

## PAPER

# Blockchain-Enabled Internet of Things (IoT) Applications in Healthcare: A Systematic Review of Current Trends and Future Opportunities

Vichayanon

Rattanawiboomsom<sup>1</sup>(✉),

Muhammad Saleem

Korejo<sup>2</sup>, Javed Ali<sup>2</sup>, UthenThatsaringkharnsakun<sup>3</sup>

<sup>1</sup>Faculty of Business,  
Economics and  
Communications,  
Naresuan University,  
Phitsanulok, Thailand

<sup>2</sup>Department of Business  
Administration, Sukkur IBA  
University, Sukkur, Pakistan

<sup>3</sup>Faculty of Law, University of  
Phayao, Mae Ka, Thailand

[vichayanonr@nu.ac.th](mailto:vichayanonr@nu.ac.th)**ABSTRACT**

The use of advanced computer technology in the healthcare industry has the potential to improve patient care and therapeutic results. The goal of this project is to improve data security, privacy, and decentralisation in healthcare by integrating blockchain and Internet of Things (IoT) technologies. The adoption of IoT devices makes it possible to gather and analyse patient sensory data in real-time; however centralised processing and storage present problems such as data manipulation and privacy issues. The study investigates the creation of a decentralised IoT-based e-healthcare system that takes these issues into account by utilising blockchain technology. In addition, the paper also emphasises how blockchain use has advanced smart contract technologies. Smart contracts provide safe user authentication for IoT device access, assuring responsibility, traceability, and data integrity. The study investigates the potentially game-changing applications of blockchain technology in healthcare, such as enhanced data interoperability, patient-centered care, reduced administrative procedures, and increased transaction transparency. The report also highlights the significance of blockchain in managing pharmaceutical supply chains, considering the essential influence on patient welfare and safety. Effective management is essential in the healthcare business because supply chain interruptions or breaches can have serious implications. The present level of research in blockchain-enabled IoT applications for healthcare is examined comprehensively using the PRISMA framework and records from the Scopus database. The three most important research topics are cloud computing, fog computing, and medical services. The results highlight the important role that blockchain-enabled IoT applications have played in enhancing data security and privacy in the healthcare industry. Real-time data gathering, precise diagnoses, individualised treatments, and simplified administrative procedures are all made possible by the integration of blockchain and IoT. Additionally, scalable solutions and insightful data for healthcare decision-making are provided via fog computing, cloud computing, machine learning, and smart contracts.

Rattanawiboomsom, V., Korejo, M.S., Ali, J., Thatsaringkharnsakun, U. (2023). Blockchain-Enabled Internet of Things (IoT) Applications in Healthcare: A Systematic Review of Current Trends and Future Opportunities. *International Journal of Online and Biomedical Engineering (iJOE)*, 19(10), pp. 99–117. <https://doi.org/10.3991/ijoe.v19i10.41399>

Article submitted 2023-04-15. Resubmitted 2023-06-01. Final acceptance 2023-06-03. Final version published as submitted by the authors.

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**KEYWORDS**

blockchain, internet of things (IoT), healthcare, machine learning, smart contracts, health services

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**1 INTRODUCTION**

The healthcare sector holds immense importance for individuals' well-being and quality of life, making it a critical focus for both developing and developed nations [1]. Continuous research and development efforts in the healthcare industry are essential as they have the potential to address numerous health challenges and illnesses [2]. Recent technological advancements have played a significant role in advancing the healthcare sector, and further progress can be achieved through the integration of state-of-the-art computer technology [3]. By leveraging cutting-edge computer technology, the capabilities of the healthcare and medical sector can be further enhanced [4]. These advanced computer technologies enable healthcare professionals, including physicians, to detect various diseases and conditions at an early stage, contributing to more effective diagnosis and treatment [5].

In addition, the use of blockchain and internet of things (IoT) technology is widespread across numerous industries, including e-healthcare [6], [7]. The healthcare industry can benefit from IoT devices, as they can collect patient sensory data in real time for analysis and processing [8], [9]. However, centralised processing, calculation, and storage of IoT data can lead to several issues, such as a single point of failure, distrust, data manipulation and tampering, and privacy avoidance [10]. These problems can be addressed by adopting blockchain technology, which offers decentralised processing and storage for IoT data [11]. Integrating blockchain and IoT technology can lead to the development of a decentralised e-healthcare system based on IoT [12], [13]. This system can address the major issues related to centralisation in IoT-based e-healthcare systems.

In addition, the recent progress in smart-contract technology has been significantly influenced by the adoption of blockchain [14]. Smart contracts find applications in several industries, including IoT, logistics, and the internet of vehicles. To ensure secure user authentication for accessing IoT devices, [15] introduced a solution and architectural framework based on blockchain technology. Their proposed architecture effectively resolves the challenges associated with current authentication methods and offers benefits, such as traceability, data integrity, and accountability, using tamper-proof logs [16]. In addition, the use of blockchain in the medical sector extends to the management of pharmaceutical supply chains, which is an essential application. Supply chain management is crucial in various industries, but it holds even greater significance in the healthcare sector due to its complexity and the potential impact on patient well-being [17]. The healthcare supply chain involves the movement of various pharmaceutical products, including medications, vaccines, and medical devices, from manufacturers to healthcare providers and ultimately to patients [18]. Any disruption, breach, or inefficiency in this supply chain can have serious consequences for patient safety and welfare [19].

This study's goal is to evaluate the impact of blockchain-enabled IoT on the healthcare industry. The project specifically intends to assess how integrating blockchain technology with IoT devices might improve medical procedures and services. Understanding how blockchain will affect the effectiveness, security, and privacy of healthcare data and systems is the main goal. In addition, the study also aims to investigate the potentially transformative uses of blockchain technology in the healthcare industry. It intends to pinpoint the revolutionary adjustments that

blockchain can make to medical procedures, including better data interoperability, greater patient-centred treatment, faster administrative procedures, and higher confidence and transparency in medical transactions.

