ACHSM Asia-Pacific Journal of Health Management shape

CONFAB 360 DEGREE 2025

EVALUATING AI-ENABLED HEALTHCARE SERVICES: A BIBLIOMETRIC AND TOPIC MODELLING ANALYSIS OF SCHOLARLY PUBLICATIONS

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ABSTRACT

This study examines emerging topics and trends in Artificial Intelligence (AI)-enabled healthcare services, with a particular emphasis on service quality, diagnosis, and treatment enhancement due to the emergence of technology. This study aimed to identify the primary themes found in scholarly publications and examine how those themes have significance in the healthcare sector.

Bibliometric and topic modelling techniques were used to analyse the extracted set of relevant publications. For bibliometric analysis, the bibliometric package Biblioshiny was used in R version 4.4.1, and Latent Dirichlet Allocation (LDA) was utilised for topic modelling. Academic papers from Scopus are included in the dataset, covering the period from 2011 to 2024.

The research analysis highlights that there is a substantial emphasis placed on the use of artificial intelligence in the healthcare industry, notably in the areas of improving diagnosis, treatment personalisation, and operational efficiency related to services provided in the healthcare sector.

KEYWORDS

Artificial intelligence, healthcare, topic modeling, bibliometric analysis, service quality, precision medicine

INTRODUCTION

Artificial Intelligence (AI) has catalyzed a revolution in the healthcare industry that can match the disruption that the industry has observed in the industrial past and it is altering diagnosis, treatment, monitoring and service delivery [1]. This change can be best conceptualized in the context of social-technical system theory, innovation diffusion theory, and theory of quality in healthcare that can explain the opportunities, in addition to, impediments in the change adoption. The term AI used in the study means computational systems that can accomplish tasks that usually demand human intelligence, including the interpretation of data, decision-making, and responsive learning, and in the given study, related to healthcare governance, diagnosis, and patient care. As much as AI has brought better precision, efficiency, and personalisation, regulatory compliance (GDPR, HIPAA, TGA), ethical aspects, cost of deployment and organisational preparedness limit its injection into reality. Hence, general statements of the allegedly revolutionary impact of AI on the healthcare system should be counter prevented by the recognition of such systemic and contextual shortcomings [2, 3]. This study seeks to achieve three objectives: first, to identify the underlying themes present in articles related to AI-enabled healthcare and service quality; second, to analyse the temporal trend of these themes to determine if they are trending positively, neutrally, or negatively over time; and finally, to identify areas within each theme that offer potential for more influential research by reviewing the existing literature. The following research questions were posed, guided by the following fundamental objectives:

1. What are the emergent topics of research in the fields of artificial intelligence-enabled healthcare services, healthcare service quality, and AI-enabled healthcare practices?
2. How has research in each area progressed over the past two decades?
3. What are the prospects for conducting significant future research in the field of AI-enabled healthcare services?

We utilised bibliometric network analysis and topic modelling to emphasise the interconnections between technology-enabled healthcare facilities and services, as well as the overall structure of health services within the technology-driven knowledge domain. Through this study, we assert that we have made at least three significant contributions to the current corpus of knowledge. First, this is an endeavour to scrutinise the available literature from its inception. Hence, it examines the patterns of scholarly articles focused on artificial intelligence in the healthcare industry, specifically exploring the management of healthcare in the context of technological advancements. Furthermore, by focusing exclusively on scholarly articles related to AI, technology, and service quality in healthcare management, we enhance the existing body of literature in this area. Moreover, emphasis on empirical contributions has resulted in broad and disjointed research streams [4]. Bibliometrics offers a systematic method for examining large quantities of data, enabling researchers to deduce patterns over time, identify recurring topics of study, detect changes in disciplinary boundaries, highlight the most productive scholars and institutions, and present a comprehensive overview of the existing research [5].

