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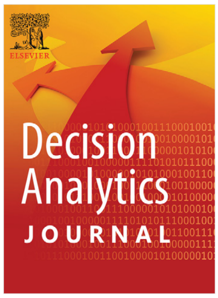

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A Bibliometric Analysis of Technology in Sustainable Healthcare: Emerging Trends and Future Directions

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Abstract

Technology application in healthcare is a recent field devoted to sustainability in the healthcare industry. However, research in this sector has grown at a rapid pace. While this expansion has been advantageous for the discipline, it has also made it more difficult to grasp its extent. As a result, answering questions such as the most important emerging trends in technology for sustainable healthcare research, the most critical breakthrough papers, the influence of these papers, and the most productive and leading researchers have become challenging. Finally, understanding the intellectual framework of the knowledge base on Technology for Sustainable Healthcare (TSH) is also difficult. This study attempted to address these issues by presenting an overview of research work in TSH and, in doing so, attempted to answer some of the previously listed problems. The PRISMA model, along with the science mapping review process using bibliometric analysis tools such as VOSviewer and Python, was employed to analyze published works in healthcare technology indexed in the Scopus database over a span of 24 years. Although research in TSH had been progressing rapidly before the COVID-19 pandemic, the current accelerated shift in TSH research over the past four years may be attributed to the pandemic itself as well as advancements in technologies such as artificial intelligence, machine learning, and the Internet of Things. We also discuss current research themes, prolific authors, institutions, journals, and relationships among published works in TSH. Finally, we present the challenges and prospects of TSH research. The findings of our study would be helpful to researchers working in technology for sustainable healthcare.

Keywords: Healthcare technology, sustainable healthcare, health informatics, machine learning healthcare, healthcare predictive analytics

1. Introduction

The advancement in computers storage and processing capacity has ushered in the growth of technology applications in the healthcare industry for sustainability [1]. Sustainable Healthcare (SH) concentrates on techniques that combine social, environmental, and economic considerations into healthcare systems and practices to ensure long-term viability and effectiveness [2]–[4]. Thus, SH recognizes the interdependencies between healthcare, environmental sustainability, and social welfare. Sustainable healthcare seeks to minimize the negative impact of healthcare activities on the environment while maximizing health outcomes and resource efficiency. This includes cutting waste, making energy use more efficient, encouraging sustainable purchasing methods, and implementing preventative actions to enhance public health. SH also promotes social justice, community involvement, and equal access to healthcare services [2], [3], [5]–[7].

Recent advancements in technology and communication have resulted in the growth of artificial intelligence (AI), machine learning (ML), the Internet of Things (IoT), big data, and cloud computing applications in different areas [8] including the healthcare industry. These technologies and big data analytics can play a significant role in advancing the principles of SH [9]. For example, (i) Precision medicine - the analysis of enormous volumes of patient data, including genetic data, medical records, lifestyle variables, and environmental data with AI and big data [9]–[13]. Making it possible for medical professionals to create individualized treatment plans, customize therapies, and anticipate illness trends, leading to more focused and efficient healthcare delivery. (ii) Remote patient monitoring - this involves the use of AI-powered gadgets, Internet of Medical Things (IoMT), and wearables to continually track patient's vital signs, gather health information, and send it to medical professionals [14]–[16]. Remote patient monitoring promotes early diagnosis of health problems, prompt treatments, and fewer frequent hospital visits, all of which enhance patient outcomes and sustain resource management. (iii) Healthcare process optimization - AI systems are employed to evaluate intricate healthcare procedures, spot inefficiencies, and suggest enhancements, resulting in better resource management, shorter wait times, better staff scheduling, and streamlined workflows, healthcare delivery becomes more effective and less expensive [17]–[19]. (iv) Predictive analytics - healthcare systems examine population health patterns, forecast disease outbreaks, and allocate resources appropriately by utilizing big data and AI. This proactive strategy contributes to sustainable healthcare practices by halting the spread of illnesses, enhancing emergency readiness, and optimizing resource use. (v) Health data management - large amounts of health data are safely stored, integrated, and analyzed using big data analytics, making it easier to conduct research, share information, and make decisions that are supported by the available data, which improves patient safety and healthcare outcomes [20]–[22].

Thus, SH includes a wholistic method of providing healthcare that considers economic, social, and environmental concerns. However, enhancement in technologies like AI, big data, ML, the IoT, Internet of Medical Things, and cloud computing are instrumental in driving SH. Several research works have applied these technologies to improve patient care, resource management, and industry sustainability. For instance, name a few, diagnostic system [23]–[26], decision prediction and detection [27]–[34], patient monitoring and care [35]–[39], as well as treatment protocol creation [40], [41], medication development [42]–[44], and tailored medicine [45]. The 17 Sustainable Development Goals (SDGs) of the United Nations seek to ensure decent lifestyles for all people on a healthy planet by 2030. Goal three (3), which promotes excellent health and well-being, and the coming of COVID-19, have sparked increased interest in the subject of healthcare technology. As of 25th March 2022, a keyword search on Google scholar with "healthcare technology" show about 60,200 results[1]. Notwithstanding its growing popularity and interest among academics and practitioners, there are few thorough characterizations of this field's knowledge structure, and research on its development is sparse. This knowledge is essential for advancing related technologies and academic activities like citing and reviewing literature.

In academic studies, literature reviews are crucial for putting-together current information and assessing the condition of an area [46], [47]. Prior to performing a new study, researchers often gather available information on a subject or problem to evaluate the condition of the existing evidence. However, most previous studies have assessed TSH works using qualitative approaches such as systematic literature reviews [48]–[53], and most have concentrated on the past 5 to 15 years. According to the following studies [54]–[56], a systematic review identifies, supports, or refutes a particular issue and is more focused and narrower in its approach. Thus, they do not provide an all-inclusive literature review in a field of study. Similarly, according to Walker et al. [57] several biases may be found in qualitative reviews, including publication bias, search bias, and selection bias. These biases jeopardize objectivity since qualitative analysis requires human judgment and the competence of researchers [58], [59]. Again, a literature review that only provides an arbitrary selection of evidence, on the other hand, is often not fully representative of the state of existing knowledge. The preference for some studies eventually leads to sample selection bias, which is a type of bias caused by selecting a non-random sample of data for further analysis in statistical analysis [46], [60].

Furthermore, most systematic review studies concerned the trends, difficulties, and application, or feasibility, of various technological platforms for specific healthcare sectors. On the contrary, the history of technology for sustainable healthcare publications reveals that this scientific subject is interdisciplinary, and "a lack of common language is one of the frequent obstacles of multidisciplinary research." As a result, an alternate strategy for assessing literature in healthcare technology that allows for structural connections, cross-disciplinary interrelationships, and research sectors would be very advantageous. Therefore, the goal of the current study is to assess research on healthcare technology using a scientific mapping review procedure (bibliometric analysis). The following are the questions (ReQ) addressed in this paper.

ReQ1: What are the critical growing trends in the application of technology such as AI, ML, IoT, IoMT, big data, and cloud computing for sustainable healthcare?

[1] https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&as_ylo=2021&q=healthcare+technology&btnG=

ReQ2: Over the last 24 years, which *authors, institutions, papers, and journals* in the literature on TSH have had the most significant impact on citations?

ReQ3: What are the critical themes investigated concerning TSH, and how do they relate?

ReQ4: What issues in TSH have received the most attention and have been studied the most frequently?

ReQ5: What does the nature of cooperation look like in the literature on TSH?