## 2 MATERIALS AND METHODS

The preferred reporting items for systematic reviews and meta-analyses (PRISMA) framework was used to screen the records as recommended, shown in Figure 1. A thorough content analysis of the selected articles was performed to classify the literature. For this purpose, we used R software to create research clusters (classifications) based on keyword frequency and co-occurrence. To conduct a literature review, we utilized a two-stage systematic approach. Firstly, we employed the PRISMA framework to extract relevant data, followed by descriptive and scientometric analyses to ensure the accuracy and validity of the records. We also used the R program to investigate major research clusters, utilizing centrality and co-occurrence keywords. A content analysis of the information acquired from two reliable databases, including Scopus, was carried out in order to synthesise the literature for this study. Using precise terms like “blockchain,” “internet of things,” and “healthcare,” a thorough search approach was used, yielding a total of 1140 entries. Subject filters, which took into account fields including computer science, engineering, medicine, social science, business, management, and accounting, were used to whittle down the findings. The total number of papers was decreased to 1099 once the filters were applied. The number was further reduced to 615 by including only articles and review papers that were published in order to assure robustness. A language filter was also used, producing 555 English-language items for the database search’s concluding stage.

Considering the extensive number of records obtained, further filtering was necessary to ensure relevance and quality. Irrelevant, duplicated, and missing information was eliminated using Microsoft Excel. Moreover, a sources-based analysis approach was adopted, which required a minimum of three articles from a single source to be included in the investigation. Following this rigorous approach, the number of records was reduced to 100, which underwent detailed research analysis.

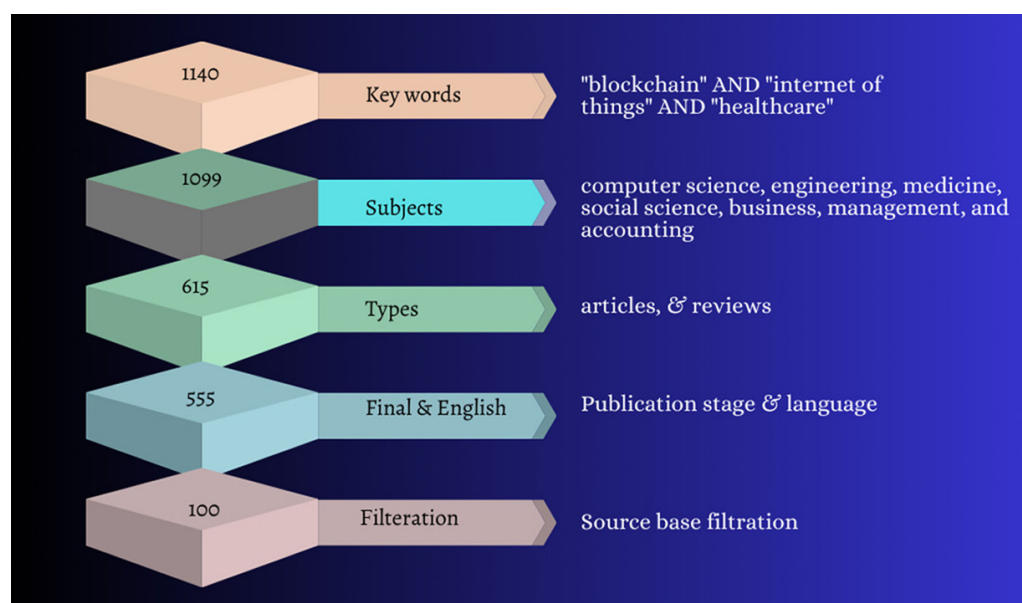


Fig. 1. PRISMA statement 2020

In addition, we employed R software for the data analysis section to identify the major characteristics of previous research conducted on the blockchain and IoT in the healthcare sector. Table 1 presents the main information and contents of the data analysed in this study. The time span covered by the data is from 2022 to 2023, with 100 documents sourced from 20 different sources such as journals and books. The annual growth rate of the data is negative, with a rate of  $-52.94\%$ . The average age of the documents is 0.68, indicating that the data is recent. Additionally, the average citations per document were found to be 6.51, with a total of 6613 references. In terms of document contents, the data contained 742 keywords plus (ID) and 302 author's keywords (DE). The data was contributed by 426 authors, with only 5 single-authored documents. Most of the documents analysed in this study were co-authored by the authors, with an average of 4.77 co-authors per document. International collaborations accounted for 61% of the total collaborations. In terms of document types, articles were the most prevalent (79), followed by reviews (21). These findings from the analysis provide valuable information about the characteristics and content of the data examined in this research.

**Table 1.** General information about records extracted

Description	Results
MAIN INFORMATION ABOUT THE DATA	
Timespan	2022–2023
Sources (Journals, Books, etc)	20
Documents	100
Annual Growth Rate %	$-52.94$
Document Average Age	0.68
Average citations per doc	6.51
References	6613
Keywords Plus (ID)	742
Author's Keywords (DE)	302
Authors	426
Authors of single-authored docs	5
AUTHORS COLLABORATION	
Single-authored docs	5
Co-Authors per Doc	4.77
International co-authorships %	61
DOCUMENT TYPES	
article	79
review	21

### 3 RESULTS

#### 3.1 Descriptive and scientometric analysis of records

Figure 2 displays the findings of an analysis conducted on the mean total citations per article (MeanTCperArt), the number of articles (N), the mean total citations

per year (MeanTCperYear), and the number of citable years (CitableYears) within a specific timeframe. As anticipated, the table illustrates a decrease in both the mean total citations per article and mean total citations per year as the articles become more recent.