The remainder of this study is structured as follows. Section 2 provides detailed explanations of the study methodology, and Section 3 includes the processes of data gathering and pre-processing. Section 4 provides an overview of the findings, which encompass descriptive statistics, word clouds, key topic matrices, topic labelling, and the progression of each topic over time. Section 5 presents conclusions and limitations.

METHODOLOGY

Bibliometric and topic-modelling methods are the research method utilized in the current study. In order to conduct a Bilbilometric analysis the Bibiloshiny R package was utilized [6].

The literature analysis was completed based on the words used in the available literature, the most common words with the help of word cloud, annual scientific production, and descriptive statistics undertaken on literature published in the period between 2011 and 2024 using Scopus database. Aria, M, Cuccurullo, C. [7]. Topic-modelling was incorporated in the study using Latent Dirichlet Allocation which was used to relate words that share certain contexts and differentiate the different meanings of the words. Different Topic Modelling techniques are the Vector Space Model (VSM), Latent Semantic Indexing (LSI), Probabilistic Latent Semantic Analysis (PLSA) and Latent Dirichlet Allocation (LDA). And since all of it has gone to new homes [8]. With the assistance of Latent Dirichlet Allocation (LDA), in the present study, the reasons why the authors use the LDA computational approach to content analysis has been analysed to support the process to explore the underlying structure of theme in a set of given texts. LDA is suitable in the study because this method significantly cuts the time and reliability to uncover topic structure on a large volume of reading. This approach uses an inductive approach and quantitative measures thus it makes it extremely applicable in exploratory and description studies. Companies or institutions ban the use of the internet because of their incapacity to control the quantity of internet users [9][10]. We chose the number of topics (k=5) minimising the perplexity and optimising the coherence to have interpretable results. These values might, however, be taken with caution since the size of the data set used is relatively small (n=63). Two healthcare informatics experts, who were neutral, reviewed topic labelling to enhance level of theoretical coverage and limited subjectivity.

DATA COLLECTION:

The study aims at disclosing the range of healthcare research in authoritative international journals on AI-enabled technology in terms of healthcare services and its quality, diagnosis, and treatment. The data used were retrieved using the Scopus database, one of the major abstract and citation databases of scholarly work [11, 12]. To get as many materials as possible on the subject, a broad list of keywords has been developed based on the substantial knowledge of the authors in the research area and the review of the literature available in the topic. The reason why Scopus was chosen has to do with a broad interdisciplinary coverage, which includes healthcare, computer science, and management studies. Although Web of Science, PubMed and IEEE Xplore would have provided beneficial sources, they had to be omitted because of limited resources and the choice to rely on only one substantial database. This choice has been recognized as a weakness given that it could make differences on the comprehensiveness and impose a selection bias. Inclusion and exclusion filters were used such as (i) the type of documents: articles, reviews, conference papers, or book chapters; (ii) language: English; (iii) publication status: final published version; and (iv) whether it touches upon AI-enabled healthcare-related themes.