Similar to the previous literature assessments, bibliometric studies include a defined description of rigorous methodology [1], [61]–[64]. Bibliometrics is a branch of science that uses statistical and mathematical approaches to assess scientific activity [65]. Through performance analysis with authors, nations, and institutions, these studies make it possible to examine the intellectual structure of the research area. Furthermore, bibliometric mapping (science maps) allows for the observation of structural links, interrelationships across disciplines and research sectors [1], [61]–[64]. Therefore, using bibliometric analysis to understand the structure of a knowledge base in a certain topic is beneficial. This paper's findings may be used as a reference for anyone interested in advancing and deploying technology for sustainable healthcare research. It can help fill a gap in the literature review. The approach used in this study to identify critical research topics is unique, and it may also be used in other academic and technical sectors.

The remainder of the paper is divided into the following sections: The methodology for the research is presented in Section 2. The findings and commentary from our experimental investigation are presented in section 3. Finally, section 4 summarizes findings, limits, and future studies.

2. Methodology

The complexity of healthcare presents roadblocks to transformative action and can stifle policymakers' preferred reform trajectories. The examination of healthcare information systems and the role of technology in healthcare renovation need systems for comprehending how change occurs within this complex setting [66]. We present the approaches and tools we used to collect and clean up our data and analysis of literature on technology for sustainable healthcare in this section.

2.1 Framework for Data Analysis

Figure 1 shows the study's review process. Keywords such as "technology," "sustainable healthcare", "health informatics", "machine learning in healthcare", "healthcare predictive analytics", "disease detection system", "health information system", and "artificial intelligence in healthcare" were used to search within the titles, abstracts and keywords of published papers indexed in Scopus. Our years of the search were restricted to papers published and indexed in Scopus from 1998 to 2022. The reason for choosing these specific keywords is rooted in their direct connection to the research goal of exploring how technology can be utilized to promote sustainable healthcare practices. The keyword "Technology" covers the broad range of technological developments relevant to the healthcare industry. "Sustainable healthcare" focuses on incorporating social, environmental, and economic factors into healthcare systems." Health Informatics" examines how information technology may be used to improve healthcare results. "Machine learning in healthcare" explores the ability of machine learning methods in healthcare applications. "Healthcare predictive analytics" examines the use of predictive analytics to optimize resource allocation and improve sustainability. "Disease detection system" examines technologies used for early detection systems. "Health information system" investigates the use of data management and analysis to improve decision-making. "Artificial intelligence in healthcare "examines the impact that AI might have on improving healthcare sustainability and efficiency. Therefore, the selected keywords offer a holistic framework for examining how technology contributes to sustainable practices within the healthcare context. Together, they contribute to the research objectives, align with the chosen methodology, and provide valuable insights into the potential advantages and advancements that can be achieved by embracing sustainable healthcare through technological innovations. We used Boolean operators like OR, AND to build compound search words from the keywords. The four stages of Preferred Reporting Items for Systematic Reviews and Meta-Analyze (PRISMA) was adopted for identifying, screening, deciding on the papers' eligibility, and finalizing the list of articles to include in this review study (see Fig. 1). The initial search string was**:** *(TITLE-ABS-*

KEY (technology AND sustainable AND healthcare) OR TITLE-ABS-KEY (artificial AND intelligence AND healthcare) OR TITLE-ABS-KEY (machine AND learning AND healthcare) OR TITLE-ABS-KEY (health AND information AND system) OR TITLE-ABS-KEY (health AND informatics) OR TITLE-ABS-KEY (sustainable AND healthcare) OR TITLE-ABS-KEY (healthcare AND predictive AND analytics) OR TITLE-ABS-KEY (disease AND prediction) OR TITLE-ABS-KEY (big AND data AND health AND analytics)) AND PUBYEAR > 1997 AND PUBYEAR < 2023 AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp") OR LIMIT-TO (DOCTYPE , "re") OR LIMIT-TO (DOCTYPE , "ch") OR LIMIT-TO (DOCTYPE , "cr") OR LIMIT-TO (DOCTYPE , "bk"))

A total of 515,242 metadata (bibliometric data) of papers classified as articles, conference paper, review, book chapter, conference review, and book (N = 515,242) were initially found. We conducted a three-stage screening process for our initial search results. In Stage I cleaning, we excluded 25,037 articles that were not published in English, resulting in a total of 490,205 papers (N = 490,205). We then removed an additional 31,942 papers that were not classified as articles or conference proceedings, leaving us with 458,263 documents (N = 458,263). In Stage II cleaning, we eliminated 1,488 papers that had a publication status indicated as "in press". Furthermore, we removed a total of 436,571 papers that were not specifically related to healthcare or categorized as review papers, leaving us with 20,204 eligible papers (N = 20,204). Thus, the final search string used in this study was: *((TITLE-ABS-KEY (technology AND sustainable AND healthcare) OR TITLE-ABS-KEY (artificial AND intelligence AND healthcare) OR TITLE-ABS-KEY (machine AND learning AND healthcare) OR TITLE-ABS-KEY (health AND informatics) OR TITLE-ABS-KEY (sustainable AND healthcare) OR TITLE-ABS-KEY (healthcare AND predictive AND analytics) OR TITLE-ABS-KEY (health AND informatics) OR TITLE-ABS-KEY (big AND data AND health AND analytics))) AND PUBYEAR > 1997 AND PUBYEAR < 2023 AND (EXCLUDE (PUBSTAGE , "aip")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (EXCLUDE (SUBJAREA , "ENGI") OR EXCLUDE (SUBJAREA , "SOCI") OR EXCLUDE (SUBJAREA , "MATH") OR EXCLUDE (SUBJAREA , "BUSI") OR EXCLUDE (SUBJAREA , "ENVI") OR EXCLUDE (SUBJAREA , "MATE") OR EXCLUDE (SUBJAREA , "ENER") OR EXCLUDE (SUBJAREA , "MULT") OR EXCLUDE (SUBJAREA , "AGRI") OR EXCLUDE (SUBJAREA , "CHEM") OR EXCLUDE (SUBJAREA , "ARTS") OR EXCLUDE (SUBJAREA , "ECON") OR EXCLUDE (SUBJAREA , "EART") OR EXCLUDE (SUBJAREA , "Undefined") OR EXCLUDE (SUBJAREA , "VETE") OR EXCLUDE (SUBJAREA , "CENG") OR EXCLUDE (SUBJAREA , "PHYS") OR EXCLUDE (SUBJAREA , "PSYC") OR EXCLUDE (SUBJAREA , "HEAL") OR EXCLUDE (SUBJAREA , "NURS")) AND (LIMIT-TO (LANGUAGE , "English"))*. It is important to mention that the search was conducted on 10 July 2023. Stage III: 20,204 records were downloaded as Comma-Separated Values (CSV) files and loaded into a Pandas Data Frame using Python and Jupyter notebook for further cleaning. Firstly, we applied the "dropna" function to eliminate all records with no author name. Secondly, we iterated through the titles to identify any title that contained any of the following words: 'guidelines', 'systematic', 'overview', 'regulations', 'regulatory', 'Opportunities', 'challenges', 'lessons learned', 'benefits', 'Evidence', 'survey', 'guideline' and 'review.' We then read the abstract of the identified papers to confirm their relevance to this study, removing those that did not align with our research objectives. In total 1,475 records were removed in this stage leaving 18,729 for our analysis analyzed in this study (N = 18729). Table 1 shows the inclusion and exclusion criteria.

