insights into the latest trends and developments within a specific research domain. Additionally, they can be used to identify gaps in the literature and to inform future research directions. In this paper, we argue that there is still value to be gained from additional bibliometric reviews, particularly when they are designed to address specific research questions. We believe that well-designed bibliometric reviews can complement traditional narrative literature reviews and contribute to our understanding of the current state of scholarship in a given field. In essence, bibliometric reviews are a beneficial complement to the existing body of literature on AI and healthcare.

A "free" search on the Web, conducted without the aim of being exhaustive, already yields a wealth of literature reviews on the topic of AI and healthcare, including numerous studies employing bibliometric methods. Among these, some are accompanied by a searchable full-text, which is essential for identifying the databases and software utilized, clarifying the research questions addressed, and outlining the limitations arising from the compilation of the reference document set, as detailed in Table 1.

Our bibliometric review differs from others in two key ways. First, we cascade the bibliographic coupling and the co-occurrence of keywords [31]. This allows us to identify not only which papers are citing each other, but also which keywords are being used in conjunction with each other. Second, we use a combination of manual and automated methods to identify the relationships between papers. This ensures that our results are both accurate and comprehensive. The paper is organized as follows: after setting the stage for our investigation in the Introduction, we delve into the methodological framework employed in our study, rooted in the scientific disciplines of bibliometrics and topic modelling, in the following section (Methods). We describe our approach to conducting a bibliometric analysis on a broad corpus of scientific contributions related to AI and healthcare. Additionally, we

Table 2
Distribution of topics over the complete collection.

Topic 16	10,34 %	patient	decis	hospit	treatment	data	inform
Topic 2	8,43 %	technolog	industri	develop	care	servic	challeng
Topic 12	6,33 %	decis	support	data	process	patient	physician
Topic 5	6,07 %	predict	machin	data	featur	techniqu	network
Topic 18	5,95 %	data	learn	process	machin	record	care
Topic 8	5,08 %	emerg	report	support	respons	organ	decis
Topic 22	4,73 %	solut	busi	area	valu	type	technolog
Topic 3	4,73 %	hospit	care	process	perform	provid	qualiti
Topic 10	4,56 %	technolog	experi	market	user	effect	factor
Topic 15	4,28 %	expert	fault	condit	mainten	diagnosi	simul
Topic 21	4,11 %	imag	cancer	test	diseas	diagnosi	trial
Topic 20	3,69 %	servic	qualiti	applic	custom	chatbot	solut
Topic 1	3,41 %	risk	safeti	chain	product	construct	condit
Topic 4	3,32 %	risk	diseas	algorithm	peopl	citi	surveil
Topic 17	3,28 %	consum	app	govern	privaci	insur	provid
Topic 14	3,13 %	strategi	price	uncertainti	access	distribut	water
Topic 9	2,98 %	data	valu	innov	challeng	set	context
Topic 6	2,97 %	qualiti	user	answer	chatbot	peopl	air
Topic 11	2,93 %	covid19	peopl	patient	technolog	coronavirus	softwar
Topic 19	2,87 %	adopt	sector	robot	hospit	covid19	care
Topic 13	2,86 %	facil	demand	locat	solut	select	devic
Topic 23	1,76 %	framework	structur	ethic	drone	engin	applic
Topic 7	1,17 %	worker	autom	construct	recommend	work	safeti
Topic 24	1,04 %	student	group	emot	monitor	care	anxieti

detail our process of uncovering the "latent" themes within the semantic structures of the documents, identifying the connections among them, and recognizing themes likely to be focal points of future research. Then, in the Results section, we present our findings, which uncover 24 distinct topics that signal future directions in the literature connecting AI and healthcare. The obtained results are discussed in Section 5. This section is crucial for understanding the specific areas of AI application in healthcare that are poised for significant advancement and exploration. In the concluding section, we reflect on the insights gained from our bibliometric review, noting the identification of key areas of interest among scholars from various disciplines, arguing for the necessity of supplementing existing reviews with those based on Topic Modeling techniques.