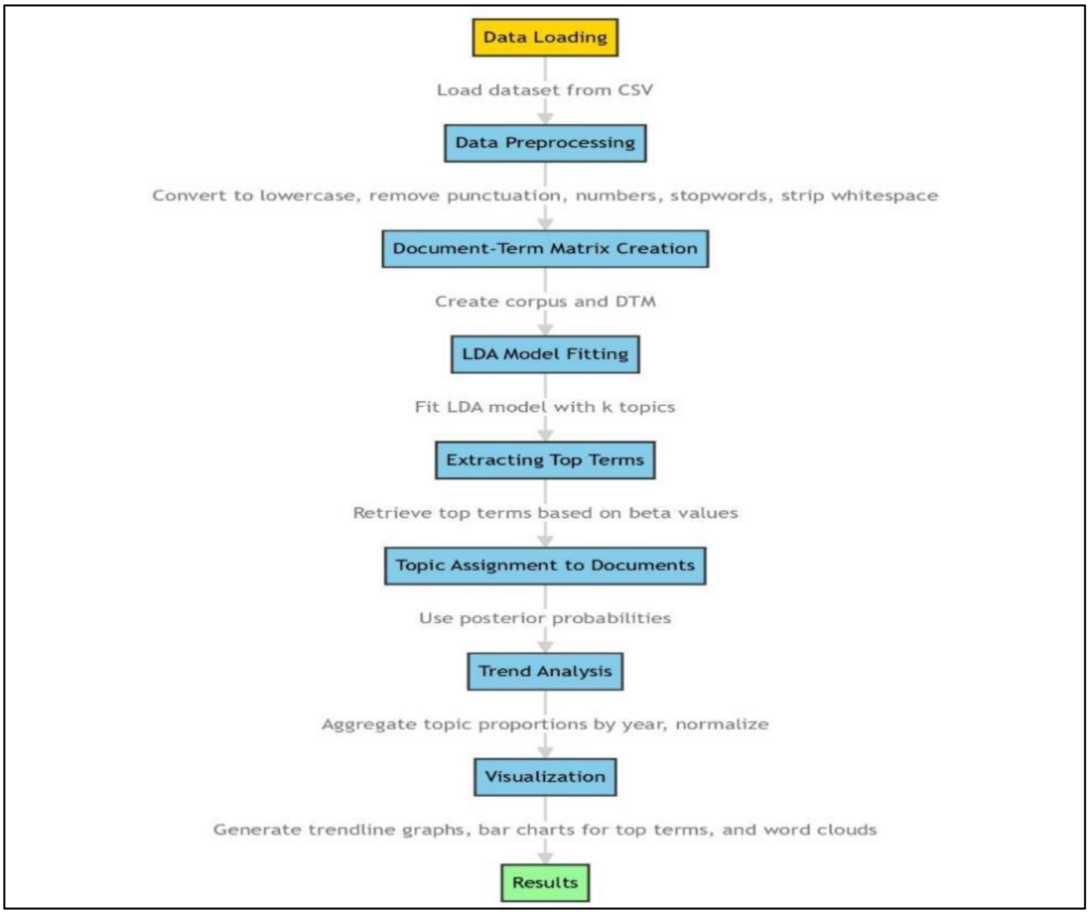
To gather a wide variety of content on the subject, a comprehensive set of keywords was created by combining the authors' considerable understanding of the field and an examination of the existing literature in the field. Various inclusion and exclusion queries were incorporated for the search of relevant literature the search refinement is as firstly the keywords deployed were AI OR artificial AND intelligence OR artificial AND intelligence AND technologie* OR ai AND tools OR artificial AND intelligence AND tool* resulted into 2323 documents further the inclusion and exclusion query to this query was limit to articles, review articles, conference paper and book chapters language choice restricted to English and article stage was at published state selected which resulted in 1917 documents.

Further narrowing to query as AI OR artificial AND intelligence OR ai AND enabled OR artificial AND intelligence AND enabled AND healthcare OR healthcare AND facility OR healthcare AND service AND quality OR healthcare AND services OR treatment OR diagnosis OR precision AND medicine OR healthcare AND systems AND efficiency OR healthcare AND practices OR quality AND healthcare AND service* resulted in 63 documents with all exclusion criteria.