For instance, in 2018, there were only 3 articles with a mean total citations per article of 175.33 and a mean total citations per year of 29.22. The citable years for this period were 6. In the subsequent year, 2019, the mean total citations per article dropped to 144.31 with 13 articles, and the mean total citations per year was 28.86. The citable years reduced to 5. Similarly, in 2020, there were 46 articles with a mean total citations per article of 79.17 and a mean total citations per year of 19.79. The citable years decreased to 4.

The downward trend continued in 2021, with 73 articles having a mean total citations per article of 22.89 and a mean total citations per year of 7.63. The citable years were 3. In the subsequent years, the mean total citations per article experienced a significant decline. In 2022, there were 134 articles with a mean total citations per article of 8.13 and a mean total citations per year of 4.07. The citable years were 2. Finally, in 2023, there were 34 articles with a mean total citations per article of 1.74 and a mean total citations per year of 1.74. The citable years for this year were 1.

Figure 2 provides valuable information regarding the trends in the mean total citations per article, mean total citations per year and the number of citable years for the period under analysis. The results indicate a general decline in the citation impact of articles over time, which may be due to the recency of the publications.

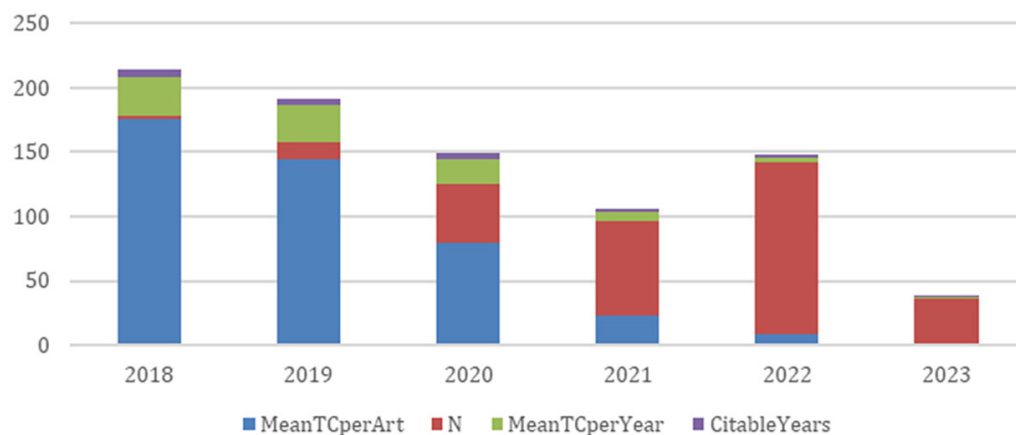


Fig. 2. Annual total citations per year

Figure 3 shows a list of sources and the number of articles retrieved from each source. The data provide insights into the most frequently cited sources in the literature on the topic under consideration. The sources include 17 journals, with *SENSORS* having the highest number of articles (16), followed by *IEEE Internet of Things Journal* (11), and *IEEE Transactions on Industrial Informatics* (9). Other sources include *Electronics* (Switzerland), *Applied Sciences* (Switzerland), *Internet of Things* (Netherlands), *Wireless Personal Communications*, *Information Sciences*, and *Sustainability* (Switzerland). Moreover, the table indicates the total number of articles collected from all sources (103).