2. Methods

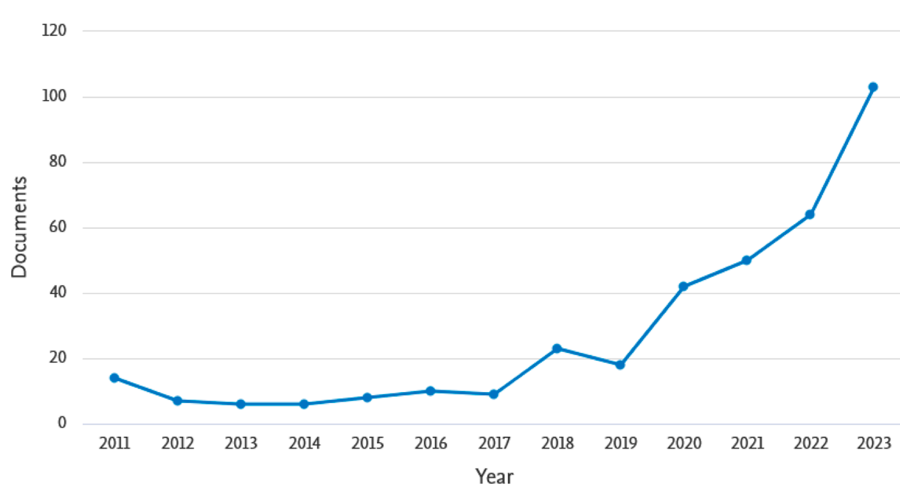
Literature reviews are an essential part of academic research, providing an overview of the existing literature on a topic and identifying gaps in knowledge [32]. There are a variety of ways to conduct literature reviews, including narrative ones, systematic [33], and bibliometric [34]. All these methods have their limitations, and more recent literature has begun to explore the use of topic modeling techniques for literature reviews [35]. This work uses a combination of both bibliometric analysis and topic modeling techniques to conduct a comprehensive literature review, due to their complementary strengths in uncovering patterns, trends, and gaps within the extensive body of literature on our topic of interest.

2.1. Data collection and descriptive analysis

The search for ["artificial intelligence" AND ("healthcare OR health")] in the keywords of articles and conference papers classified in the Scopus Subject Area "Business Management Accounting" with the limitations detailed in the Appendix returned 383 results (263 articles and 101 conference papers).

The main features of the database thus obtained are summarised in Graphs 1 and 2 and briefly described below. The development over time of scholarly attention to the topic is described in Graph 1, which allows us to observe, as a preliminary remark, that this attention has been growing exponentially since 2017: this accounts for the recent consideration by scholars and a foreseeable tumultuous development in the future.

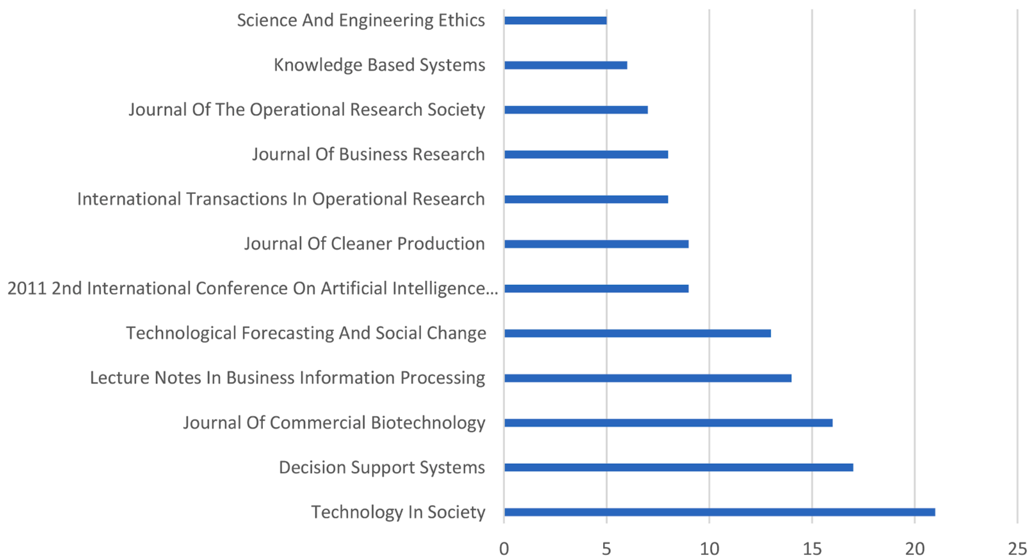
Graph 1 – Over time development of scholars' attention to the topic of AI and healthcare



Source: Authors' elaboration based on the data collected in Scopus.

