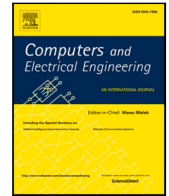


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A visual review of artificial intelligence and Industry 4.0 in healthcare[☆]

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ABSTRACT

The COVID-19 outbreak has led to a substantial loss of human life throughout the world and has a tremendous impact on healthcare services. Industry 4.0 technologies have established effective supply chain management towards the fulfillment of customized demands in the healthcare field. In addition, the internet of things, artificial intelligence, big data analytics, and 3D printing have been extensively used to combat the COVID-19 pandemic and assist in providing value-added services in the healthcare sector. Henceforth, this paper presents a scientometric analysis on the literature of aforementioned Industry 4.0 technologies in the context of COVID-19. It provides extensive insights into co-citation and co-occurrence analysis of high cited publications, participating countries, influential authors, prolific journals, and keywords using the CiteSpace tool. The analyses reveal that China has produced the highest research outputs, although India is the most collaborative country in this field. The current research hotspots include supply chain, 4D printing, and social distancing technologies. Furthermore, it explores emerging trends, intellectual structure of publications, research frontiers, and potential research directions for further work in the Industry 4.0 assisted healthcare domain.

1. Introduction

The fourth industrial revolution has completely revamped the traditional structure of healthcare field [1]. Industry 4.0 and its advanced Information and Communications Technologies (ICT) have been extensively used to control the spread of COVID-19 outbreak. ICT has addressed several challenges and produced promising solutions during this pandemic such as the establishment of effective supply chain management towards the fulfillment of unprecedented demands of health resources, identification of infection in early stages, and smart manufacturing. Industry 4.0 is based on the concept of Cyber-Physical Systems (CPS). In the healthcare field, it is also known as Medical Cyber-Physical Systems (MCPS). It enables to control and monitor the physical processes through the integration of advanced technologies. It has created huge potential for many industrial domains to improve operational efficiency. MCPS are futuristic systems that provide effective functionalities to handle emergency situations and externally control and monitor medical treatment [2]. It provides the paradigm of automated processes, flexibility in product design, rapid and high-quality manufacturing through the advancement of ICT. Industry 4.0 technologies have potential to improve information exploitation, develop futuristic health frameworks. It heavily relies on disruptive technologies such as Artificial Intelligence, Internet of Things

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(IoT), big data analytics, and 3D printing (additive manufacturing) [3]. These technologies have potential to establish a smart and robust healthcare system capable of dealing with future pandemics like COVID-19.

Artificial intelligence acknowledges to be a powerful tool in Industry 4.0 and has been used extensively in this pandemic viz; analyzing the complicated health data, reducing the impact of infodemic, helping to gain insight of best treatment, analyzing the symptoms of suspects using medical imaging such as computer tomography scan and X-ray imaging for the detection of virus [4].

In contrast, IoT is responsible for automated manufacturing in the fourth industrial revolution. It is one of the emerging trends in Industry 4.0 revolution. IoT enables connectivity among different medical devices in the healthcare sector. It connects all devices with internet and acquires the information of patient's health using sensors [5]. In COVID-19 disaster, IoT is used for testing and monitoring real-time patients' conditions, tracing the infected patients, surveillance of crowded areas to ensure the implementation of quarantine.

Big data analytics is used to store large volumes of data in an organized manner that can be easily accessed and analyzed for better decision making. In the pandemic situation, big data has been significantly used to collect real-time data from online sources such as social media and predict the curve of COVID-19 cases [6]. Moreover, big data is used to preserve the records of patients that helps the doctors to decide the best treatment for them.

3D printing is one of the main pillars of the fourth industrial revolution that provides excellent flexibility in the design and manufacturing process. 3D printing technology has been extensively employed to handle medical emergencies during the COVID-19 period. It is utilized to fulfill the urgent requirement of ventilators for COVID-19 patients. It produces reusable and recyclable face masks and other health equipment geared towards the prevention of COVID-19 spread.

This paper provides extensive insights into above-mentioned technologies in the context of COVID-19. The scientometric analysis is an essential methodology to define the potential future research directions in the particular field of research. It employs a scientific and empirical approach to systematically explore evolutionary trends, status quo and other research dynamics in a specific research domain. This paper describes some recent healthcare models and frameworks, based on the above-mentioned technologies, developed by researchers to enhance healthcare services.