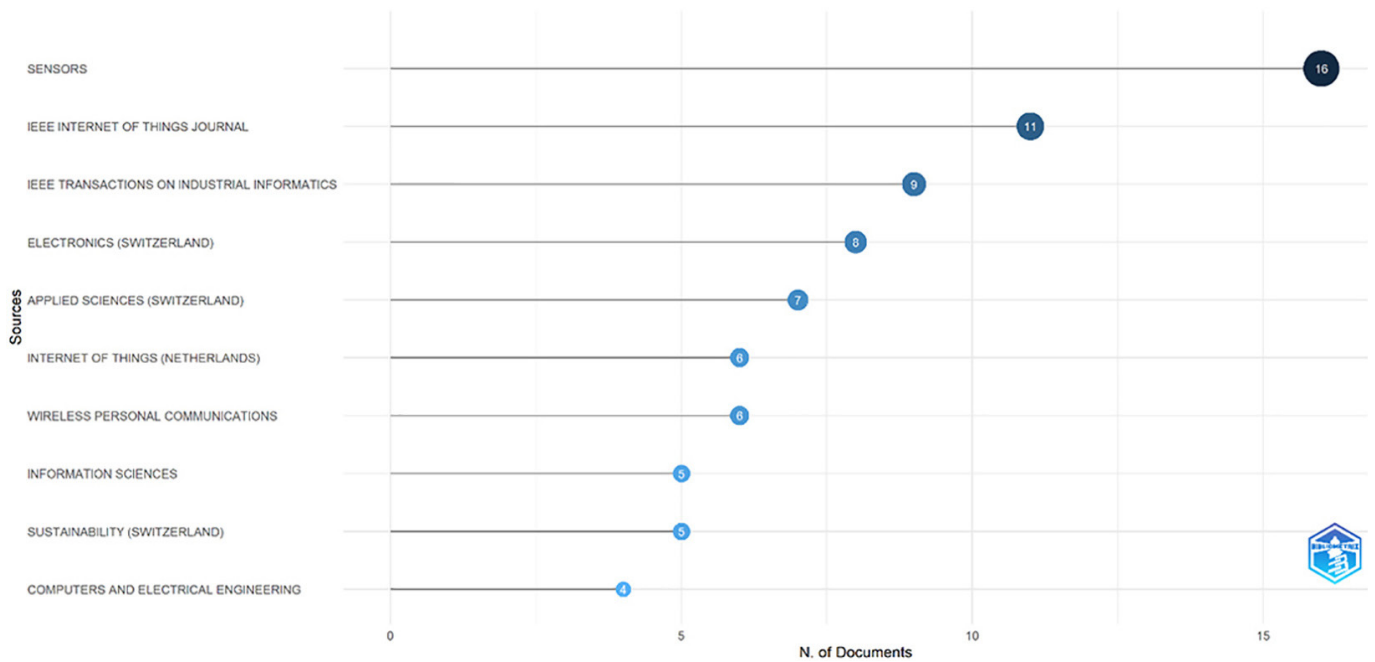


Fig. 3. Most relevant sources

Table 2 shows bibliometric indicators for various scientific journals in the field of computer science and engineering. The bibliometric indicators include h-index, g-index, m-index, total citations (TC), number of papers (NP), and the starting year of publications (PY\_start). The h-index represents the number of articles that have received at least h citations, the g-index represents the highest number of papers with g or more citations, and the m-index is the h-index divided by the number of years since the first publication. The data reveals that *IEEE Access* has the highest h-index (23) and a g-index of 49, while *Sensors* (Switzerland) has the highest m-index (3.667). *IEEE Access* also has the highest number of total citations, with 2483, followed by *Sensors*, with 1226 citations. The journal *Computers, Materials and Continua* has the highest number of papers, with 10 publications in 2021. The starting year of publications varies from 2018 to 2022. Overall, the data suggest that the selected journals and conference proceedings have varying levels of impact and are subject to diverse publication trends.

Table 2. Source impact bibliometric indicators for scientific journals

Element	h Index	g Index	m Index	TC	NP	PY Start
IEEE Access	23	49	3.833	2483	51	2018
IEEE Internet of Things Journal	15	24	3	1069	24	2019
Sensors (Switzerland)	12	12	2.4	1226	12	2019
Electronics (Switzerland)	11	19	2.2	518	19	2019
Sensors	11	17	3.667	299	25	2021
Journal of Network and Computer Applications	8	8	2	803	8	2020
Computer Communications	7	11	1.75	619	11	2020
IEEE Transactions on Industrial Informatics	6	10	1.5	183	10	2020

(Continued)

**Table 2.** Source impact bibliometric indicators for scientific journals (*Continued*)

Element	h Index	g Index	m Index	TC	NP	PY Start
Computer Networks	5	6	0.833	444	6	2018
Computers And Electrical Engineering	5	6	1.25	160	6	2020
Computers, Materials and Continua	5	7	1.667	63	10	2021
IEEE Journal of Biomedical and Health Informatics	5	6	1.25	134	6	2020
Internet of Things (Netherlands)	5	8	1.25	106	8	2020
Wireless Personal Communications	5	8	1.667	67	9	2021
Applied Sciences (Switzerland)	4	9	0.8	265	9	2019
Computational Intelligence and Neuroscience	4	6	1.333	60	6	2021
International Journal of Advanced Computer Science and Applications	4	6	0.667	48	7	2018
Information Sciences	3	4	1.5	18	5	2022
Internet of Things	3	4	1	24	9	2021
Sustainability (Switzerland)	3	6	0.75	52	6	2020
Wireless Communications and Mobile Computing	3	6	1	47	6	2021
Blockchain Applications for Healthcare Informatics: Beyond 5g	2	2	1	12	10	2022
EAI/Springer Innovations in Communication and Computing	2	3	0.5	15	14	2020
Intelligent Automation and Soft Computing	2	3	1	10	6	2022
Journal of Supercomputing	2	5	0.667	73	5	2021
Studies in Systems, Decision and Control	2	3	0.5	12	4	2020
Transactions on Emerging Telecommunications Technologies	2	5	0.667	47	5	2021

Table 3 provides information about the ranking, frequency, cumulative frequency, and zone classification of various sources in the field of research. The ranking column indicates the position of each source based on its importance or frequency of occurrence. The frequency column represents the number of times the source appears in the dataset, while the cumulative frequency column shows the cumulative total of frequencies up to that point.

The sources are categorized into different zones. In this case, Zone 1 includes the top-ranked sources, which are *Sensors* (ranked 1st), *IEEE Internet of Things Journal* (ranked 2nd), and *IEEE Transactions on Industrial Informatics* (ranked 3rd). Zone 2 consists of sources such as *Electronics* (Switzerland), *Applied Sciences* (Switzerland), *Internet of Things* (Netherlands), and *Wireless Personal Communications*. Zone 3 includes sources like *Sustainability* (Switzerland), *Computers and Electrical Engineering*, *IEEE Journal of Biomedical and Health Informatics*, and *Computer Communications*, among others.

**Table 3.** Core sources by Bradford's Law

Source	Freq	Cum Freq
Sensors	16	16
IEEE Internet of Things Journal	11	27
IEEE Transactions on Industrial Informatics	9	36
Electronics (Switzerland)	8	44
Applied Sciences (Switzerland)	7	51
Internet of Things (Netherlands)	6	57
Wireless Personal Communications	6	63
Information Sciences	5	68
Sustainability (Switzerland)	5	73
Computers and Electrical Engineering	4	77
IEEE Journal of Biomedical and Health Informatics	4	81
Computer Communications	3	84
IEEE Access	3	87
Journal of Supercomputing	3	90
Transactions on Emerging Telecommunications Technologies	3	93
Computer Networks	2	95
Intelligent Automation and Soft Computing	2	97
International Journal of Advanced Computer Science and Applications	1	98
Journal of Network and Computer Applications	1	99
Wireless Communications and Mobile Computing	1	100

## 4 LITERATURE CLUSTERING

We employed a two-stage systematic approach in conducting our literature review. In the first stage, the PRISMA framework was utilised to extract the pertinent data, and descriptive and scientometric analyses were carried out to ensure the accuracy and validity of the records. Additionally, the centrality and co-occurrence keywords were employed to examine the major research clusters using the R programme. Later, each cluster underwent content analysis of the retrieved data to compile the literature.