The scientific journals that host the most contributions on the topic are presented in Graph 2, testifying the strong technological roots and the relevance of the theoretical and technical issues in the support of enhanced decision-making.

Graph 2 – Analyzed documents by source



Source: Authors' elaboration based on the data collected in Scopus.

2.2. Bibliometric analysis

In the early days of information science, people looked for ways to organize and make sense of the rapidly growing body of scientific knowledge [34]. Among the methods conceived we find bibliographic coupling [36], co-citation analysis [37,38], and the co-occurrence of keywords or words in abstracts and/or full text. All of these can be used to identify groups of papers on similar topics, as well as relationships between different fields of research. Bibliographic coupling of documents is a measure of the similarity between two documents based on the number of references they share in common. Bibliographic coupling has been used to study a wide range of topics, from the history of science to the spread of ideas. It is a powerful tool for understanding the structure of knowledge, and it continues to be used by scholars all over the world. Co-citation analysis, on the other hand, measures the similarity between two documents based on the number of times they are cited by other documents. Finally, keywords or words co-occurrence coupling measures the similarity between two documents based on the topics they discuss. Each of these methods has its strengths and weaknesses, and all three can be used to complement each other to create a more complete picture of document similarity. We opted for bibliographic coupling in our analysis due to its unique ability to map the intellectual structure of a field. By examining shared references between documents, this method offers insights into how knowledge areas converge, revealing the foundational works and emerging themes. This approach aligns with our goal to understand the evolving landscape of AI applications in healthcare, identifying core topics and potential areas for future research.

2.3. Topic modeling

Topic modeling is a method for exploring large collections of documents. It can help automatically discover the hidden structure in given data and cluster similar documents together. This can be a valuable way to explore a dataset or to make sense of a large amount of unstructured data. The seminal work of Blei et al. [39] introduces the Latent Dirichlet Allocation (LDA) algorithm, which is now widely used in topic modeling. Latent Dirichlet Allocation (LDA) is used to discover hidden themes in a collection of documents and has been applied to a wide range of literature review tasks such as automatically identifying key topics [40], detecting emerging trends [41], and recommending similar papers [42].

Topic modeling provides an alternative solution to manual clustering of articles and allows the identification of non-obvious connections between ideas expressed in a collection of works [43].

In addition to this, probabilistic topic modeling [44] is a particular approach to topic modeling based on statistical methods. It is a flexible and powerful technique that can be used to discover hidden themes in large amounts of scientific papers.

Among the softwares available for topic modeling we used KH Coder, an open-source software for computer-assisted qualitative data analysis, particularly quantitative content analysis and text mining [45].