1.1. Literature review and health frameworks

This section covers the findings of recent research studies in the context of COVID-19 pandemic and Industry 4.0 technologies. After careful examination of recent literature, it found that very few scientometric studies have been conducted on the relationship between Industry 4.0 and COVID-19. Haghani et al. [7] performed scientometric research on three coronavirus diseases, namely COVID-19, Severe Acute Respiratory Syndrome, and Middle East Respiratory Syndrome. This paper used a scientometric approach to describe a comparative analysis of the aforementioned illnesses. Thavorn et al. [8] conducted a scientometric analysis on published literature related to COVID-19. This research explored the research collaboration network of country, institute, author co-citation, and visualized them using the VOSviewer tool. Additionally, the findings of this research indicated that several digital technologies, especially IoT and artificial intelligence had significantly used to combat this pandemic. Abdel-basset et al. [9] proposed a model that employs emerging technologies for COVID-19 analysis. This model is intended to address the shortage of Personal Protective Equipment (PPE) and assure the safety of the medical team. Ouf et al. [10] employed a machine learning-based model to predict the treatment course of hospitalized COVID-19 patients. Haghani et al. [11] organized a scientometric analysis on the literature of COVID-19 pertaining to several aspects of safety, including cyber safety, economic safety, and supply chain safety. In contrast, most review articles have focused on the sustainability of supply chain management and addressed different issues posed by COVID-19 such as resilience and disruption costs, ordering and distribution practices [12].

Corsi et al. [13] discussed how big data analytics are substantially used for prediction, monitoring, and tracking of COVID-19 cases. The study's findings indicated that social media and internet search engines were the primary data sources where the majority of people collected information related to COVID-19. Riswantini et al. [14] discussed the role and contribution of big data research in five primary domains, including healthcare, social life, government policy, business and management, and the environment from a COVID-19 viewpoint. The findings of this article showed that healthcare and social life are significant research areas. Researchers frequently used the amalgamation of big data and artificial intelligence techniques to achieve better results. In contrast, many research articles claimed that big data has a significant impact on the following fields: predictive analytics, decision support systems, and COVID-19 strategy enhancement [15].

Along with big data and artificial intelligence, the IoT is the most commonly used Industry 4.0 technology for controlling and preventing COVID-19 related consequences [16]. Ahmed et al. [17] developed a model to analyze and predict the pandemic situation using IoT and big data. Farahani et al. [18] proposed and described an IoT-based patient-centric eHealth ecosystem model. This research enlightened the various services, applications, current challenges, and reviewed various papers related to IoT eHealth. Zahedi et al. [19] proposed a framework to make a robust supply chain network through the use of IoT. This framework can assess the sensitivity of response time and selected routes. Azzaoui et al. [20] proposed a Social Network Services Big Data Analytic Model for COVID-19 prediction in smart healthy cities in order to minimize the effects of an infodemic and raise public awareness about pandemics.

In whole, several COVID-19 and Industry 4.0 papers are published in reputed journals. However, there has been no recent scientometric paper in this literature yet encountered. The analysis addresses this research gap and provides an extensive overview of Industry 4.0 technologies and their utilization to control the COVID-19 outbreak.

1.2. Objectives

This paper aims to provide a comprehensive scientometric analysis on the literature of Industry 4.0 technologies related to COVID-19 research. It presents a quantitative assessment of Industry 4.0 technologies in the discipline of science and technology. The key purposes of this research are as follows:

- (1) To identify the integration of significant technologies and their use in the COVID-19 pandemic.
- (2) To assess the global research status in terms of country, author, sources, and publications domain.
- (3) To analyze intellectual structure and keyword co-occurrence network for the extraction of evolving research areas, technological trends and research hotspots in this knowledge domain.

Furthermore, this paper helps researchers and other academic fraternities to understand the fundamental structures and status quo of the COVID-19 research.

1.3. Paper organization

The structure of this document is as follows: Section 1, Introduction, presents the disruptive technologies of Industry 4.0 and their applications used in COVID-19 pandemic. Section 2 explores the adopted methodology for this paper including the Sample and Data, visualization tools, and Searching Strategy employed for this research. Section 3 shows country collaboration network analysis and Section 4 summarizes the most prominent journals with their citation impact. Section 5 represents the Document Co-citation Network Analysis, which includes the analysis of the largest 13 clusters. Along with, it explores top articles by citation and bursts. Section 6 includes Author Co-citation Network Analysis which identifies the most influential authors in this knowledge domain. Section 7 presents Keyword Co-occurrence Network Analysis, it explores research focus and recent ICT trends of Industry 4.0 technology. Section 8 concludes the summary and results of the analysis.

2. Methodology

Sample and Data

Google Scholar, Scopus, Web of Science are the three reference and citation indexed databases primarily used for bibliometric studies. These databases provide scientometric indicators for researchers to obtain relevant information and resources. Google Scholar is a free, open-access database that provides broad coverage of scholarly publications than prior databases. Scopus and web of science are online subscription-based databases that offer more accurate citation indexing than Google scholar and are also considered as the best alternate of each other. However, some studies acknowledged that the Scopus database provides more coverage than the web of science in terms of citation indexing. This research has retrieved a dataset from the Scopus database. Scopus is one of the most comprehensive databases of academic publications launched by Elsevier in 2004. It provides various insights to the researchers and interactive analytical tools for processing the structure of data of documents [21].