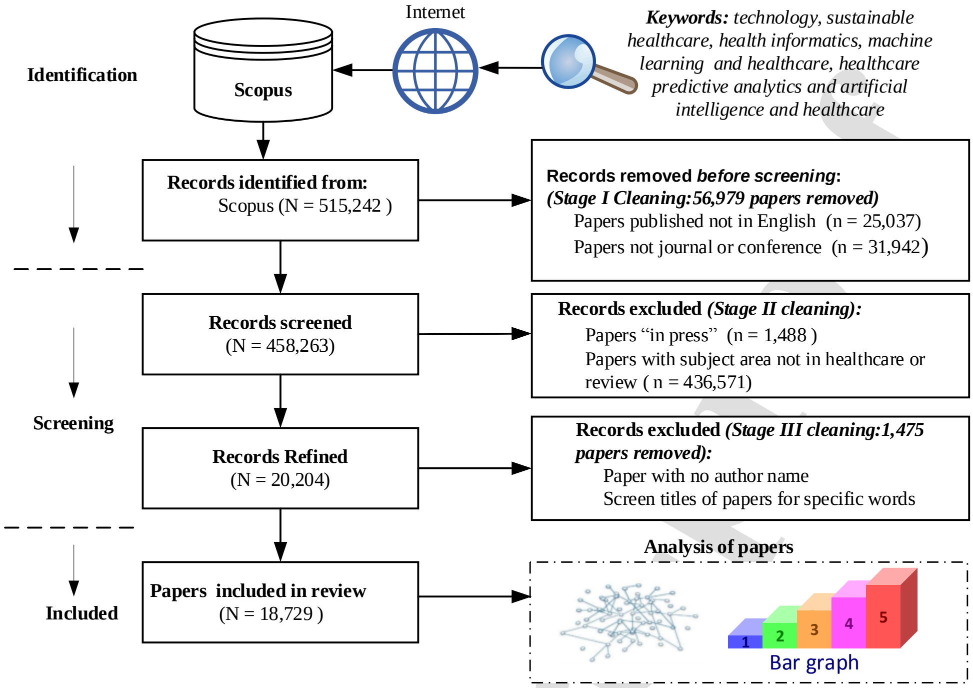

Figure 1: Study review process

Table 1: Study inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
1. Papers published from 1998 to 2022. 2. Papers with publication status "final." 3. Papers published in journals and conferences. 4. Papers with full author information	1. Paper not published in the English language. 2. Papers that are not in the field of healthcare technology. 3. Document type not article or conference proceedings 4. Papers "in press" 5. Papers with no author(s) names 6. Papers with subject area not in healthcare or review

2.2 Analysis tools and setup

For analysis and visualization, we employed a variety of applications. For the part of our data cleaning and descriptive analysis, we utilized Python and associated tools such as Pandas, seaborn, matplotlib and VOSviewer to display the networks. All analyses were done on a Lenovo ThinkPad W541 laptop with a 12 GB Intel Core i7 processor and a 1TB SSD.

3. Results and Discussions

This section summarizes the study's findings. The most important findings are addressed, and suggestions for further study are made. Bibliometric mapping is a recent approach for analyzing the intellectual structure of a research topic. The co-occurrence of author keywords and the bibliographic coupling of nations are used to investigate this structure. The VOSviewer program (University of Leiden, Netherlands) was used to create these maps, enabling the creation, exploration, and visualization of two-dimensional (2D) bibliometric networks that are simple to analyze and use in each research topic. This program has been used in a wide range of scientific fields. We present our findings in the following sections. A total of 18,729 documents were analyzed including 14,444 (77.1%) classified as articles (journal publications) and 4284 (22.8%) conference paper. Table 2 shows the summary results. The high-volume publications examined illustrate the growing call for and application of technology in the healthcare industry. Again, it reflects the recognition of the potential of technologies to augment analysis patient outcomes, improve healthcare delivery, and advance medical research; signifying a solid foundation of knowledge and insights derived from rigorous studies conducted in academic environments. Articles published in reputable journals hold significant value due to their potential impact on the scientific community. With 14,444 Journal articles out of 18,729 documents, there is a potential for broad dissemination of research findings and influence on future studies in the field. Similarly, conference papers serve as a platform for presenting early-stage research, emerging trends, and innovative approaches that can later be expanded upon in journal articles. The inclusion of 4,284 conference papers out of 18,729 emphasizes the importance of sharing research findings and exchanging ideas through academic conferences and symposiums. The review of both articles and conference papers highlights the multidisciplinary nature of technology application in healthcare, drawing expertise from diverse fields such as medicine, computer science, engineering, and informatics. This interdisciplinary collaboration is vital for addressing complex healthcare challenges and effectively leveraging technological advancements. Table 2 shows the summary results.

Table 2: Summary of results

Total number of papers	18,729
Total number authors	18,122
Total number of sources	155
Total number of affiliations	160
Total number of keywords	26555
Total number of Subject areas	8
Total number of citations	386355
Total number of countries	158

3.1 Trends in publication, citation, and authors

The number of publications and citations may be used to predict how a study topic will evolve. Figure 2 illustrates the publishing patterns from 1999-2022. Several key points should be noted. Out of the 18,829 documents analyzed, 39.5% were published between 2019 and 2022. The graph demonstrates a consistent growth in the number of studies focused on technology for sustainable healthcare, with a slight decline in 2009 followed by a surge of interest from 2010. There was another dip in 2015, but since then, the number of publications has risen rapidly, particularly from 2018 onwards. However, the notable proportion of recent publications (2019-2022) signifies a strong emphasis on up-to-date research within the field. This points out an active engagement by researchers and scholars, contributing novel knowledge and insights during this period. Moreover, it suggests the emergence of new trends, developments, and advancements in the field, underscoring the relevance and currency of research conducted within this timeframe. This dynamism reflects the ever-evolving nature of the subject area, where advancements and breakthroughs occur at an accelerated pace, necessitating constant monitoring and staying abreast of the latest research to remain aligned with the rapidly evolving landscape. Although healthcare technology research experienced only marginal growth prior to the COVID-19 crisis, we posit that the present rapid transition in healthcare technology research since 2019 may be attributed to the impact of the COVID-19 pandemic.