The pre-processing phase for the topic modelling analysis was carried out in two phases, the first of which consisted of stemming and lemmatizing the words included in our sample. Stemming and lemmatization are crucial preprocessing steps in text mining, aiding in both reducing data dimensionality and enhancing machine learning algorithm performance. Stemming simplifies words to their base form or stem; for instance, "running" becomes "run." Lemmatization, while similar to stemming, goes a step further by identifying a word's canonical form or lemma, not just its stem. Thus, "running" would be lemmatized to "to run". It's important to note that while these processes streamline text analysis by normalizing word variations, they inherently do not account for multiple meanings or select among different senses of a word directly. To address the concern of capturing and selecting the appropriate meaning or "mother word" while eliminating other meanings, it is necessary to employ additional context-based techniques. These include the use of Part-of-Speech (POS) tagging and context-aware lemmatization algorithms, which help in discerning the appropriate base form of a word based on its usage within a sentence. KH Coder includes tools like the Stanford POS Tagger and the Snowball stemmer for part-of-speech tagging and stemming, allowing us to refine our preprocessing for topic modeling, ensuring to a certain degree that the dimensionality reduction does not oversimplify the textual data to the point of losing essential semantic nuances. In the second step of the preprocessing phase, structured abstract labels, copyright statements, Html tags and numbers were removed in addition to the following series of general stopwords: "*research, studi, paper, manag, approach, result, method, use, time, articl, implic, find, author, issu, publish, emerald, design, author, scienc, keyword, taylor, franci, research, studi, paper, manag, approach, result, method, use, time, articl, implic, find, author, issu, publish, emerald, design, author, scienc, keyword, taylor, franci, health, system, healthcare, intellig, ai, model, ieee, review*". The search terms used (healthcare, intelligence, management) were also excluded due to their prevalent occurrence across the dataset, aiming to highlight the principal words connected to them.

3. Results

3.1. Bibliometric analysis

Similarly to previous studies in the field (see Table 1 above), this study extensively incorporates VOSviewer, a distinguished software designed for visualizing and analyzing bibliometric networks, in order to conduct the bibliometric analysis [46]. Originated from Leiden University, VOSviewer is adept at creating comprehensive maps from bibliographic data, encompassing authorship, citations, and notably, bibliographic coupling networks [47]. Such networks reveal the interconnectedness of scholarly articles through shared references, offering insights into the cohesion of research themes and the evolution of scientific discourse. VOSviewer's utility extends beyond visualization; it includes an array of analytical tools that dissect the intricate relationships within academic literature. A notable feature of VOSviewer is its adaptability, allowing for customized overlays and modifications in visual presentation to suit specific research inquiries. These capabilities not only make the tool a cornerstone for bibliometric studies but also enhance understanding of geographical and thematic linkages across scientific inquiries.

To conduct our bibliographic coupling analysis using VOSviewer, we first exported the collected bibliographic data from the database (Scopus) in a specific format (CSV) compatible with the software. We then decided the minimum number of citations of a document to consider. Setting a higher threshold can help focus on more influential or central documents in a field, ensuring the analysis highlights the most significant contributions. Conversely, a lower threshold allows for a broader exploration, capturing emerging trends and lesser-cited works that might be gaining traction. We chose to run the analysis using a threshold value of 3, considering the rapid pace of innovation and the diverse range of subtopics, aiming to capture both well-established research areas and emerging innovations. Thus, of the 383 documents included in the sample, the largest set of connected items sharing at least 3 citations consisted of 147 items. The resulting bibliographic map, obtained running the clustering and layout algorithms, is presented using overlay visualization in Fig. 1.

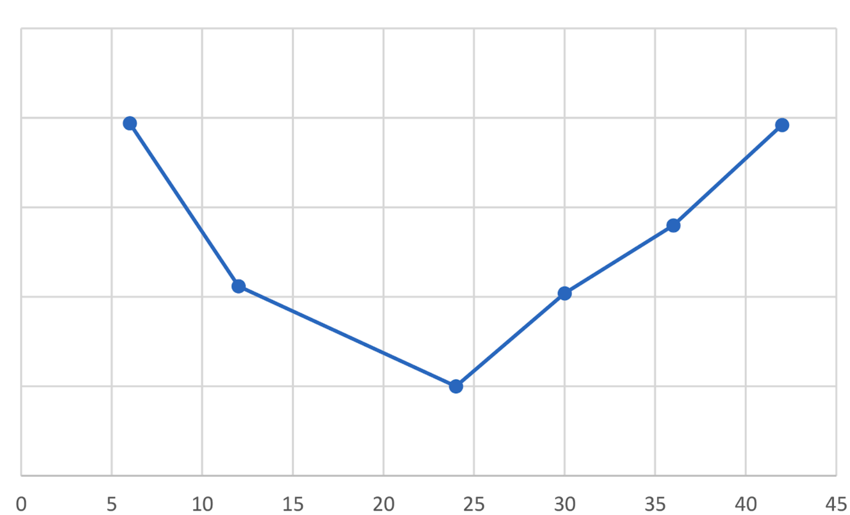
The different nodes represent individual articles, with the lines indicating shared references, suggesting these articles are related in terms of their content. The size of each node reflects the number of citations or the importance of each article within the network. The varying colors represent the publication year, providing a temporal view of the research activity. The clusters of closely positioned nodes suggest areas of concentrated research or topics that have seen a lot of collaborative or parallel work. In particular, the clusters we were able to identify cover a range of studies, such as AI's impact on healthcare services during COVID-19 [48], ethics and implementation of AI in public surveillance, and decision support systems in clinical settings. Other clusters discuss AI in marketing science, violence risk management, and the importance of information systems for food traceability. Further topics include AI's effects on hotel management during pandemics, hospital readmission prediction models, and multicriteria decision making in healthcare facility location. There's also focus on AI's role in home healthcare systems, the ethical design of healthcare drones, and blockchain applications in health data privacy.