Visualization Tools

Most popular knowledge mapping tools like VOSviewer, Pajek, Gephi, and CiteSpace employ to analyze and visualize the scientific literature [22]. CiteSpace is the best software tool significantly used to detect and represent the publication metrics. It helps to extract in-depth knowledge about the relationships between publications and delineates the different research dynamics of the particular knowledge domain. The network in CiteSpace is represented in terms of nodes and edges. Node with red color represents citation bursts of node, which signifies that node received sudden growth of citations for a specific period. Similarly, a node with outer pink color represents betweenness centrality that signifies the strength and connectivity between the nodes, which measure the transformative potential of a scientific contribution. The silhouette value represents the homogeneity of clusters. The modularity value indicates the degree to which the network is divided into different clusters.

Data Analysis Procedure with Searching Strategy

On October 4th, 2021, all data were exported from the Scopus database using the query: TITLE-ABS-KEY ("COVID-19" OR "Sars-cov-2" OR "2019-nCov") AND ("Industry 4.0" OR "fourth industrial revolution" OR "Industry 4.0 Technologies"). Industry 4.0 technologies include 3D printing, big data analytics, artificial intelligence, and IoT as search strings. TITLE-ABS-KEY (title-abstract-keyword) is a search field. To obtain more relevant records, the searched data was further refined by following parameters:

- Subject area: Computer Science and Engineering
- Document Type: Article
- Source Type: Journal
- Publication Year: 2019–2021

After filtration of searched data, a total of 4763 records were selected to perform Scientometric analysis.

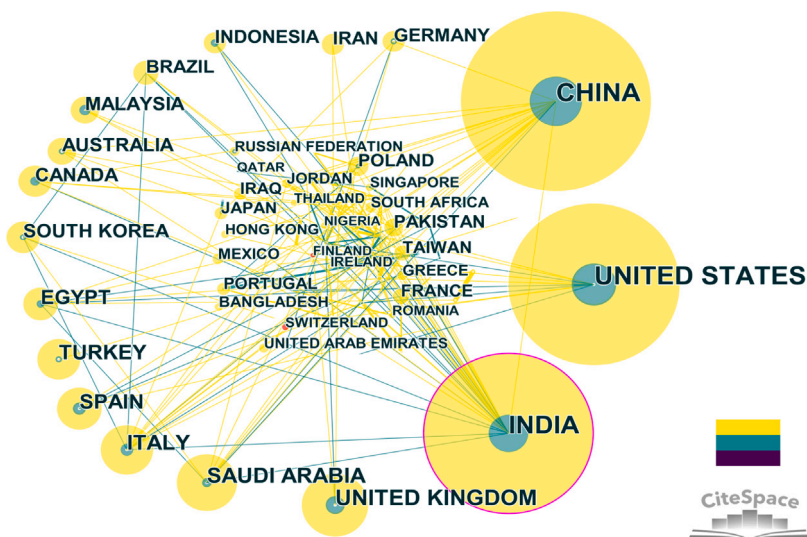


Fig. 1. Visualization of Country Collaboration Network.

Table 1
Top-10 Most Productive Nations.

Sr. No.	Country	Frequency	Share (%)	Centrality	Citation	Ratio
1	China	610	12.81	0.07	3056	5.01
2	United States	549	11.53	0.04	2932	5.34
3	India	536	11.25	0.1	2676	4.99
4	United Kingdom	213	4.47	0	1694	7.95
5	Saudi Arabia	197	4.14	0.1	632	3.21
6	Italy	171	3.59	0.06	1036	6.06
7	Spain	148	3.11	0.02	876	5.92
8	Turkey	139	2.92	0.02	825	5.94
9	Egypt	114	2.39	0.05	823	7.22
10	South Korea	108	2.27	0	850	7.87

3. Country collaboration network analysis

This analysis provides the geographical distribution of publications in this research field. The objective of this analysis is to assess scientific information about the number of publications, citation impact, and the share of total publications of a particular nation.

The country collaboration network exhibits 146 nodes and 327 connections, with a density of 0.0309. Each node in Fig. 1 represents a distinct country or province. The node size indicates the total publications produced by the corresponding nation; a bigger node size signifies that the node has a greater number of publications. The links between two nodes represent the collaboration attempt. The direct links between the nodes in the network show the close connections of that nations. The node and link colors indicate the time by year, i.e., dark purple (2019), aqua (2020), and yellow (2021). The top-10 most prolific nations in terms of publication numbers are listed in Table 1. This table shows the country along with the frequency (number of articles), share of total documents (%), centrality, citation counts, and ratio (average citation per publication). China is the most significant contributor in terms of documents (610) with a share of 12.80%, followed by the United States (549), India (536), the United Kingdom (213), Saudi Arabia (197), Italy (171), Spain (148), Turkey (139), Egypt (114), and South Korea (108) in this research domain. In terms of centrality strength, India is at the center of picture with a value of 0.10, followed by China (0.07) and Italy (0.06). It indicates that these countries have strong connections with other countries and act as mediators in the COVID-19 research. In terms of citation count, all countries (as mentioned in Table 1) hold the same rank as per their frequency value except Saudi Arabia. This country received the least citations (632) with a ratio of 3.21%. It indicates that the research articles of this nation have yet to yield a substantial influence in this field of research. In contrast, the United Kingdom has contributed quality publications with an average citation ratio of 7.95.