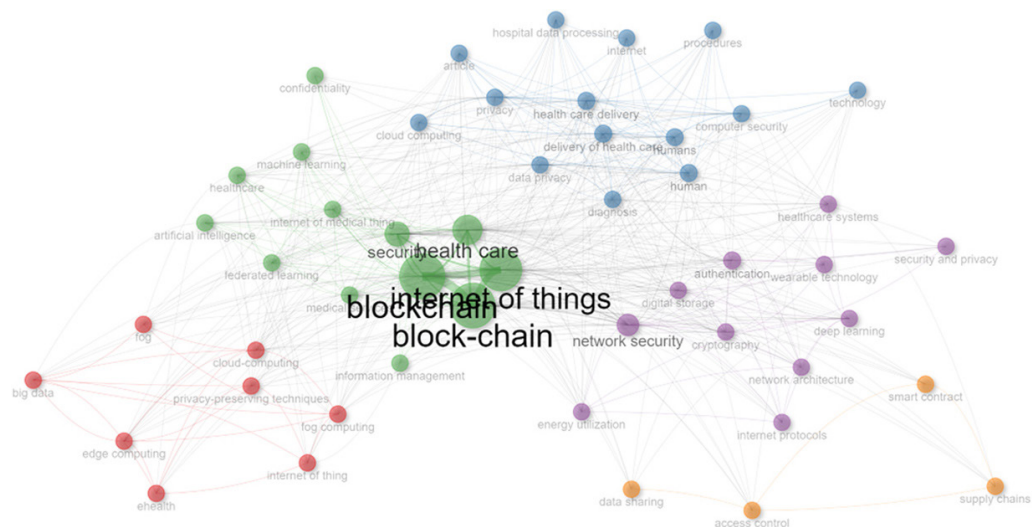


Fig. 4. Cluster map

A list of keywords can be regarded as a condensed representation of a specific research theme, incorporating the criteria of density and centrality, which can be applied to any research topic. Figure 4 shows a cluster map based on the author's keywords. Density determines the level of similarity between all terms within the list, while centrality determines the level of similarity between a specific subject and others. To visually represent the thematic relationships, a thematic map, also known as a strategic diagram, is utilized, which classifies the topics into four quadrants based on their significance and density. Figure 5 demonstrates the presence of various features within each of the four quadrants.

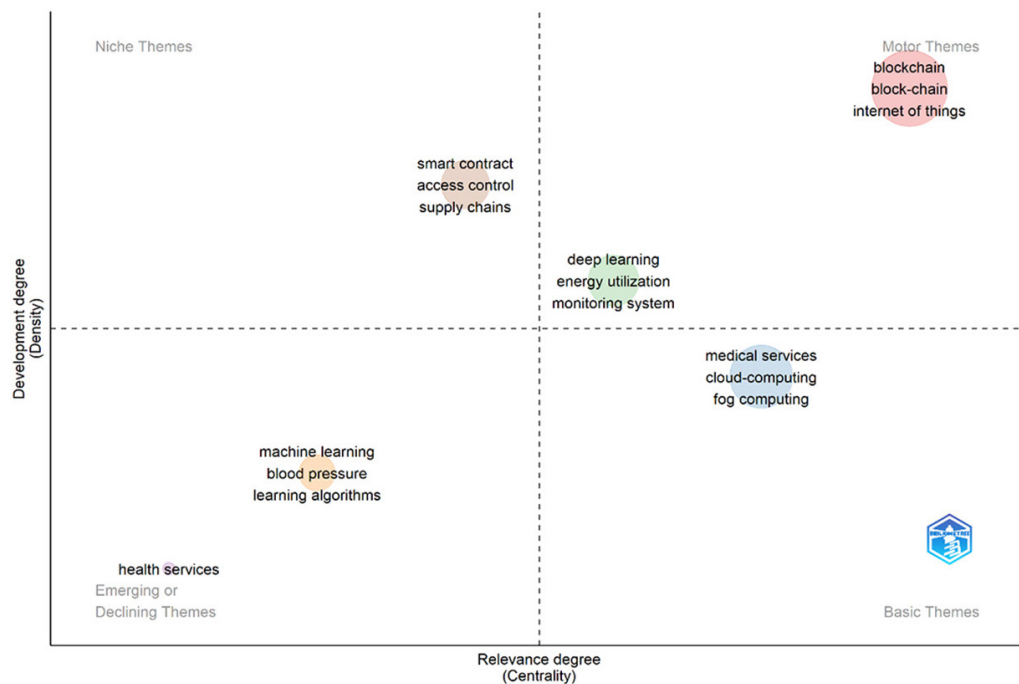


Fig. 5. Thematic map

Table 4 presents information about different clusters, including their Callon centrality, Callon density, rank centrality, rank density, and cluster frequency.

Callon centrality represents the centrality measure for each cluster, indicating the extent of influence or importance within the research network. The higher the Callon centrality value, the more central or influential the cluster is. For example, the cluster “blockchain” has a Callon centrality of 43.92370792, suggesting a high level of centrality within the research network.

The Callon density reflects the density of connections or relationships between terms within each cluster. A higher Callon density value indicates a greater interconnectedness or similarity among the terms within the cluster. For instance, the cluster “blockchain” has a Callon density of 140.1142954, indicating a dense network of interconnected terms.

The rank centrality and rank density columns provide the ranking of each cluster based on their centrality and density measures, respectively. The lower the rank value, the higher the centrality or density of the cluster.

Finally, the cluster frequency column shows the number of occurrences or frequency of each cluster within the dataset. For example, the cluster “blockchain” appears 633 times, indicating its prevalence within the research corpus.