3.2. Topic modeling

The bibliometric analysis has offered a structured overview of existing research connections and influential works within the AI in healthcare literature. However, as delined in the methodology, to deepen the understanding and uncover the subtler, thematic undercurrents that permeate this body of work, we're complementing this approach with topic modeling analysis. Topic modeling can reveal underlying patterns and topics not immediately obvious through bibliometric means, providing a more nuanced and forward-looking perspective on where the field might be heading.

To start, the determination of the optimal number of topics to consider in the topic modeling analysis was carried out using the perplexity function of KHcoder, which returned 24 (Graph 3) as the optimal number of topics. Perplexity can be defined as a measure of how well a probability model predicts a sample. In other words, it measures how surprised the model is by new data. A low perplexity means that the model is not surprised by new data, and therefore it is considered to be a good model. The idea is to find the point where the perplexity starts to increase sharply. This point indicates that adding more topics does not improve the model and may even make it worse. Therefore, this point should be considered as the optimal number of topics.

Graph 3 – Optimal number of topics (perplexity)



The results obtained from the analysis are thus presented in Table 2, in the form of a list of 24 topics extracted from the literature, each assigned a percentage indicating its relative prominence in the dataset. Each topic is characterized by a set of keywords that commonly co-occur in the documents. The highest percentage topic relates to "Patient Health," suggesting a significant focus on patient-oriented research within AI in healthcare. Other notable topics include "Health Industry," "DSS (Decision Support Systems)," "Prediction," and "Machine Learning," each reflecting different research concentrations in the field. The diverse range of topics, from "Ethics" to "Quality" and "COVID-19," illustrates the multifaceted nature of AI applications in healthcare research. These results reveal the prevailing themes and the spread of scholarly focus, informing potential directions for future investigation.

4. Discussion

In addition to indicating the topics to which the attention of Scholars is most directed (Table 2), the analysis of its trend over time relating to each topic allows us to highlight those for which attention is increasing, decreasing or substantially stable (see Fig. A1 in the Appendix – Supplementary Materials). An upward trajectory in the graph associated with a particular topic suggests that scholarly focus on that topic is growing. Conversely, a downward trend would indicate waning interest. Stable lines across time could imply a consistent level of interest without significant changes.

Given their higher relative prominence and their emergent nature in the current research landscape, we decided to focus on the first five topics. These topics represent core areas where AI is making significant inroads in healthcare, reflecting trends that are pressing, transformational, and indicative of future directions. By concentrating on these topics, the study aims to delve deeper into the most impactful and innovative areas, likely to yield valuable insights for both immediate application and long-term strategy in health AI research and practice.