4. Prominent journals

Journal analysis identifies reputed information sources in this research field. This analysis represents the most influential journals in a specific research unit based on the citation pattern of the journal. Table 2 presents the list of top-10 cited journals in the domain of COVID-19 research. This table depicts the source title, citation count (TC), publication share (np), average citation count

Table 2
Top-10 Most Prestigious Journals.

Sr. No.	Source Title	TC	np	Average	np (%)	IF
1	IEEE Access	1952	228	8.56	4.78	3.367
2	Computers in Biology and Medicine	1335	89	15	1.86	4.589
3	IEEE Transactions on Medical Imaging	962	16	60.12	0.33	10.048
4	Sustainable Cities and Society	854	82	10.41	1.72	7.587
5	Transportation Research Part E: Logistics and Transportation Review	717	13	55.15	0.27	6.875
6	Physical and Engineering Sciences in Medicine	581	5	116.2	0.10	1.43
7	Applied Intelligence	575	51	11.27	1.07	5.086
8	International Journal of Information Management	549	18	30.5	0.37	14.098
9	Computer Methods and Programs in Biomedicine	492	22	22.36	0.46	5.428
10	Computers, Materials and Continua	458	109	4.20	2.28	3.772

per document (Average), publication share in percentage (np %), and impact factor (IF) of the journal. The journal analysis shows that “IEEE Access” is the most influential and contributing journal in this field. It is an open-access journal that received 1952 citations from 228 publications with an average citation count of 8.57. The “Computers in Biology and Medicine” is the second most influential journal that received 1335 citation counts from 89 publications with an average citation count of 15.

The third most contributed journal is the “IEEE Transactions on Medical Imaging”. This journal has received 962 citations from 16 articles with an average citation count of 60.12. “Sustainable Cities and Society” is the fourth most influential journal that received 84 citation counts from 82 publications with an average citation count of 10.41. The fifth most significant journal is “Transportation Research Part E: Logistics and Transportation Review”. This journal has received 717 citation counts from 13 publications with an average citation count of 55.15. “Physical and Engineering Sciences in Medicine” is the sixth most influential cluster in this research field. This journal has received 581 citations from 5 articles with the highest average citation of 116.2. “Applied Intelligence” is the seventh influential journal that received 575 citation counts from 51 publications with an average citation of 11.27. The eighth most influential journal is “International Journal of Information Management”. This journal has received 549 citation counts from 18 papers with an average citation count of 30.5. The “Computer Methods and Programs in Biomedicine” is the ninth most reputed journal. This journal has gained a 492 citation count from 22 research articles with an average citation count of 22.36. The “Computers, Materials and Continua” is the tenth most influential journal. This journal has attained a 458 citation count from 109 publications with an average citation count of 4.20. In terms of impact factor, the International Journal of Information Management (14.098), IEEE Transactions on Medical Imaging (10.048), and Sustainable Cities and Society (7.587) are the most prestigious journals in Covid-19 research from the perspective of computer science.

5. Document co-citation analysis

Document Co-citation Analysis (DCA) aims to explore important research topics, thematic clusters, and evolution trends in this field. It helps to assess the intellectual structure of Industry 4.0 technologies in COVID-19 research. Fig. 2 depicts that the network is classified into 15 distinct clusters with a mean silhouette value of 0.963 and modularity of 0.8749. This research has selected the top-13 clusters with a size greater than 15. Table 3 represents the cluster details such as ID number, size, silhouette value, mean year, and Log-Likelihood Ratio (LLR) labels of all clusters. CiteSpace offers three weighting algorithms for extraction of cluster labels: Term Frequency–Inverse Document Frequency (TF-IDF), LLR, and Mutual Information (MI). The LLR algorithm is used to generate the cluster labels. Recent analysis indicates that LLR labels give enough coverage across many articles and provide distinct titles for each cluster. It provides core professional terms for each cluster label [23]. The Cluster ID is proportionate to the cluster’s size. For instance, cluster #0 is the largest cluster with a size of 36 and cluster #12 is the smallest cluster with a size of 17. The cluster size indicates the total number of records featured in the cluster.

Fig. 3 depicts the timeline view of DCA. A cluster with a solid line represents the activeness of research activities. In contrast, a cluster with a dotted line indicates inactive status, indicating that no research activity has evolved for a specific period of time. The time period is represented on the top of the figure that provides a clear understanding of the trends, and active and inactive duration of the clusters.