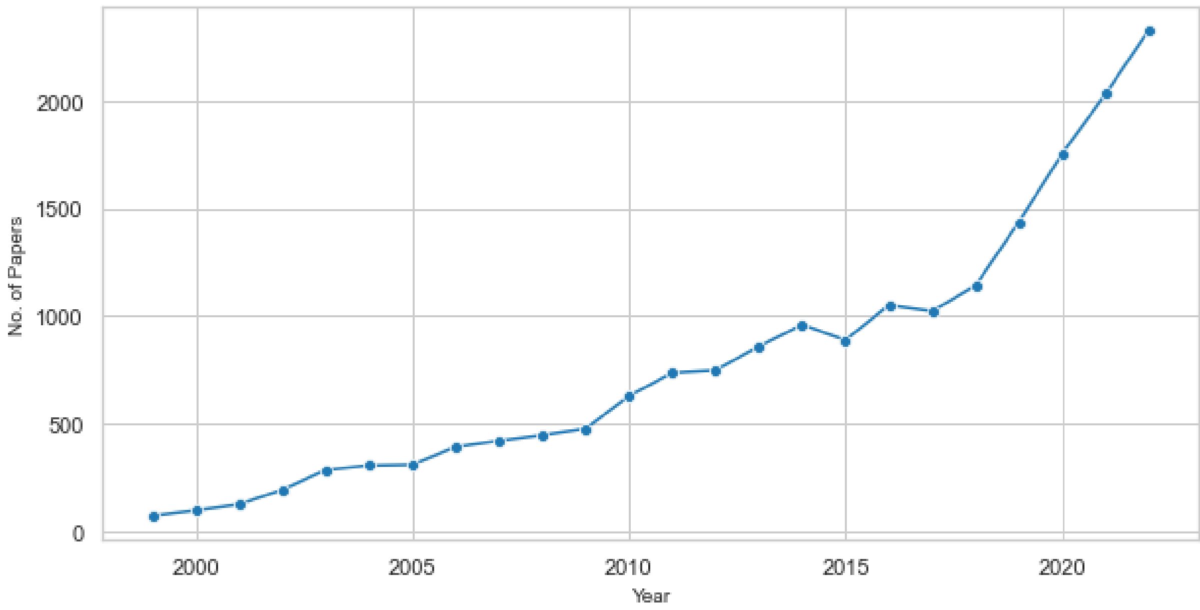

Figure 2: Year-wise publication of papers

Figure 3 presents the top thirteen publishers in technology for sustainable healthcare, offering intriguing insights into the research landscape. The findings reveal a diverse and thriving environment, with multiple publishers actively supporting the advancement of knowledge in this field. Leading the pack, Elsevier and the Institute of Electrical and Electronics Engineers Inc. emerge as significant contributors, publishing 1514 and 1268 papers respectively, displaying their vital role in disseminating research. Additionally, BioMed Central Ltd and the Association for Computing Machinery made substantial contributions with 891 and 678 papers respectively, underscoring the importance of biomedical and computing-related studies in this domain. Noteworthy publishers such as Oxford University Press (624 papers), BMJ Publishing Group (615 papers), and JMIR Publications Inc. (522 papers) demonstrate their active involvement in advancing knowledge and fostering research. Furthermore, Springer, Academic Press Inc., and Frontiers Media S.A. have also made notable contributions, publishing 469, 352, and 322 papers respectively, highlighting their commitment to this research area. Although NLM (Medline), Lippincott Williams and Wilkins, and CEUR-WS have fewer publications in comparison, their valuable research contributions in this field should not be overlooked.

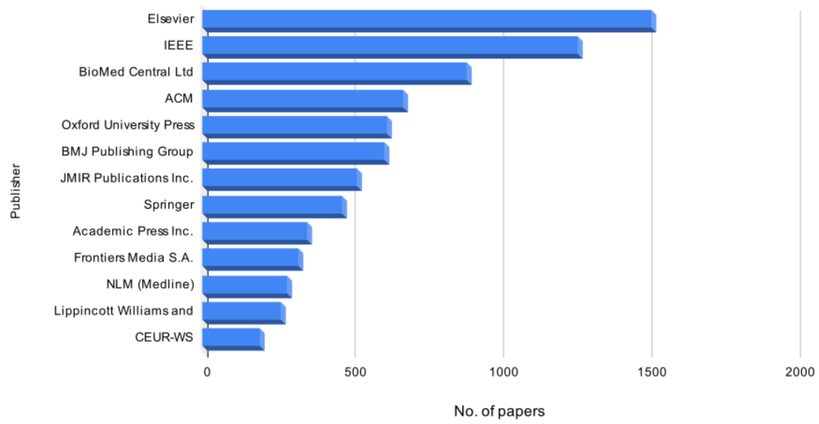

Figure 3. Most productive publishers

We observed that machine learning, health informatics, medical informatics, healthcare, and artificial intelligence are the most frequent keywords in technology for sustainable healthcare research. The high occurrence of "Machine Learning" suggests a growing interest in using algorithms to analyze data and make predictions in disease diagnosis, treatment planning, and patient monitoring. "Health Informatics" and "Medical Informatics" keywords indicate the focus on using informatics tools to improve healthcare processes, data analysis, and decision-making. "Artificial Intelligence" reflects the integration of advanced algorithms in healthcare systems for tasks like image analysis and clinical decision support. The "Healthcare" keyword highlights efforts to enhance healthcare delivery and patient outcomes through technological advancements. The significant occurrence of "Covid-19" reflects the surge in studies related to using technology to address pandemic challenges. "Electronic Health Records" signifies the focus on digitizing medical records for efficient information management. "Informatics" indicates the use of data analysis and management approaches in healthcare. "Deep Learning" highlights the utilization of deep neural networks in tasks like image recognition and predictive modeling.

Table 3: Top 23 frequent keywords in the technology for sustainable healthcare literature

Keyword	**Frequency of occurrences**
Machine Learning	1493
Health Informatics	1003
Medical Informatics	768
Healthcare	671
Artificial Intelligence	665
Electronic Health Records	534
Covid-19	527
Informatics	433
Deep Learning	418
Big Data	398
Health Information Technology	327
Electronic Health Record	282
Internet	277
Natural Language Processing	277
Data Mining	256
Epidemiology	220
Ehealth	189
Information Technology	189
Classification	180
Mental Health	162
Health Policy	156
Mhealth	151
Digital Health	119

Table 4 shows the top fifteen (15) most cited publications (titles), year of publication, total citations, and publication source. This is extremely helpful for determining themes that researchers in an area focus on. Studying high-quality papers might help upcoming researchers enhance their writing talents. These were the most prolific works in the area. The average citation for the entire 18,729 document analyses in this research was 18.7. The most cited document, authored by Wolfe et al. [67] (2716 citations), aimed to develop clear and practical guidelines for diagnosing fibromyalgia that could be applied in primary and specialized healthcare settings. In this study, random forest and recursive partitioning techniques were employed to assist in establishing a case definition for fibromyalgia, as well as criteria and a symptom severity (SS) scale. Followed a document authored by Dai et al. [68] published in 2005 (1407 citations). The next was authored by Schardt et al. [69] (1374 citations) followed a paper on acute physiology and chronic health assessment by Zimmerman et al. [70] (1164 citations).

Table 4:The top fifteen most referenced documents

S/N	**Title**	**Ref**	**Pub. Year**	**Citations**	**Source title**
1.	The American College of Rheumatology preliminary diagnostic criteria for fibromyalgia and measurement of symptom severity	[67]	2010	2716	Arthritis Care and Research
2.	Evolving gene/transcript definitions significantly alter the interpretation of GeneChip data	[68]	2005	1407	Nucleic Acids Research
3.	Utilization of the PICO framework to improve searching PubMed for clinical questions	[69]	2007	1374	BMC Medical Informatics and Decision Making
4.	Acute Physiology and Chronic Health Evaluation (APACHE) IV: Hospital mortality assessment for today's critically ill patients	[70]	2006	1164	Critical Care Medicine
5.	ConSORT-eHealth: Improving and standardizing evaluation reports of web-based and mobile health interventions	[71]	2011	1064	Journal of Medical Internet Research
6.	Intelligible models for healthcare: Predicting pneumonia risk and hospital 30-day readmission	[72]	2015	830	Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining
7.	The toxcast program for prioritizing toxicity testing of environmental chemicals	[73]	2007	727	Toxicological Sciences
8.	Artificial Intelligence (AI) applications for COVID-19 pandemic	[50]	2020	718	Diabetes and Metabolic Syndrome: Clinical Research and Reviews
9.	Big data in health care: Using analytics to identify and manage high-risk and high-cost patients	[74]	2014	714	Health Affairs
10.	Hidden in Plain Sight-Reconsidering the Use of Race Correction in Clinical Algorithms	[75]	2020	668	New England Journal of Medicine
11.	Development of a large-scale de-identified DNA biobank to enable personalized medicine	[76]	2008	651	Clinical Pharmacology and Therapeutics
12.	The Multiphase Optimization Strategy (MOST) and the Sequential Multiple Assignment Randomized Trial (SMART). New Methods for More Potent eHealth Interventions	[77]	2007	645	American Journal of Preventive Medicine
13.	Management of multidrug-resistant organisms in health care settings, 2006	[78]	2007	630	American Journal of Infection Control
14.	Serving the enterprise and beyond with informatics for integrating biology and the bedside (i2b2)	[79]	2010	617	Journal of the American Medical Informatics Association
15.	An interpretable mortality prediction model for COVID-19 patients	[80]	2020	571	Nature Machine Intelligence

The most cited authors correspond to the most influential in the study field. Of 18729 documents, there were 18122 authors. Out of the 18,122 authors, 100 (0.55%) had at least a publication with three hundred (300) citations. and ten published papers. Of the 306 authors, 2.21% (138) had an average of 24.0625 citations, while 45.8% (140) of them had an average citation of between 10% and 23.57%. Overall, the 306 authors have an average of 6.3478 citations. Table 4 shows the total citations, number of publications, and average citations per year of prolific authors in the field. We selected authors that have at least 1500 citations. It is worth noting that Table 5 is sorted based on the number of citations. D. W. Bates is the most cited author (6093) with seventy-two (72) publications. Next is D. F. Sitting, with 2543 citations and fifty-five (55) publications. J. S. Ash followed with eighteen (18) papers and 2260 citations, and B. Middleton with 2076 citations and twenty-three (23) papers. We noticed that this scholars' work, particularly that of D. W. Bates, seems to have significantly influenced the area.