4.1. Topic 16 – patient

The use of artificial intelligence in hospitals has the potential to improve patient care in several ways. For example, AI can be used to help with diagnosis, by providing support to doctors in making treatment decisions. AI can also be used to help manage patients' records and to provide information to doctors and nurses about patients' conditions. In addition, AI can be used to develop new treatments and drugs and to test them on patients. Li et al. [49] describe how an AI-driven solution was used to reduce patient waiting time in a hospital without an appointment system to improve healthcare service quality. The study found that it is feasible to use an AI-driven solution to reduce patient waiting time, that analytical models help identify characteristics of patient flow problems, that the implementation of a few performance factors gives most of the improvements, and that theory of constraint (TOC) is a method that can be applied to improve patient service quality. Meyer et al. [50] proposed a method to improve decision strategies by using data mining classification techniques to predict and eliminate treatment failures. The method is demonstrated by examples of its application to a chronic disease care problem in healthcare and a manufacturing task. Arpith et al. [51] develop a system that would allow patients to share their medical records with doctors using a decentralized system. The system would use a Decentralized Application as an interface to the Blockchain network. Artificial Intelligence and Machine Learning would be used to give patients and doctors further insight into medical records. However, an equally important aspect that warrants our attention is the consumer resistance to AI-driven healthcare. Longoni, Bonezzi & Morewedge [52] explore consumer receptivity to AI in medicine revealing a significant hurdle: the perception of uniqueness neglect. This concept captures the consumer's concern that AI, despite its advanced capabilities, may not fully appreciate the individual's unique characteristics and circumstances as effectively as a human healthcare provider might. This suggests a deep-seated skepticism towards the capacity of AI to provide personalized care.

4.2. Topic 2 - health industry

The use of artificial intelligence (AI) in the medical equipment industry is growing rapidly. This is due to the rapid development of AI technology, which has led to significant improvements in the accuracy and efficiency of medical equipment. AI-based medical equipment can help doctors to diagnose and treat diseases more accurately and quickly, as well as to provide personalized treatment plans for patients. In addition, AI-based medical equipment can also help reduce the cost of healthcare by reducing the need for expensive diagnostic tests and procedures. [53] discuss different ways that artificial intelligence can be used in healthcare and how it should be regulated by law. The author makes some suggestions about how to improve legal support for using digital technologies in healthcare. Madanian [54] summarizes the applications of RFID concerning the tracking of patients' records, reminding doctors of appointments, and helping with decision-making. Ozalp et al. [55] argue about how digital platforms are changing the healthcare and education industries. It explains how platforms like Google and Facebook are providing data services to these industries, and how this is helping them to improve their products and services.

4.3. Topic 12 – DSS

DSSs are often used in healthcare to support clinical decision-making, such as diagnosis and treatment selection. They can also be used to help with administrative tasks such as resource allocation and budgeting. Healthcare decision-makers face a number of challenges when trying to make good decisions. They must deal with a large and constantly changing body of knowledge, as well as uncertainty about the future. DSS can help by providing access to relevant information and decision models. DSS can also help decision-makers to communicate and collaborate with other members of the healthcare team. By sharing information and ideas, DSS can help to improve the quality of decisions made. There is a growing body of evidence that demonstrates the effectiveness of DSS in healthcare. Several studies have shown that DSS can help to improve the quality of clinical decision making: Sathyadevi [56] uses different algorithms to classify diseases and compare their effectiveness. The researchers found that the CART algorithm was the most accurate in classifying diseases. Abouzahra et al. [57] are discussing a study of a particular kind of computer system that helps doctors make decisions. The study found that some things (like how the system affects patients) make doctors more likely to keep using the system, while other things (like how it threatens their professional identity) make them less likely to keep using it. Hectors et al. [58] present a new way to calculate the fatigue life of welded railway bridges. The old way, which is used in the Eurocode, is not as accurate as this new method. This method uses hot spot stresses to get a more accurate calculation. This will help decision-makers when it comes to railway bridge maintenance.