5.1. Cluster analysis

The co-citation network is divided into groups known as clusters. A cluster contains the number of co-cited references that are strongly connected with each other. The connectivity and homogeneity of these references can be measured with silhouette value; a value close to 1 indicates strong connectivity of co-cited references. In cluster, these references are referred to as members of the cluster or size of the cluster as shown in Table 3. Cluster analysis indicates research frontiers, important research topics, and evolving trends in this knowledge structure.

Cluster #0 labeled as “Different size” is the largest cluster possessing 36 members. The mean year of this cluster is 2019, with a silhouette score of 0.986. This cluster begins in 2016 and remains up to 2020. This cluster encompasses the following main research topics: segmentation accuracy, sieve connection structure, and multi-scale input structure.

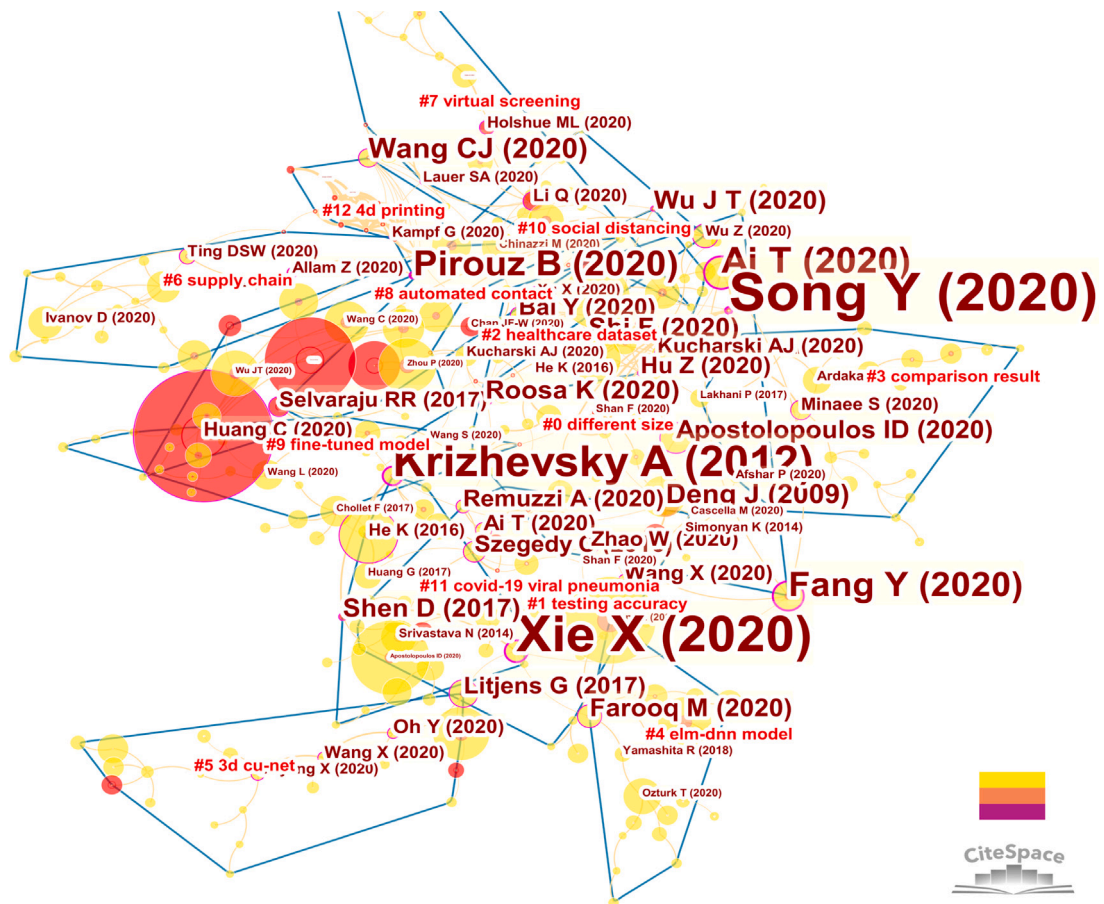


Fig. 2. Cluster View of Document Co-citation Network.

Table 3
Clustering Result of DCA.

ID	Size	Silhouette	Year	LLR
0	36	0.986	2019	Different Size
1	32	0.915	2017	Testing Accuracy
2	27	0.905	2016	Healthcare Dataset
3	24	0.966	2019	Comparison Result
4	23	1	2012	ELM-DNN Model
5	22	1	2019	3d CU-NET
6	21	0.939	2014	Supply Chain
7	21	0.923	2017	Virtual Screening
8	21	1	2020	Automated Contact
9	20	0.973	2012	Fine-Tuned Model
10	20	1	2019	Social Distancing
11	18	0.963	2017	COVID-19 pneumonia
12	17	0.936	2018	4d Printing

Cluster #1 is the second-largest cluster having a size of 32 members. The mean year and silhouette score of this cluster are 2017 and 0.915 respectively. This cluster begins in 1998 and remains up to 2020. This cluster includes the main deep transfer model, classical data augmentation, and real twins in the “Testing accuracy” research area.