DATA PREPROCESSING FOR TOPIC MODELLING ANALYSIS

The Latent Dirichlet Allocation (LDA) topic modelling in R needs to process several steps to extract and visualise themes upon a textual data. Figure 3 indicates the outline of the process of topic modelling. The first data are usually given in the CSV format to R. In the preprocessing data step, the punctuation symbols, numbers, and the stop words as well as whitespace were removed, and the text was subjected to the lowercase text. A document-term matrix (DTM) is formed after preprocessing; this is a matrix of phrase frequencies in the documents. Topic modelling is created on this matrix. The main element of this method is that the Latent Dirichlet Allocation (LDA) model is used to process the document term matrix (DTM), and the number of topics (k) depends on the purpose of the study. After fitting the model, the most outstanding phrase in each topic category is retrieved and is normally done through the determination of the highest magnitude of the beta values. A document is then assigned to topics in accordance with posterior probabilities, which relay the affiliation to each theme. The analysis of the trend was done by combining and standardising the ratio of subjects by year to see changes over time. The issue of the number of topics (k=5) was chosen with optimisation of coherence score and minimisation of perplexity so that the results can be explained. Nevertheless, because the data (n=63) is somewhat small, these values are to be understood critically. Two independent people who have a degree in healthcare informatics reviewed topic labelling to enhance theoretical coverage and minimize subjectivity.

FIGURE 1: TOPIC MODELING PROCESS FLOW CHART ADOPTED (AUTHOR SELF-CREATED)



ANALYSIS

This study has two main components. First, a bibliometric analysis was conducted using biblioshiny to describe the data. Second, topic modelling using LDA (R version 4.4.1) was performed to identify latent themes and topics in the selected databases.

BIBLIOMETRIC ANALYSIS

Table 1 provides a succinct overview of the significant and pertinent information from the utilised dataset. The final analysis utilised important variables and data from a bibliometric analysis conducted between 2011 and 2024. This material provides a comprehensive summary of these facts. This study encompasses 54 sources, which consist of 63 documents and have an annual growth rate of 16.15%. The documents include a mean age of 1.95 years and an average of 21.51 citations per document. The keyword "plus" has a total count of 677 occurrences in the Keywords Plus (ID) category and 249 occurrences in the Author's Keywords (DE) category. The author made 266 contributions, with just 3 of those being single-authored documents.

TABLE 1: CONCISE SUMMARY OF IMPORTANT AND RELEVANT INFORMATION IN THE DATASET USED.

Description	Results
MAIN INFORMATION ABOUT DATA	
Timespan	2011:2024
Sources (Journals, Books, etc.)	54
Documents	63
Annual Growth Rate %	16.15
Document Average Age	1.95
Average citations per doc	21.51

References	0
DOCUMENT CONTENTS	
Keywords Plus (ID)	677
Author's Keywords (DE)	249
AUTHORS	
Authors	266
Authors of single-authored docs	3
AUTHORS COLLABORATION	
Single-authored docs	3
Co-Authors per Doc	4.49
International co-authorships %	47.62
DOCUMENT TYPES	
article	53
review	10

FIGURE 2: WORD CLOUD FOR ABSTRACTS (AUTHOR SELF-CREATED)

Additional word clouds were built on the abstract of the article using the cluster option in the biblioshiny and the keywords of the authors which is shown in Figure 1 and 2 respectively. The word cloud 1 includes the 63 abstracts of articles, and it is needless to mention that the word cloud is a visual presentation that reveals the most prominent topics within analyzed information. The font size of every word in the cloud is proportional to the frequency and significance of the word. The most notable phrases used in the cloud are the phrases artificial intelligence and the phrase medical care or rather the phrase healthcare implying that this is the predominant topics or rather the themes. The other key terms include the phrases of internet of things," deep learning," blockchain, and cloud computing, which highlights a strong focus on technology advancement and their application. Although these visualisations allow a thematic overview, they fail to depict systemic problems and their causes like asymmetries of power, publication trends biases, or barriers to clinical adoption. The terminology and its involvement of socio-technical dimensions highlights that some topics related to AI are underdiscussed, because of technological optimism, and other regulatory, ethical, and practical integration areas are underrepresented.