4.4. Topic 5 – prediction

Predicting clinical outcomes is a challenging task that requires the application of complex mathematical models and a wide range of statistical techniques. Many factors can influence the outcome of a clinical trial, and it is difficult to account for all of them in a model. Furthermore, the outcomes of individual patients may vary significantly from one another, making it even more difficult to make accurate predictions. Despite these challenges, researchers are continually working to improve their ability to predict clinical outcomes. In recent years, advances in machine learning have made it possible to develop models that are better at predicting the outcomes of individual patients than traditional models based on data from entire trials. These methods have proved particularly useful in predicting the long-term outcomes of patients who have undergone surgery or other medical procedures. Despite these advances, predicting clinical outcomes remains an extremely challenging task. Further improvements will likely be made in the future as researchers continue to explore new methods and data sources for predicting patient outcomes. Topuz et al. [59] are discussing how machine learning techniques can be used to help predict kidney transplant outcomes. A study was done that looked at different ways to predict outcomes and found that a combination of different machine learning techniques and literature review was the most accurate. Ceylan & Atalan [60] look at different ways to use artificial intelligence to predict healthcare spending in Turkey. It uses a lot of big words, but basically, they tried different methods and found that the best way to predict healthcare spending is by using a combination of the random forest method and the genetic algorithm-based feature selection method. Gangavarapu et al. [61] discuss using data modeling and prediction algorithms to predict clinical outcomes from raw clinical notes. Srinivasan et al. [62] describe a new algorithm that can predict health problems better than existing methods. The new method, called RBAIL, is faster and more accurate than other methods, and can also adapt to changing data better. The algorithm has been validated with different types of data and is observed to work well.

4.5. Topic 8 – emergency

Health emergencies, especially those caused by the emergence of new viruses like the novel coronavirus, influenza A, and monkeypox, can arise suddenly and with little warning, challenging even the most prepared systems. The speed and unpredictability with which these viruses spread necessitate real-time data analysis, predictive modeling, and rapid decision-making processes to manage public health crises effectively. These viruses' rapid spread and mutation call for innovative and adaptive responses. Artificial intelligence (AI) steps into this breach, offering tools for real-time data analysis and predictive modeling that can dramatically improve emergency responses. The application of AI in these scenarios is manifold, from tracking virus spread and predicting outbreak patterns to assisting in vaccine development and evaluating public health strategies. For instance, the study by Yang et al. [63] sheds light on how data can be harnessed to comprehend and tackle epidemics like the coronavirus, while the IMPRESS system presented by Liapis et al. [64] exemplifies a decision support framework designed to enhance the coordination of emergency health operations, integrating data from diverse sources to streamline response activities. Zhu et al. [65] further discuss how AI technology, in conjunction with 3S technology, can not only aid in the prevention and control of public health emergencies but also bolster the government's response capabilities. Moreover, the adjustments made by organizations to continue functioning during pandemics, as studied by Kuika Watat et al. [66], often incorporate AI to adapt to new working conditions and maintain service delivery. AI's predictive power, therefore, becomes invaluable in not just managing the current crisis but also in preparing for future ones, ensuring that healthcare systems and governments can respond with agility and informed precision. The integration of Artificial Intelligence (AI) and robotics, as highlighted in a study focused on the hotel industry, reveals parallel advancements in response to COVID-19. This study proposes a research agenda emphasizing AI's role in enhancing hygiene, cleanliness, and healthcare services, crucial areas during the pandemic [67]. By examining the hotel sector's response to the pandemic, including the adaptation of AI for improved guest safety and service, we can draw valuable insights for the healthcare industry. This cross-sectoral analysis not only illustrates the versatility of AI applications in crisis situations but also signals a shift in management practices and consumer behavior, which healthcare providers can leverage to enhance patient care and emergency preparedness.

4.6. Topic 13 – health facilities location

The issue to locate health facilities is a significant one. The location of these facilities can have a profound impact on the quality of care that patients receive. There are many factors to consider when determining the best location for a health facility, including access to transportation, availability of resources, and the needs of the community. Studies on this topic represent only 2.86 % in the entire sample surveyed but are growing. Dell'Ovo et al. [68] research about finding the best location for a healthcare facility in Milan, Italy. The Flexible and Interactive Tradeoff (FITradeoff) method is used to help make the decision. This method is easy for decision-makers because it doesn't require a lot of effort. The paper describes how the decision was made and includes the opinions of four different people who were interviewed as part of the process. Dell'Ovo et al. [69] propose a new way to pick the location of healthcare facilities. The way it is usually done is by taking into account several issues and having different stakeholders weigh in on the decision. However, this new method, called the Flexible Interactive Tradeoff method, requires less effort from the decision-maker and still takes into account all the issues. Erdoğan et al. [70] introduce FLP Spreadsheet Solver, an open-source program that can help you make decisions about where to put facilities. The program uses a Tabu Search algorithm, which looks at different options and then chooses the best one. The paper includes a case study about using the program to help choose locations for healthcare facilities.