**Table 4.** Thematic evolution

Cluster	Callon Centrality	Callon Density	Rank Centrality	Rank Density	Cluster Frequency
blockchain	43.92370792	140.1142954	6	6	633
medical services	21.16242955	106.8209399	5	3	194
deep learning	11.52454397	118.4451659	4	4	65
health services	0	50	1	1	2
machine learning	3.926666667	95.18518519	2	2	17
smart contract	8.713888889	120.5996732	3	5	51

Figure 5, showing the thematic map, illustrates that health services and machine learning are considered emerging or declining based on their standing in the literature. Table 5 provides information about specific words or phrases, their occurrences, and centrality measures in a network. The term “machine learning” appears five times in the network. It has a high betweenness centrality of 165.4395237, indicating that it serves as an important bridge between other words or phrases. It also has a relatively high closeness centrality and PageRank centrality, suggesting its proximity to other terms and its overall importance in the network.

**Table 5.** Machine learning and health services cluster

Words	Occurrences	Betweenness Centrality	Closeness Centrality	Page Rank Centrality
machine learning	5	165.4395	0.002141	0.005724
blood pressure	3	105.5435	0.002066	0.003038
learning algorithms	3	70.37901	0.002083	0.002652
k-near neighbor	2	23.38911	0.002053	0.002138
nearest-neighbour	2	23.38911	0.002053	0.002138
nearest neighbor search	2	23.38911	0.002053	0.002138
health services	2	16.03738	0.001595	0.001081

Figure 5 depicts medical services as the basic theme, and the term “medical services” appears 14 times in the dataset and is assigned to Cluster\_Label “medical services” in Table 6. It has a high betweenness centrality of 572.3843163, indicating that it acts as a bridge connecting other terms in the dataset. The closeness centrality is 0.002247191, suggesting that it is closely connected to other terms. The Page Rank centrality is 0.011945371, indicating its importance based on the number and importance of other terms linking to it.

Other terms such as “cloud computing” (11 occurrences), “edge computing” (6 occurrences), and “fog computing” (8 occurrences) also belong to the “medical services” cluster. These terms have different centrality measures, indicating their varying importance in the dataset.

Additionally, terms related to data management and technology, such as “big data,” “data sharing,” and “data analytics,” appear multiple times with moderate centrality values. Other terms related to healthcare sectors, privacy preservation, smart healthcare, and emerging technologies, such as “blockchain” and “neural networks”, also have occurrences and centrality measures associated with them.

**Table 6.** “Medical services” cluster

Words	Occurrences	Betweenness Centrality	Closeness Centrality	Page Rank Centrality
medical services	14	572.3843	0.002247	0.011945
cloud-computing	11	580.0305	0.002242	0.009805
edge computing	6	87.67593	0.001946	0.004772
fog computing	8	360.912	0.002232	0.007505
privacy-preserving techniques	7	239.5287	0.002193	0.005641
big data	6	199.4287	0.002137	0.005255
data sharing	6	218.5869	0.002183	0.004884
eHealth	4	77.19246	0.002062	0.003793
fog	6	207.3521	0.002198	0.005806
internet of thing	6	271.2356	0.002165	0.005082
information management	5	169.9123	0.002165	0.004357
cloud storage	4	56.49015	0.001992	0.003473
data analytics	2	29.29381	0.002075	0.002093
healthcare sectors	4	74.36919	0.001984	0.003063
privacy preservation	4	70.78435	0.002008	0.004332
privacy preserving	4	63.74544	0.002041	0.002964
smart healthcare	4	106.9084	0.002088	0.003597
automation	3	81.0201	0.00207	0.003355
benchmarking	3	23.28359	0.001984	0.002336
blockchain technology	3	53.5391	0.001949	0.002384
healthcare 4.0	3	94.94921	0.002053	0.00293
hospitals	3	89.64145	0.002083	0.003147
neural networks	3	75.5858	0.002123	0.00328

(Continued)

**Table 6.** “Medical services” cluster (Continued)

Words	Occurrences	Betweenness Centrality	Closeness Centrality	Page Rank Centrality
personal computing	3	71.36454	0.002075	0.003133
sensitive data	3	75.77084	0.002041	0.002745
surveys	3	93.82314	0.002141	0.002892
classification (of information)	2	12.9702	0.001946	0.00149
collaborative work	2	63.04037	0.002123	0.002785
computing system	2	23.70487	0.002033	0.001874
convolutional neural network	2	39.97959	0.002024	0.002236
data integrity	2	24.02812	0.002066	0.002062
data storage	2	35.82232	0.002083	0.002118
differential privacies	2	24.56952	0.001901	0.002442
distributed computer systems	2	17.87664	0.002024	0.002226
electronic data interchange	2	69.97467	0.002062	0.002494
electronic health	2	23.10469	0.002062	0.001991
encryption schemes	2	7.21174	0.002004	0.001646
filesystem	2	30.73945	0.002079	0.00221
health records	2	23.39576	0.002075	0.00195
healthcare industry	2	26.19828	0.002045	0.002026
healthcare services	2	22.73585	0.001972	0.001431
industrial internet of thing	2	33.42216	0.002092	0.002278
intelligent buildings	2	9.306671	0.001808	0.002282
interactive computer systems	2	14.82173	0.002028	0.001915
internet of things technologies	2	22.7689	0.002053	0.001859
job analysis	2	9.209524	0.002	0.001751
learning models	2	29.88151	0.002075	0.001789
medical computing	2	9.894099	0.001996	0.001399
medical record	2	13.648	0.002028	0.001802
patient health	2	9.005685	0.00188	0.002078
real time systems	2	14.82173	0.002028	0.001915
records management	2	41.63408	0.00202	0.002264
research communities	2	10.62578	0.001938	0.001623
search engines	2	20.13475	0.00207	0.001911
security systems	2	49.16133	0.002049	0.002281
sensitive information	2	7.21174	0.002004	0.001646
smart applications	2	13.21942	0.001916	0.001684
smart homes	2	83.50876	0.002075	0.002706
task analysis	2	9.209524	0.002	0.001751

The evolution map in Figure 5 is the smart contracts theme that exists in the Niche Themes, and Table 7 depicts that term “smart contract” appearing 6 times in the dataset, and it is assigned to the Cluster\_Label “smart contract.” It has a betweenness centrality of 167.1297444, indicating that it acts as a bridge connecting other terms in the dataset. The closeness centrality is 0.00212766, suggesting that it is closely connected to other terms. The Page Rank centrality is 0.004328029, indicating its importance based on the number and importance of other terms linking to it. Other terms such as “access control” (5 occurrences), “supply chains” (5 occurrences), and “distributed ledger” (4 occurrences) also belong to the “smart contract” cluster. These terms have different centrality measures, indicating their varying importance in the dataset.