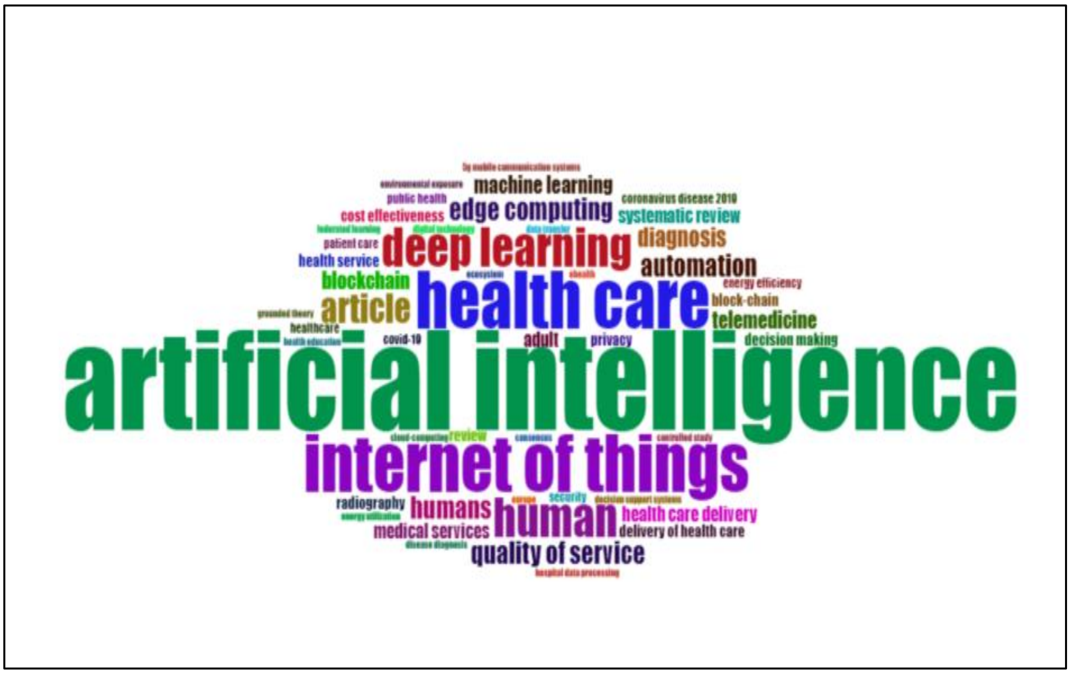
Figure 2 demonstrates the word cloud created using all the keywords stated in 63 articles. The word cloud describes that the terms "artificial intelligence" and "health care" are the most prominent, suggesting that they are the main subjects in the collection. The figure above indicates a notable emphasis on the implementation of artificial intelligence in health care.

Additional significant terms encompass "internet of things," "deep learning," "human," and "quality of service." The significance of these terms emphasises important areas of focus, including the incorporation of cutting-edge technology, such as IoT and deep learning in healthcare systems, together with the examination of human factors and service quality.

Specialized subtopics and issues within the broader subject are indicated by terminology such as "automation," "diagnosis," "telemedicine," "edge computing," and "privacy." The inclusion of the terms "machine learning", "systematic review", and "cost effectiveness" indicates the concentration of methodological strategies and economic assessments within this framework.

In summary, the word cloud reveals a notable convergence of cutting-edge technologies, including artificial intelligence and IoT, within the healthcare sector.

FIGURE 3 WORD CLOUD FOR AUTHORS' KEYWORDS (AUTHOR SELF-CREATED)



TOPIC MODELING:

Although the word clouds give an overall view of the study patterns within the literature, they fail to give quantitative facts on the associations between various notions. Unless one had the quantitative data on all the significant terms, it would be difficult to gather the related words and organize them in the categories. Topic modelling through LDA was used to obtain the proper data on the correlation between various terms by generating specific topics through a combination of correlated terms in the dataset through the analysis of hidden structures and underlying structures. As Torous et al. [13] state, there are other limits or boundaries, which are described as living in the past or looking back. Figure 1 depicts the specifics of the process flowchart of the topic modelling that was adopted in this study. According to the extraction of the most related keyword, there are in total, 5 topics extracted as reflected in the table below (Table 2). Although these visualisations provide a thematic overview, they fail to capture system related complications like power asymmetries, publication bias, or barriers to clinical adoption. Socio-technical integration brings forward the notion that some of the AI subjects are over-covered by technological optimism, and regulatory, ethical, and practical integration research areas remain understudied.