5. Conclusions

This bibliometric and topic modeling review underscores the dynamic interplay between technological advancement and healthcare delivery, highlighting areas of substantial interest among scholars and identifying emergent trends that promise to redefine patient care, operational efficiencies, and decision-making processes. As AI technologies continue to evolve, their application within healthcare settings has demonstrated a remarkable capacity to enhance precision medicine, streamline administrative tasks through robotic process automation, and aid in diagnostics and predictive analytics. However, the integration of AI into healthcare is not without its hurdles. Challenges related to the seamless adoption of AI technologies, including data privacy concerns, the need for interdisciplinary collaboration, and the ethical implications of AI decisions, persist. These obstacles underscore the importance of a nuanced approach to the development and implementation of AI solutions, one that balances innovation with ethical considerations and patient safety. While the trajectory for AI and big data in healthcare is promising, with substantial evidence of their potential to transform the industry, considerable work remains to ensure that these technologies fulfill their promise in a way that is ethical, equitable, and enhances the quality of patient care.

This article presents important implications for managers and policymakers. For managers, the article stresses the importance of fostering an environment that encourages innovation while ensuring that AI implementations are aligned with ethical standards, patient safety, and privacy regulations. It suggests that managers should not only focus on the technological aspects of AI but also on organizational readiness, including staff training, change management, and stakeholder engagement. For policymakers, the findings emphasize the need for developing robust frameworks that support the sustainable, equitable deployment of AI across the healthcare ecosystem. This involves crafting policies that facilitate research and development, address data governance issues, and ensure that AI benefits are accessible to all segments of the population, thereby mitigating disparities in healthcare access and quality. Furthermore, the article advocates for continuous collaboration between technologists, healthcare professionals, regulators, and patients to navigate the complexities of AI integration effectively. By doing so, it aims to harness AI's potential responsibly, ensuring that innovations in AI contribute to a more effective, efficient, and equitable healthcare system.

In addition to the natural limitations of bibliometric analysis methodologies and the potential oversight of recent top-journal papers due to our reliance on Scopus analysis and topic modeling, we recognize the inherent constraints of these approaches. The algorithms behind bibliographic coupling and topic modeling might not capture all relevant high-impact papers, especially those in top journals, due to their specific search and analysis parameters. This could lead to certain seminal works being overlooked, underscoring the importance of complementing these methodologies with thorough manual review and analysis to ensure comprehensive coverage of the field While this bibliometric review of the literature on artificial intelligence and healthcare allows identifying of some privileged areas of attention by scholars of different disciplines (this is the case, for example, of ethics in the disciplinary field "healthcare science & services "Or" Internet of Things "in the computer science, information systems area) from another reveals the limits of hard clustering techniques, as demonstrated by the presence of some keywords in several groups (one for all, the keyword" big data ").

The numerous existing reviews (structured, bibliometric, systematic, etc.) must be integrated by reviews based on Topic Modeling techniques, which make it possible to identify topics, historical trends (classical and emerging topics), associations between the documents and to predict, on a probabilistic basis, which scientific fields will be most likely to see development in the future.

CRediT authorship contribution statement

Fabrizio D'Ascenzo: Conceptualization, Formal analysis, Supervision, Validation, Writing – review & editing. **Andrea Rocchi:** Conceptualization, Formal analysis, Investigation, Validation, Visualization, Writing – review & editing. **Francesca Iandolo:** Conceptualization, Investigation, Validation, Visualization, Writing – original draft. **Pietro Vito:** Investigation, Methodology, Software, Visualization, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.sftr.2024.100198.

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