Additionally, terms related to smart cities, decentralization, Ethereum, and smart devices appear multiple times with moderate centrality values. Terms like “trust,” “centralized,” and “cities” are also present in the dataset, albeit with lower occurrences and centrality measures. The table also includes terms related to computation theory, cyber-physical systems, embedded systems, and queueing theory, which are associated with smart contracts in some way.

**Table 7.** “Smart contract” cluster

Words	Occurrences	Betweenness Centrality	Closeness Centrality	Page Rank Centrality
smart contract	6	167.1297	0.002128	0.004328
access control	5	189.506	0.002141	0.004502
supply chains	5	99.97064	0.002041	0.003925
distributed ledger	4	111.1558	0.002119	0.00333
smart city	4	193.7731	0.002024	0.003521
decentralised	3	94.86633	0.002028	0.00295
ethereum	3	18.66422	0.001972	0.002082
smart devices	3	43.08253	0.00202	0.002574
trust	2	50.80168	0.002012	0.002149
centralised	2	27.73032	0.002024	0.002393
cities	2	28.95312	0.001996	0.00268
city	2	28.95312	0.001996	0.00268
computation theory	2	13.15758	0.00188	0.00198
cyber-physical systems	2	43.71395	0.002114	0.002774
embedded systems	2	41.19333	0.001957	0.002225
queueing theory	2	75.30906	0.002128	0.002885

According to Table 8, the term “blockchain” appears 66 times in the dataset and is assigned to the Cluster Label “blockchain.” It has a betweenness centrality of 1068.195427, indicating that it acts as a bridge connecting other terms in the dataset. The closeness centrality is 0.002369668, suggesting that it is closely connected to other terms. The Page Rank centrality is 0.050673317, indicating its importance based on the number and importance of other terms linking to it.

Other terms such as “internet of things” (61 occurrences), “block-chain” (66 occurrences), and “health care” (37 occurrences) also belong to the “blockchain” cluster. These terms have different centrality measures, indicating their varying importance in the dataset. Additionally, terms related to security, privacy, authentication, and data management appear multiple times with varying centrality values. Terms like “artificial intelligence,” “cryptography,” and “delivery of health care” are also present in the dataset, albeit with lower occurrences and centrality measures. The table also includes terms related to healthcare systems, network architecture, wearable technology, and cloud computing, which are associated with blockchain in some way.

**Table 8.** “Blockchain” cluster

Words	Occurrences	Betweenness Centrality	Closeness Centrality	Page Rank Centrality
blockchain	66	1068.19543	0.00237	0.050673
Internet of things	61	1929.42885	0.002488	0.046468
block-chain	66	983.889436	0.002336	0.049956
health care	37	1916.97403	0.002475	0.029652
security	27	1400.6107	0.002398	0.022171
network security	25	1939.64255	0.002532	0.020431
privacy	12	490.58492	0.002203	0.011707
computer security	12	396.517059	0.002222	0.012744
authentication	16	526.931339	0.002257	0.013464
data privacy	13	593.740159	0.002268	0.012913
digital storage	14	1005.58538	0.002358	0.011923
artificial intelligence	9	318.216208	0.002179	0.00683
cryptography	13	738.616964	0.002304	0.011368
delivery of healthcare	13	457.664599	0.002294	0.013808
health care delivery	13	457.664599	0.002294	0.013808
internet of medical thing	13	481.554005	0.002242	0.010589
human	12	416.223317	0.002304	0.013947
humans	12	416.223317	0.002304	0.013947
Internet	8	290.158731	0.002179	0.00526
healthcare systems	9	445.691216	0.002217	0.00823
diagnosis	8	279.05096	0.002146	0.007884
technology	4	92.2287372	0.002016	0.004278
federated learning	7	265.405088	0.002183	0.007741
healthcare	7	314.217787	0.002151	0.007547
cloud computing	5	157.438119	0.002151	0.005059
network architecture	6	241.283596	0.002169	0.00593
security and privacy	6	231.53983	0.002137	0.004472

(Continued)

**Table 8.** “Blockchain” cluster (Continued)

Words	Occurrences	Betweenness Centrality	Closeness Centrality	Page Rank Centrality
wearable technology	6	170.514837	0.002132	0.005839
article	5	148.302994	0.002165	0.007048
confidentiality	3	40.1753716	0.002066	0.002998
hospital data processing	5	175.303116	0.002114	0.005186
Internet protocols	5	134.563377	0.001988	0.004962
procedures	5	113.037488	0.002049	0.005466
5g mobile communication systems	4	151.97956	0.002096	0.004207
covid-19	3	69.0829891	0.002123	0.003942
health risks	4	70.1363005	0.00211	0.004473
medical imaging	4	57.3557122	0.001919	0.005216
security mechanism	4	117.283763	0.002096	0.003746
sensitive data	4	165.428431	0.002123	0.004372
wireless sensor networks	4	63.2334354	0.00202	0.004145
authentication scheme	3	19.7052841	0.001972	0.002359
cybersecurity	3	82.137024	0.001996	0.003143
learning	3	50.1585379	0.002004	0.004693
learning systems	3	124.464116	0.002132	0.003347
medical diagnostic imaging	3	39.476506	0.001992	0.003764
military applications	3	56.2924931	0.002041	0.002266
patient treatment	3	71.3702868	0.002033	0.003258
public key cryptography	3	27.1174884	0.001988	0.002615
smart grid	3	58.1741145	0.002092	0.002959
adult	2	32.4559199	0.002105	0.00334
algorithm	2	41.3688482	0.00211	0.003122
algorithms	2	41.3688482	0.00211	0.003122
authorization	2	16.1672642	0.001996	0.002257
crime	2	60.0091026	0.00211	0.002893
diagnostic imaging	2	35.9339427	0.002092	0.003359
electric power transmission networks	2	24.8101526	0.002053	0.002125
emergency services	2	107.489925	0.00216	0.0031
health care application	2	38.4302387	0.00202	0.002384
health care system	2	32.4559199	0.002105	0.00334
human lives	2	26.0601002	0.002092	0.00286
information security	2	66.8283954	0.002137	0.002808