TABLE 2: TOPIC LABELS

Topic	Topic Labels	Most used words (based on frequency and beta value)
1	Review the internet digital trauma health	healthcare, intelligence, artificial, technologies, review, intelligent, usage, smartwatch, satisfaction, applied
2	Technologies model health via federated learning	learning, healthcare, review, federated, health, challenges, approach, practice, intelligence, artificial.
3	An artificial deep framework enabled review	healthcare, health, framework, digital, artificial, intelligent, remote, patient, intelligence, care
4	Intelligence learning healthcare	trauma, support, intelligence, enabled, decision, artificial, application, healthcare, perspectives
5	Healthcare-enabled artificial learning	enabled, learning, deep, things, model, internet, medical, data, optimization, based

Figure 4 (see apprendex I) represents the top terms inside a separate topic, as determined by the beta values of those terms in a topic-modelling analysis.

The first chart in Figure 4 pertains mainly to terms such as "internet," "digital," "trauma," and "health." The significance of these terms lies in the evaluation of digital technologies and their use in the medical field, particularly with trauma treatment. Digital technologies are transforming mental health care, particularly in trauma and post-traumatic stress disorder (PTSD) treatment. Smartphones, wearables, and sensors enable the development of digital features of PTSD, is improve prediction and assessment [13]. Integrating technology offers opportunities for self-monitoring and self-management, also facilitates remote intervention, and hence overcomes barriers to traditional care [14]. Key considerations include privacy, intuitive design, inclusive language, and the standardisation of care processes [15, 16].

The second chart in Figure 4 highlights the terms "technologies", "model", "health",, and "federated" technologies. Federated learning (FL) has emerged as a promising approach in healthcare, enabling the development of machine-learning models across distributed datasets while preserving data privacy and security [17, 18]. This technology addresses the challenges of data silos, privacy concerns, and regulatory requirements in healthcare, allowing collaborative model training without compromising sensitive patient information [19].

The third chart in Figure 4 demonstrates the topics as "artificial," "deep," "framework," "enabled," and "review." The chart clearly highlights that artificial intelligence, deep-learning frameworks, and the evaluation of these technologies are prominent in healthcare. Enormous potential has been demonstrated by Artificial Intelligence (AI) and Deep Learning (DL) frameworks to revolutionise healthcare, predominantly in medical imaging, diagnostics, and decision support systems. Shaban-Nejad et al. [20] stated the importance of Explainable AI (XAI) methods in medical image analysis, advocating the need for transparency and trust in AI decisions within clinical settings. They also highlighted that it is vital to overcome the "black-box" nature of AI systems and promote their adoption in healthcare [20]. The field of AI continues to evolve, and it is central for healthcare professionals to enthusiastically engage with and lead the development of AI-powered solutions to reap maximum benefits in patient care.

The fourth chart (Figure 4) displays the keywords such as "intelligence", "learning", and "healthcare", together with additional terms that are connected to these concepts, indicating that there is an emphasis on intelligence systems and learning models in healthcare applications. Artificial intelligence (AI) and machine learning are transforming health care systems through various applications. Health intelligence leverages AI and data science to provide insights, reduce waste, and increase the efficiency of healthcare delivery [21].

An expanding corpus of research underscores the crucial functions of AI and learning models in health care. Reinforcement learning (RL) has emerged as a viable technique for addressing complex healthcare issues through its application to adaptive treatment protocols, smart core networks, and edge intelligence. Automated methods can enhance supported living and health monitoring, especially for the elderly and individuals with mental health conditions [2].