Table 5: Top 15 highly cited authors

Authors	**No. of Papers (P)**	**Total Citations (TC.)**	**Avg. Citation (AC.)**
Bates, D.W.	72	6093	84.625
Sittig, D.F.	55	2543	46.2364
Ash, J.S.	18	2260	125.5556
Middleton, B.	23	2076	90.2609
Ammenwerth, E.	27	2010	74.4444
Overhage, J.M.	18	1989	110.5
Blumenthal, D.	18	1948	108.2222
Hesse, B.W.	19	1817	95.6316
Wang, F.	36	1634	45.3889
Bakken, S.	55	1632	29.6727
Hripcsak, G.	40	1580	39.5
Singh, H.	35	1577	45.0571
Pratt, W.	29	1541	53.1379
Sheikh, A.	28	1527	54.5357

**Note* AC = TC/P

3.2 Top publication venues

We observed a significant level of popularity for healthcare technology across multiple journals. A total of 155 journals had published at least one paper in this field, indicating the publishers' keen interest in this evolving domain. Among these publication venues, 32 (20.6%) had twenty (20) or fewer documents published within the search period, while 24 (15.5%) had one hundred (110) or more documents published. Table 6 presents the top five (5) publication venues that published at least four hundred (400) documents in this area of study during the search period ranked based on documents counts. The International Journal of Medical Informatics with 841 documents, followed by the Journal of the American Medical Informatics Association with 761 documents, BMJ Open with 454 documents, the Journal of Biomedical Informatics with 405 documents and ACM International Conference Proceeding Series with 405 documents. On the other hand, the Journal of the American Medical Informatics Association had the highest CiteScore (11.7) among the top five (5) publication venues based on Scopus metrics, as defended in Eq. (1).

$$CiteScore(SC) = \frac{Total\ Citations\ at\ (T)}{Total\ Documents\ at\ (T)} \quad (1)$$

The total count of citations obtained by articles, reviews, conference papers, book chapters, and data papers published by a journal in each period (T), divided by the number of publications published within the same period (*T*), is the

CiteScore[2] of the publication venue for a particular period (T). The Source Normalized Impact per Paper (*SNIP*) metric compares the number of citations received to the number of citations predicted for the topic area of the series[3]. The SCImago Journal Rank[3] (SJR) measures the number of citations received by a publication venue and the prominence or reputation of the journals from which the citations originate, which are used to calculate the scientific impact of academic publications.

Table 6: Top 10 publication venues ranked based on the number of publications.

#	Journal Name	TP	SC	SNIP[a]	SJR	Publisher	H-Index
1	International Journal of Medical Informatics	841	9.5	2.019	1.197 **Q1**	Elsevier	122
2	Journal Of the American Medical Informatics Association	761	11.7	2.324	2.44 **Q1**	Oxford University Press	169
3	BMJ Open	485	4.4	1.321	1.059 **Q1**	BMJ Publishing Group	139
4	Journal of Biomedical Informatics	454	8.2	2.115	1.083 **Q1**	Academic Press Inc.	121
5	ACM International Conference Proceeding Series	405	*	*	0.2	ACM	137

*TP = total publication; * = not applicable; Figure for 2022 provided by Scopus (SC = Cite Score; SNIP = Source Normalized Impact per Paper; SJR = Journal Rank),* **H-Index (***Figure for 2022 provided by SCImagoJR)*

3.3 The most prolific nations and institutions

A total of 158 nations have made contributions to publishing works on healthcare technology in journals and conferences. The distribution of publications across different nations reflects the diversity and global nature of healthcare technology research. It implies that researchers from various countries are actively engaging in this field, bringing unique perspectives and approaches to the table. Figure 4 illustrates the top twelve (12) nations with the highest research output in healthcare technology. Analyzing the publications and citations from different nations, regions, and institutions allows us to identify the most active and innovative locations in a research area, which can influence future collaborations among researchers worldwide. The United States (US) leads with the highest number of papers (8270) in healthcare technology, followed by the United Kingdom with 2174 documents, Canada with 1213, India with 1204, Australia with 1061, China with 793, Italy with 672, Germany with 664, the Netherlands with 569, Spain with 447, and other nations contributing as well. It is important to note that this does not necessarily indicate the highest level of international contribution or network engagement in healthcare technology. The results indicate that the United States is actively making significant contributions to advancements and innovations in healthcare technology. Additionally, the inclusion of other countries like the United Kingdom, Canada, India, Australia, and China among the top contributors highlights a global interest and collaborative efforts in leveraging technological solutions to address healthcare challenges. Again, the results emphasize the significance of global collaboration and knowledge exchange in healthcare technology research. Lastly, the involvement of multiple countries in contributing to the body of knowledge signifies the opportunity for international partnerships, sharing of successful approaches, and collective endeavors to advance the field.

[2] https://www.scopus.com/
[3] https://www.scimagojr.com/

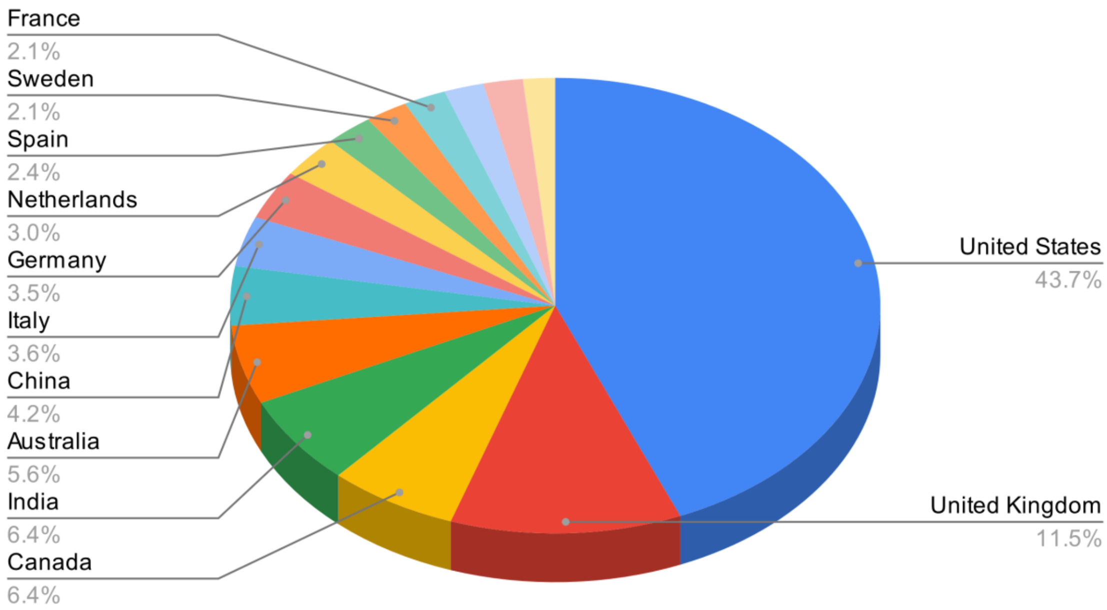

Figure 4: Document counts by countries.