Cluster #2 is the third-largest cluster with a size of 27. The mean year of this cluster is 2016, with a silhouette score of 0.905. This cluster begins in 1992 and remains up to 2020. This cluster includes the following top research topics: data-driven approach, collective attention, and asymptomatic transmission in the “Healthcare dataset” research area.

Cluster #3 labeled “Comparison result” is the fourth largest cluster possessing 24 members. The mean year of this cluster is 2019, with a silhouette score of 0.966. This cluster begins in 2015 and remains up to 2020. This cluster includes the following top

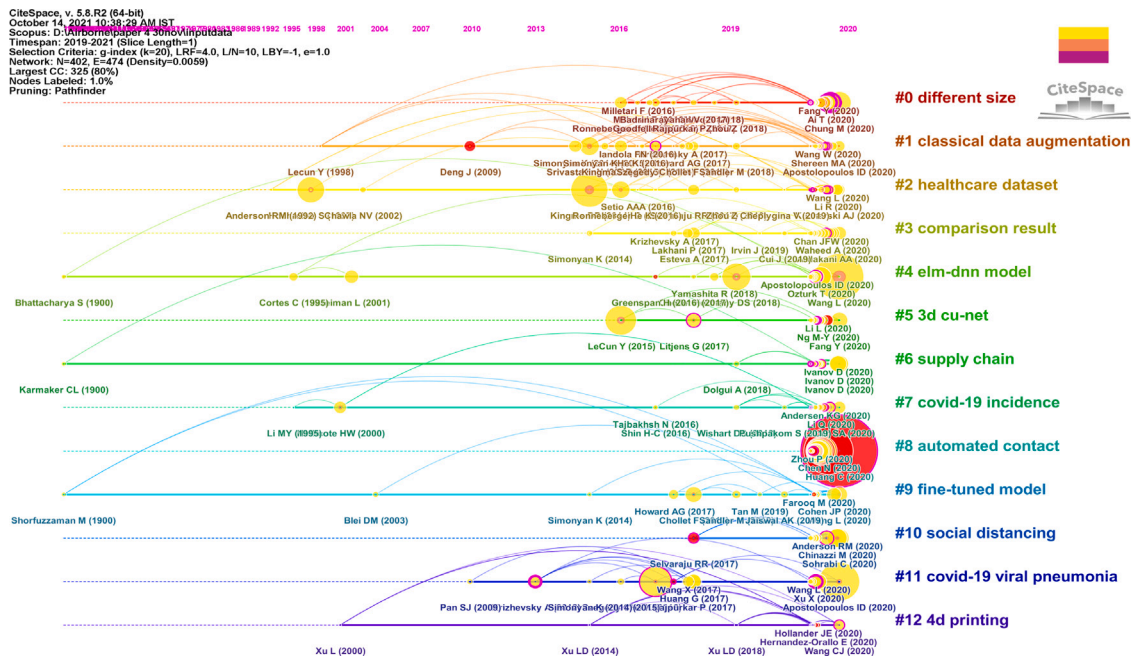


Fig. 3. Timeline View of Document Co-citation Network.

research topics: the Deep Booted Hybrid Learning (DBHL) framework, the highest validation accuracy, and a new deep learning framework.

Cluster #4 is the fifth largest cluster with a size of 23. The mean year and silhouette score of this cluster are 2017 and 1, respectively. This cluster begins in 2012 and remains up to 2020. The main research topics of this cluster are open dataset, convolution layer, and decoder networking under the research area named “ELM-DNN model”. The ELM-DNN (Extreme Learning Machine-Deep Neural Network) model is used for COVID-19 detection with computed tomography scan images [24].

Cluster #5 is the network’s sixth-largest cluster, with a size of 22, silhouette value of 1, and a mean year of 2019. This cluster begins in 2019 and remains up to 2020. This cluster includes the following prominent research topics: infected area, real-world scenario, and Bi-LSTM (Bidirectional Long Short Term Memory) network in the “3D CU-NET” research area. 3D CU-NET is a conventional neural network architecture that is used to diagnose and identify COVID-19 infected areas [25].

Cluster #6 labeled “Supply chain” is the seventh oldest populous cluster containing 21 members. The mean year of this cluster is 2014, with a silhouette score of 0.939. This cluster begins in 1900 and remains up to 2020. This cluster includes the following top research topics: disruption propagation, global supply chain, and disruption risk.

Cluster #7 is the eighth largest cluster having a size of 21. The mean year and silhouette score of this cluster are 2017 and 0.923 respectively. This cluster begins in 1994 and remains up to 2020. The main research topics of this cluster are COVID-19 incidence, small molecules, host cells in the research area named “Virtual screening”.