An image typically categorises the most significant concepts and terms in the dataset into five basic groups. The subjects encompass all facets of the interplay between technology and healthcare, focusing on digital technologies, federated systems, artificial intelligence (AI), and the assessment and use of these innovations in health-related fields. Table 2 presents a synopsis of the five subjects. Machine learning (ML) and artificial intelligence (AI) are transforming healthcare by improving patient care, clinical decision support, monitoring, and interventions [2]. These technologies enable complex data mining, language and picture processing, and real-time risk assessments [21]. Nonetheless, challenges persist in ensuring that AI-driven healthcare is equitable and that it adheres to medical ethics [21]. As AI continues to advance, e-healthcare platforms will assume a progressively more significant role in safeguarding patients' physical and mental health [21].

TOPIC TRENDS OVER TIME:

The line graphs depicted in Figure 5 (see appendex II) demonstrate the trends in topic proportions from 2011 to 2024. The years covered by the graphs are from 2011 to 2024. Each graph illustrates a distinct subject matter, illustrating how the focus on each subject matter has shifted over time.

Artificial Intelligence and Learning in Healthcare: The trendline for this topic has an upward slope, which indicates that the topic shows an increasing trend. In 2017, the proportion reached its highest point, then suffered some oscillations, and has recently climbed again, indicating that there is a growing interest in this field.

Intelligence Learning with Healthcare Intelligence Healthcare: The trend line of this topic demonstrates that there is a general upward tendency, with major peaks occurring in the years 2019 and 2021. The upward slope of the trend line indicates that there has been a consistent concentration on this subject, even though there has been some variation in certain years.

Technologies Model Health via Federated, the trend line of the topic exhibits a negative trend, as indicated by the downward slope of the trend line. The significance of the subject has drastically reduced since it reached its highest point in 2011-2012, with a minor rebound occurring in recent years.

Internet and Digital Trauma Health, the trendline that is growing, indicates that this subject is moving in a somewhat positive direction. At some point around the year 2018, there was a substantial increase in the proportion of topics, which was then followed by variations, indicating varying levels of emphasis but usually increasing interest.

The topic **Artificial Deep Framework Enabled Review**, the trendline in this case exhibits a discernible rising slope, which indicates that there is increasing interest in this subject. After a period of very low interest in the subject until 2017, there was a gradual growth that reached its highest point around 2023-2024.

The overall analysis revealed that the graphs together indicate a growing emphasis on artificial intelligence and related technologies in the healthcare industry, with an upward trend in many of the areas investigated. The topic of federated technologies, on the other hand, demonstrates a growing trend of decreasing interest.

CONCLUSION

Medical care has undergone substantial modifications with the help of AI-powered solution by assisting in making the diagnostic process even more efficient and tailored to the specific needs of a particular patient, simplifying the process of operating the process. This has been extremely efficient in improving patient care and expediting the administrative task such that health professionals can devote more time on the patients. However, certain barriers remain, such as the trustworthiness of data published by different organizations and addressing the concept of transparency in regard to AI algorithms, especially in the models founded on deep learning. A huge problem could be the data security and privacy when all this personal health information must be revealed to achieve the application of AI. To resolve these concerns, they will have to align to the current regulatory frameworks, including General Data Protection Regulation (GDPR), Health Insurance Portability and Accountability Act (HIPAA), and Therapeutic Goods Administration (TGA), etc., to meet compliance and trust.

Companies that use AI in healthcare can increase the quality of the provided services, lower costs, and optimize their use of resources. Still, proper governance frameworks are required because they are required to address ethical and legal concerns, such as data security and sharing the benefits of the system fairly. Proper training of healthcare professionals is important to make AI complete the picture in human judgment instead of displacing it. Research studies need to focus on the societal, legal, and ethical effects of AI in healthcare, create user-friendly data management tools and provide equal access to AI innovations. Interdisciplinary collaboration is important in implementing AI in the clinical field, especially in cases where resources are scarce.

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APPENDIX I - FIGURE 4: TOPIC MATRIX USING LDA IN R

APPENDIX II- FIGURE 5 GRAPHS SHOWING TRENDING TOPICS