Figure 5 illustrates the top eighteen (18) institutions, ranked by production (number of documents published). Out of the 18,729 documents analyzed in the study, 580 (12.7%) were affiliated with the Harvard School of Medicine, establishing it as the leading institution in research work in TSH. Following closely behind, the University of Washington had 328 (7.2%) affiliations, while the Brigham and Women's Hospital had 321 (7%). It is worth mentioning that most of the institutions (see Figure 5) are in the United States (US). Furthermore, most institutions with many publications are US universities, the US's remarkable contribution to this area of study. Figure 6 shows the subject area distribution of research work in healthcare technology. We observed an interdisciplinary nature of technology for sustainable healthcare research, with collaborations between medicine and computer science driving advancements in this field. The abundance of research conducted in healthcare technology within the medical discipline indicates a strong emphasis on utilizing technological advancements to improve medical practices, patient care, and overall healthcare delivery. This emphasizes the significance of interdisciplinary collaborations between healthcare professionals and technologists to foster innovation, improve patient care and enhance healthcare outcomes. Additionally, the substantial research conducted in healthcare technology within the field of computer science signifies the growing acknowledgement of computational methods, data analysis, artificial intelligence, and other technological tools in addressing healthcare challenges. This highlights the increasing integration of technology into healthcare research and practice, with computer scientists playing a pivotal role in the development and implementation of innovative solutions.

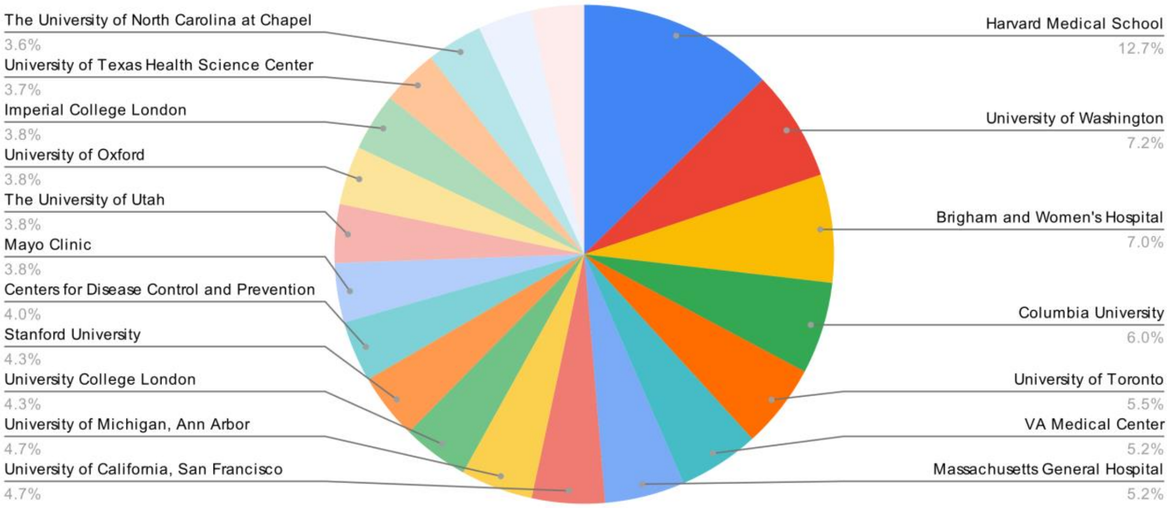

Figure 5:The top eighteen (18) affiliation (institutes) in technology for sustainable healthcare

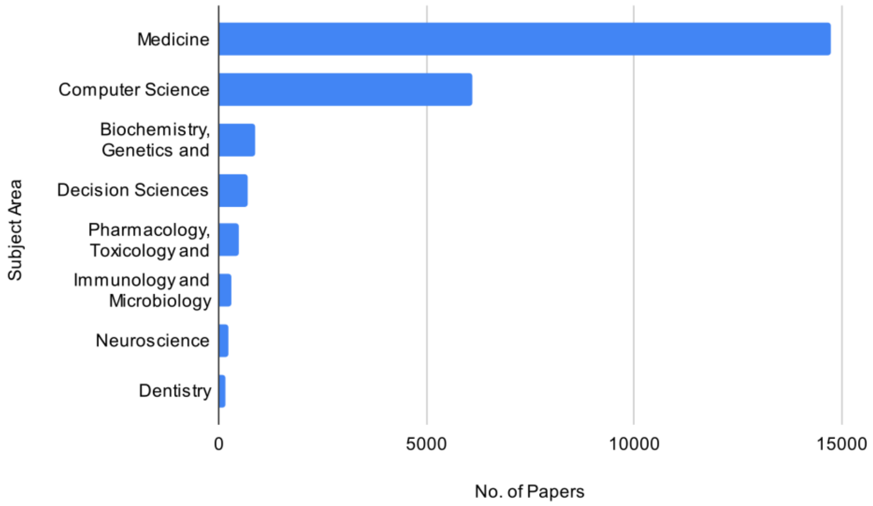

Figure 6: Subject area distribution of documents

3.4 Co-authorship Analysis

Figure 7 shows the co-authorship analysis of the reviewed paper with VOSviewer. We restricted the plot to authors who co-authored five papers with at least five hundred (500) citations. The arrows represent the co-authorship links between them. The number of publications co-authored by a researcher in the dataset is reflected in the size of each node. We observed a high dynamic of knowledge sharing, interdisciplinary collaborations, and the flow of ideas within technology for sustainable research field. The outcome affirms the early results (see Table 3). We observed that D. W. Bates has co-authored several papers in healthcare technology, followed closely by Y. Wang. Again, the clones among authors indicate a higher collaboration rate among authors in this field. Figure 8 shows the origins of co-authors. Most of the co-authors are from the United States (US), which firms the outcome in Figure 4 depicting more papers in this field coming from the US. From the country co-citation network (see Figure 8) we observed a good degree of research collaboration, knowledge dissemination, and the social fabric of the academic community. Further we see interconnectedness of institutions in US, Canada, China and more in the technology for sustainable healthcare research domain.