(Continued)

**Table 8.** “Blockchain” cluster (Continued)

Words	Occurrences	Betweenness Centrality	Closeness Centrality	Page Rank Centrality
information use	2	17.2180562	0.001961	0.002156
iot	2	25.293068	0.002083	0.002491
medical applications	2	60.5621059	0.002137	0.002768
medical data	2	68.2667665	0.002049	0.002856
medical information systems	2	67.7453283	0.002132	0.002586
medical service	2	22.8853753	0.002	0.003367
online systems	2	31.8793287	0.001961	0.002039
optimization	2	64.5450816	0.002132	0.002435
physically unclonable functions	2	11.5450552	0.001984	0.002114
privacy-preserving authentication	2	38.8729771	0.002053	0.002536
private key	2	27.4008521	0.002053	0.002688
smart power grids	2	24.8101526	0.002053	0.002125
Viruses	2	38.8632353	0.002114	0.002035
wearable devices	2	21.3299389	0.00207	0.002242
wireless medical sensor network	2	7.50599941	0.001869	0.002433
wireless networks	2	17.2180562	0.001961	0.002156

## 5 DISCUSSION

This research aims to investigate the impact of blockchain and IoT on the health-care sector. To achieve this objective, a comprehensive literature review was conducted using records extracted from the Scopus database. The search query included the keywords “blockchains,” “internet of things,” and “healthcare.” Only English-language articles and review papers were considered, resulting in a final selection of 100 relevant records. Stringent measures were implemented to eliminate irrelevant and duplicate documents, following the guidelines outlined in the PRISMA Statement 2020 [20], [21].

For data analysis, the R software biblioshiny technique was employed. In the initial stage, the total annual citations for the selected articles were determined. Furthermore, the contribution of major sources and the average number of citations for each source were examined. The literature was then analyzed in terms of clusters, thematic maps, thematic evolution, and major clusters.

The findings indicate that blockchain and IoT are prominent research areas and emerging major themes in recent years. However, during the analysis, it was observed that there is relatively limited research activity focused specifically on smart contracts in the healthcare domain. The analysis of the basic theme revealed that medical services, fog computing, and cloud computing are key themes and terms frequently used in the literature.

Notably, the results suggest a declining or emerging trend in the occurrence of machine learning and health service terms, indicating that these areas have received



limited attention in the current literature. Overall, the study provides insights into the current state of research on the influence of blockchain and IoT on the healthcare sector, highlighting both the major research themes and potential areas for future exploration.

## 6 CONCLUSION AND FUTURE RESEARCH

The study's conclusions emphasise the important effects of using blockchain and IoT technologies to the healthcare industry. Researchers have been actively looking into how blockchain technology can improve the security and privacy of health records in recent years. Blockchain solutions are receiving more attention as a result of the pressing need to solve security issues facing healthcare organisations and protect sensitive patient data.

Healthcare facilities have improved as a result of the adoption of blockchain technology. The widespread use of IoT devices makes it possible to gather and analyse real-time data on a massive scale. This data-driven strategy enhances healthcare delivery by facilitating more precise diagnosis, individualised treatments, and effective patient health monitoring. The combination of blockchain and IoT has immense potential to revolutionize healthcare practices and enhance patient outcomes.

Furthermore, the study emphasizes the significance of fog computing, cloud computing, machine learning, and smart contracts in the healthcare industry. Fog computing and cloud computing facilitate the storage, processing, and analysis of extensive healthcare datasets, offering scalable and cost-effective solutions. Machine-learning techniques leverage these datasets to extract meaningful insights, aiding in decision-making and predictive analytics. Smart contracts automate and enforce the execution of healthcare agreements, streamlining administrative processes and fostering trust among stakeholders. The findings underscore the significance of these technologies in shaping the future of healthcare. They offer promising avenues for enhancing healthcare services, optimizing resource utilization, and improving patient care. The study's insights serve as a valuable foundation for further research and development in these areas, guiding future endeavours to maximize the benefits of blockchain, IoT, fog computing, cloud computing, machine learning, and smart contracts in the healthcare domain.

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## 8 AUTHORS

**Vichayan Rattanawiboomsom**, Faculty of Business, Economics and Communications, Naresuan University, Phitsanulok, Thailand (e-mail: [vichayanr@nu.ac.th](mailto:vichayanr@nu.ac.th)).

**Muhammad Saleem Korejo**, Department of Business Administration, Sukkur IBA University, Pakistan (e-mail: [saleem.korejo@iba-suk.edu.pk](mailto:saleem.korejo@iba-suk.edu.pk)).

**Javed Ali**, Department of Business Administration, Sukkur IBA University, Pakistan (e-mail: [javedali@iba-suk.edu.pk](mailto:javedali@iba-suk.edu.pk)).

**Uthen Thatsaringkharnsakun**, Faculty of Law, University of Phayao, Thailand (e-mail: [uthenthat@gmail.com](mailto:uthenthat@gmail.com)).