Cluster #8 labeled “Automated contact” is the most recent cluster having 21 members. The mean year of this cluster is 2020, with a silhouette score of 1. This cluster emerged in 2020. This cluster includes the following main research topics: healthy cases, spike protein, and binding mechanism.

Cluster #9 is the tenth-largest cluster having a size of 20. The mean year and silhouette score of this cluster are 2012 and 0.973, respectively. This cluster begins in 1900 and remains up to 2020. The main research topics of this cluster are COVID-19 detection model and norms, and the lung region in the research area named “Fine-tuned model”.

Cluster #10 labeled “Social Distancing” is the eleventh largest cluster containing 20 members. The mean year of this cluster is 2019, with a silhouette score of 1. This cluster begins in 2018 and lasts up to 2020. This cluster includes the following top research topics: human activities, lockdown measures, and human mobility.

Cluster #11 is the twelfth largest cluster with size 18. The mean year and silhouette score of this cluster are 2017 and 0.963, respectively. This cluster begins in 2010 and lasts up to 2020. The main research topics of this cluster are dataset size, clinical symptoms, and target task in the research area named “Covid-19 viral pneumonia”.

Cluster #12 is the smallest cluster in this network labeled as “4d printing” with 17 members. The mean year of this cluster is 2018, with a silhouette score of 0.936. This cluster begins in 2000 and remains up to 2020. This cluster encompasses the following top research topics: scientific publishing, smart materials, and the medical field.

Table 4
Top-Ranked Articles by Citation Count.

Citation Counts	References
149	“Huang C, 2020, Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China @ Lancet, 395, 497-506”
99	“Wang L, 2020, COVID-Net, 0, 0”
98	“Chen N, 2020, Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China, 395, 507-513”
72	“Kingma DP, 2014, Adam, 0, 0”
62	“LeCun Y, 2015, Deep learning @ Nature, 521, 436-444”
62	“Zhou P, 2020, A pneumonia outbreak associated with a new coronavirus of probable bat origin @ Nature, 579, 270-273”

5.2. Major cluster analysis

The major cluster analysis represents the further in-depth analysis of the top-5 clusters. This analysis summarized the relevant citer articles and top-ranked articles by citation and burst into five largest clusters.

Cluster #0 and #3 named “different sizes” and “comparison results” include 36 and 24 papers, respectively. Both clusters have the most active and relevant citer article is “Machine learning for medical images-based COVID-19 detection and diagnosis” which was published in 2021 in “International Journal of Intelligent Systems” by “Rokaya Rehouma”. This paper describes the application of machine learning to COVID-19 detection, prediction, and prognosis. It enlightened the recent progress of machine learning and deep learning in this pandemic.

Cluster #1 titled “testing accuracy” includes 32 papers. Among the list of articles, the most active and relevant citer article of this cluster is “A Review on deep learning techniques for the Diagnosis of Novel Coronavirus (COVID-19)” which was published in “IEEE Access” by “Md. Milon Islam” in 2021. This article explored many recent deep learning-based frameworks developed to diagnose COVID-19. Additionally, it sheds light on research-developed data segmentation approaches and performance evaluation tools for COVID-19 diagnosis.

Cluster #2 named “healthcare dataset” includes 27 articles. Among the list of articles, the most active and relevant citer article of this cluster is “Industry 5.0: potential applications in COVID-19” submitted by “Mohd Javaid et al.” in the “Journal of Industrial Integration and Management” in 2020. This paper provides in-depth knowledge of innovative technologies in the context of COVID-19. It discusses how these technologies can build a smart healthcare environment with real-time capabilities. Likewise, it outlined the key challenges that may come across the implementation of Industry 5.0 technologies in healthcare and how these technologies will be beneficial to doctors and patients as well.

Cluster #4 titled “ELM-DNN model” includes 23 articles. Among the list of articles, the most active and relevant citer article of this cluster is “COVID-19 diagnosis in chest X-rays using deep learning and majority voting” which was published in 2021 in “Applied Sciences” by “Marwa Ben Jabra”. This paper conducted comparative research among deep learning-based models, in terms of their accuracy, for COVID-19 diagnosis. This article evaluated the efficiency of deep learning using chest X-ray images.

5.2.1. Citation count

Table 4 shows top-six references by citations. The first reference is Huang C (2020) belongs to cluster #8, with citations of 149. The second reference is Wang L (2020) belongs to cluster #4, with citations of 99. The third reference is Chen N (2020) belongs to cluster #8, with citations of 98. The fourth reference is Kingma DP (2014) belongs to cluster #2, with citations of 72. The fifth reference is LeCun Y (2015) belongs to cluster #5, with citation counts of 62. The sixth reference is Zhou P (2020) belongs to cluster #8, with citation counts of 62.