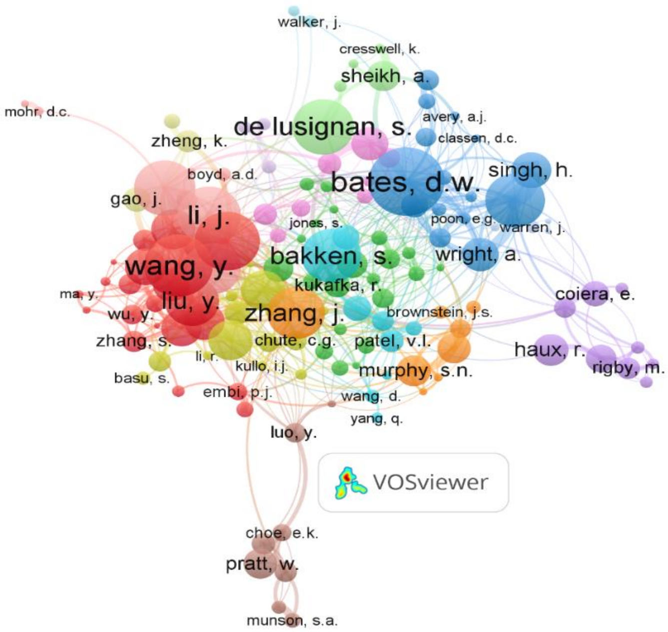

Figure 7: Co-authorship analysis of reviewed papers

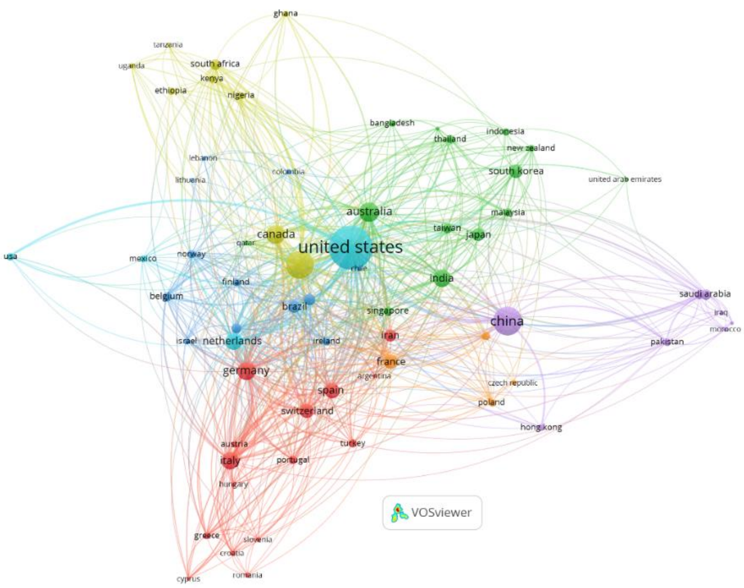

Figure 8: Country co-citation network of the reviewed papers

3.5 Co-occurrence of keywords

Using keyword analysis, we examined the distribution of knowledge in this field. Furthermore, the connections between various themes were evident, which aided us in identifying new study avenues. Figure 9 shows the co-occurrence of keywords in the documents evaluated in this study. There was a total of 26,555 keywords in 18729 documents studied in this paper. In our network construction, we applied the density-based spatial clustering [81] with the full counting approach. To ensure a feasible number of clusters for statistical analysis, a minimum of 5 simultaneous occurrences of each term is required as proposed in the literature [82]. Out of the 26,555 keywords, 2020 keywords met this threshold. To begin, the keywords with large circles suggest that they have been used often in publications by scholars in this field. We can notice that the circles for ‘machine learning’, ‘health informatics’, ‘medical informatics’, ‘artificial intelligence’, ‘disease’, ‘detection’, ’covid’, ‘health information technology, ‘information’, ‘challenges’, ‘healthcare’, ‘information’, ‘trail, ‘intervention’ and other decision-related terms are larger than the circles for other categories. ‘Quality,’ ‘implication,’ ‘study protocol’ and other medical application-related terms showed less often than decision-making keywords. Scholars might do studies in the future based on these high-frequency keywords to follow current trends or uncover new avenues based on phrases that occur less often. When it comes to keyword co-occurrence, we observe that the lines around ‘approach,’ ‘machine,’ ‘detection ‘, Covid,’ ‘quality,’ ‘effect,’ ‘trail,’ and ‘informatics’ are dense, which represents the core contents of this research field. In addition, ‘diabetes,’ ‘communication technology, ‘IoT,’ ‘pandemic,’ ‘architecture,’ ‘validation,’ ‘telemedicine,’ ‘randomized controlled trail,’ ‘meaningful use’ and other nearby terms are primarily independent, indicating that these concerns were not well-studied at the time. The categories in which these keywords fall might lead to breakthroughs for researchers.

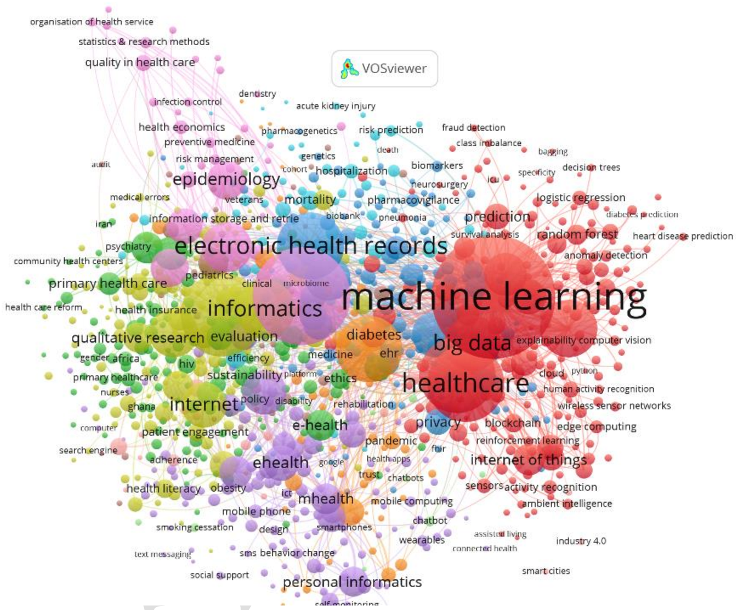

Figure 9: Keywords co-occurrence network of the reviewed papers

The implications of these results are significant for researchers in the field of healthcare technology. Firstly, the high frequency of certain keywords, such as 'machine learning', 'health informatics', 'medical informatics', 'artificial intelligence', 'disease', 'detection', 'COVID', 'health information technology', 'information', 'challenges', 'healthcare', 'trail', 'intervention', and other decision-related terms, suggests their prominence and widespread usage in scholarly discourse. These keywords represent important areas of focus within the field and indicate current trends and areas of interest. On the other hand, less frequently occurring keywords, including 'quality', 'implication', 'study protocol', and other medical application-related terms, suggest that these topics may warrant further exploration and research. Scholars may consider studying these fewer common keywords to uncover new avenues of investigation or contribute to emerging areas within healthcare technology. The observation of dense lines of keyword co-occurrence around terms like 'approach', 'machine', 'detection', 'COVID', 'quality', 'trail', 'informatics', indicates the core contents and central themes of this research field. These keywords represent the foundational concepts and areas of focus within healthcare technology. In contrast, the independent occurrence of keywords like 'diabetes', 'communication technology', 'IoT', 'pandemic', 'architecture', 'validation', 'telemedicine', 'randomized controlled trail', 'meaningful use', and other related terms suggests that these specific concerns have not received as much research attention at the time of this study.

From Figure 9, it is evident that the key themes in research on decision analytics in technology for sustainable healthcare aim to advance the utilization of analytics techniques in supporting decision-making processes, enhancing patient outcomes, optimizing resource allocation, and addressing ethical considerations in healthcare settings. Our findings indicate that the following areas have garnered significant attention:

1. Development of decision support systems: This involves creating sophisticated tools that leverage analytics techniques like machine learning and optimization to assist healthcare professionals in making informed and effective decisions. Applications include treatment planning, resource allocation, and risk prediction.
2. Real-time data analysis: This entails harnessing real-time data streams from various sources such as wearable devices and electronic health records to enable timely decision-making and proactive interventions. Predictive analytics is employed to identify patterns, trends, and anomalies in the data to inform healthcare decisions.
3. Ethical considerations: The plot reveals that ethical implications of utilizing decision analytics in healthcare, including privacy, bias, transparency, and accountability, have garnered attention. Research in this area focuses on ensuring fair, equitable, and ethically sound decision-making processes.
4. Human-computer interaction: The study of the interaction between healthcare professionals and decision analytics tools to enhance usability, user experience, and trust is an area of interest. Researchers concentrate on designing intuitive interfaces, providing interpretability of analytics results, and promoting effective collaboration between humans and algorithms.

However, decision-making in complex environments, which involves investigating decision analytics approaches for addressing challenges in resource-constrained settings or multi-stakeholder environments, and developing models and algorithms capable of handling uncertainty, variability, and conflicting objectives, has received less attention (see Figure 9).

4. Future trends in technology for sustainable healthcare

Sustainable healthcare technology has been a prominent issue in recent years, and it is one of the major research topics. The preceding sections discussed past and contemporary technological developments and their contributions to the healthcare business. In this part, we highlight latest trends, problems, and possibilities in future technology application research for sustainable healthcare. The results of this study present opportunities for researchers to further explore, expand, and contribute to the field of healthcare technology. Specifically:

1. **In-depth exploration of high-frequency keywords:** The study identifies keywords that have been frequently used by scholars in the field, such as 'machine learning', 'health informatics', 'medical informatics', 'artificial intelligence', and 'disease detection'. Future studies could delve deeper into these topics, examining their applications, challenges, and potential for further advancements.
2. **Investigation of less commonly studied keywords:** Keywords like 'quality', 'implication', 'study protocol', and other medical application-related terms were found to occur less frequently. Future studies can focus on these underexplored areas to gain a deeper understanding of their significance, implications, and potential contributions to healthcare technology.
3. **Emerging topics and trends:** The study reveals keywords related to 'COVID', 'health information technology', 'information', 'challenges', 'trail', and 'intervention' as prominent in the field. Further exploration of these emerging topics in greater detail, investigating their impact on healthcare technology, addressing challenges, and identifying innovative solutions.
4. **Keyword co-occurrence analysis:** The dense lines of co-occurrence observed around terms like 'approach', 'machine', 'detection', 'COVID', 'quality', 'trail', and 'informatics' suggest strong connections and interrelationships between these concepts. Understanding the synergies and interactions among these keywords, exploring how they contribute to the overall advancements in healthcare technology.

5. **Investigating less-studied concerns:** Keywords like 'diabetes', 'communication technology', 'IoT', 'pandemic', 'architecture', 'validation', 'telemedicine', 'randomized controlled trial', and 'meaningful use' were found to have independent occurrences, indicating potential areas that have not received much research attention. An extra look into these specific concerns, exploring their applications, challenges, and potential impact on healthcare technology.
6. **Real-time big data processing**: To accomplish SDG 3, infrastructure, and processing of the vast volumes of data created by the health sector must be efficient and real-time. Real-time big data processing and analytics enabled by apps, on the other hand, has become both fascinating and challenging. The necessity to manage such substantial amounts of data has become unavoidable in the healthcare industry. Since big data contains extreme noise, cleaning and mining the essential data from such a massive data space takes much time (computationally expensive) and work. Furthermore, machine learning is critical in translating data into meaningful information that people can understand. Because of the large quantity of data accessible, advanced machine learning and deep learning algorithms and methodologies are required. The procedure must occur in a dispersed context, posing a problem [83]. Scale, security, integrity, performance, concurrency, parallelism, and reliability are some of the issues of big healthcare data on software architecture. To deal with it, architects must rethink architectural solutions to fulfil functional and non-functional volume, diversity, and velocity needs [83].
7. **Ethical Issues (privacy) and Security:** While the development of new technologies for sustainable healthcare allows for better and more service automation in the industry, allowing for faster disease diagnosis and pandemic treatment, such as the novel Covid-19, there are some confidentiality and safety risks associated with this innovative technology that must be scrutinize and addressed right away. Technological improvements in the healthcare business allow for collecting more personal data, leading to serious privacy concerns that require immediate attention. Not only does confidential data need to be protected, but so does public data and infrastructure that are linked to the Internet. As a result, adequate methods must be created and implemented to mitigate the risk of privacy and security breaches. Utilizing technology, patient health data, and machines securely and safely remains an issue.
8. **Risks of Cyberattack:** The fast expansion of the Internet of Medical Things (IoMT), which includes medical equipment and apps, as well as an increase in the amount and availability of healthcare data, has increased cyberattacks in the healthcare industry. Devices in the IoMT ecosystem may lack basic security, making them susceptible to cyber-attacks. In this regard, current research might look at low weight integrated encryption and security techniques to provide high security.
1. **Risk of a Dynamic Workforce:** To better serve their patients, modern healthcare personnel are equipped with technologies, gadgets, and data. As a result of this and the pandemic, the conventional paradigm has given way to a more dynamic one in which healthcare staff may treat patients remotely. However, enterprises are exposed to incorrect worker authentication and authorization; because of this, it is also becoming more challenging to keep track of workers’ actions.

By focusing on above mention areas, future studies can contribute to advancements, address emerging challenges, and drive innovation in this rapidly evolving field.

4.1 Conclusions

Over time, the utilization of computers and related technologies in healthcare has primarily been limited to administrative functions. However, with advancements in technology and evolving regulations, computers have gained widespread acceptance in various aspects of healthcare institutions. They are now extensively employed at patients' bedsides, medical carts, nurse stations, laboratories, operating rooms, and other critical locations within healthcare settings. In recent times, significant advancements in computing technology have greatly expanded the wealth of information accessible to healthcare professionals. Healthcare databases have empowered doctors to access comprehensive knowledge on specific illnesses and treatment approaches. Furthermore, computers have the capability to conduct simulations to better understand the causes of diseases and explore potential remedies. Through collaboration with other machines, they enhance their capabilities and increase the likelihood of achieving successful outcomes. Hence several previous studies aimed at applying computers and their associated technologies in healthcare for sustainability. From a review of the published journal and conference papers from 1998 to 2023 indexed in the Scopus database; this report provides an overview of technology for sustainable healthcare research landscapes. In addition, to understand this field, a bibliometric analysis tool (VOSviewer) and Python were used to perform the analysis. The findings included growth trends, some of the most persuasive papers, the most productive novelists and research institutes, the most prominent publishing sites, and some current focus patterns. According to this report, predictive and diagnostic analytics, which comprises methodologies, supporting infrastructure, and applications, dominates research on technology for sustainable healthcare. Therefore, it is critical to recognize that technology for sustainable healthcare is inextricably linked to analytics.

Furthermore, privacy and security problems must be addressed for technology to be sustainable in healthcare. Artificial intelligence, machine learning, social networks, cloud computing, and the Internet of things contribute to sustainable healthcare technology. Cloud computing's resources and services help manage and process substantial amounts of healthcare data.

Some data-related and study design constraints define this investigation. Primarily, the dataset employed in this research was entirely derived from the Scopus database. Though Scopus is among the key worldwide scientific databases, it is recommended to pair with other recognized global databases such as Web of Science (WoS) and IEEE, Dimensions and Google Scholar. Furthermore, our keyword search was restricted to six ("technology," "sustainable healthcare," "health informatics," "machine learning in healthcare," "healthcare predictive analytics," and "artificial intelligence in healthcare"), and only journal articles and conferences were searched in the study. The use of keywords in the article title as clustering input is the second constraint. Although keywords in the title may represent the contents of a published paper, they may not accurately reflect the substance of an article. Because what the author intends to say is not always summed up in the title, the analysis' findings might be misconstrued. We advocate additional in-depth content analysis in the future, including enhancements based on the restrictions listed above. Also, conducting a more extensive content analysis to determine how significant publications have affected or are currently impacting the discipline may be an intriguing option for future research. Finally, other Bibliometrics tools could be used to conduct more detailed analysis in technology for sustainable healthcare research to locate evolving "research fronts" and "philosopher bases," where a research front is the up to date of research area, and a philosopher base is the articles cited by the research front. This study would help us understand the future of technology for sustainable healthcare and research trends.

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Highlights

1. Bibliometric analysis of technology for sustainable healthcare studies in Scopus from 1998 – 2022.
2. Addresses technology for sustainable healthcare research questions: trends, authors, institutions, themes, cooperation.
3. Investigates critical themes and their interconnections in the investigation of technology for sustainable healthcare studies.
4. Scans the most prominent issues and frequently studied topics in the field of technology for sustainable healthcare.
5. Insights for researchers in technology for sustainable healthcare, guiding future studies towards achieving sustainable healthcare outcomes.

Declaration of Interest

We, the authors, declare that there are no conflicts of interest. Also, we disclose that we have no financial or personal relationships with individuals or organizations that may have influenced the content of this manuscript.