5.2.2. Bursts

Burst articles present emerging research topics that have received paramount attention from researchers for a specific period of time. Fig. 4 represents the list of top-10 citation burst references. The red lines represent the burst duration of the references. The burstiness of all these articles starts in 2020. The high strength value of references shows a substantial impact and influence on the development of COVID-19 research. After careful evaluation of burst articles, it was found that deep learning assisted screening, smart city networks, CT imaging with deep learning, and additive manufacturing are the main topics covered by most burst articles. The top citation burst article proposed a screening model for COVID-19 using a deep learning system. Through CT scans and deep learning techniques, this system aims to differentiate COVID-19 from influenza-A viral pneumonia and healthy cases. The authors obtained an accuracy of 86.7 percent for their findings.

The top second burst article addressed how to improve standard data sharing protocols in smart city networks from the perspective of a pandemic or other hazardous event. This paper outlined the use of artificial intelligence technology to manage health monitoring and share patients’ health records.

The top third burst article created a deep learning-based segmentation system to automatically quantify the lung infection regions of interest and their volumetric ratio. This method quantifies COVID-19 using CT scans.

References	Strength	Begin	End	2019 - 2021
Xu X, 2020, Deep Learning System to Screen Coronavirus Disease 2019 Pneumonia @ , V0, P0	8.89	2020	2021	
Allam Z, 2020, On the coronavirus (COVID-19) outbreak and the smart city network, V8, P46	4.93	2020	2021	
Shan F, 2020, Lung Infection Quantification of COVID-19 in Ct Images with Deep Learning @ , V0, P0	4.43	2020	2021	
Hernandez-Orallo E, 2020, Evaluating how smartphone contact tracing technology can reduce the spread of infectious diseases, V8, P99083-99097	4.43	2020	2021	
Shen D, 2017, Deep learning in medical image analysis @ Annu Rev Biomed Eng, V19, P221-248	3.94	2020	2021	
Greenspan H, 2016, Guest editorial deep learning in medical imaging, V35, P1153-1159	3.94	2020	2021	
Wang C, 2020, A novel coronavirus outbreak of global health concern @ The Lancet, V395, P470-473	3.94	2020	2021	
Gozes O, 2020, Rapid Ai Development Cycle for the Coronavirus (COVID-19) Pandemic, V0, P0	3.94	2020	2021	
Shi F, 2020, Review of artificial intelligence techniques in imaging data acquisition, segmentation and diagnosis for COVID-19 @ Review of artificial intelligence techniques in imaging data acquisition, segmentation and diagnosis for COVID-19 @ , V0, P0	3.94	2020	2021	
Iyengar K, 2020, Challenges and solutions in meeting up the urgent requirement of ventilators for COVID-19 patients @ Diabetes & Metabolic Syndrome, V14, P499-501	3.94	2020	2021	

Fig. 4. Top-Ranked Articles by Burst.

The top fourth burst article proposed an epidemic framework to assess the cost and effectiveness of smartphone-based contact tracing technology. This technology can be beneficial to control the spread of COVID-19. Contact tracing technology is the integration of technologies such as the global positioning system, wi-fi, Bluetooth, and mobile applications.

The top fifth burst article conducted a review study on the recent advancements in deep learning in the medical imaging field. It discussed the role of deep learning approaches in tissue segmentation, computer-aided disease monitoring and surveillance, identification of anatomical and cellular features.

The top sixth burst article explored the applications of deep learning in the realm of medical imaging. Additionally, this article discussed numerous approaches and methods associated with deep learning systems.

The top seventh burst article presented an in-depth analysis of COVID-19 and its dissemination across the countries. Furthermore, this article discussed the diagnostic testing employed by healthcare providers while dealing with COVID-19 patients. Consequently, this article discussed the virus's human-to-human transmission and the sudden increase in COVID-19 cases.

The top eighth burst article developed an automated CT image processing approach based on artificial intelligence to diagnose, qualify, and track COVID-19 suspects. The top ninth burst article reviewed artificial intelligence techniques for diagnosing and prognosing COVID-19 using X-ray and CT images. The objective of this paper is to increase the accuracy and work efficiency towards this viral infection. The objective of this study is to improve the accuracy and efficiency of work using AI-empowered image acquisition.

The top tenth burst article presented an in-depth analysis of the growing need for ventilators for COVID-19 patients. This article discussed a variety of issues and their associated remedies. This paper depicts that 3D printing technology can produce an adequate number of ventilators for the Coronavirus frontline.

6. Author co-citation analysis network

The aim of the Author Co-citation Analysis (ACA) is to identify the network of most-cited authors connected with co-citation links. This analysis considered the first author of cited reference only. In this work, the ACA network comprises 558 nodes and 397 links. Each node represents a distinct author and links represent co-citation connections between the authors, as shown in Figs. 5 and 6. This network has a silhouette value of 0.9774 and modularity of 0.9416. These metrics reflect the credibility of a clustered network. The large font size of the node's label in Fig. 5 indicates the high burstiness value of the node. In contrast, the large font size of the node's label in Fig. 6 represents the high centrality value of the node.

Table 5 summarizes the list of top-10 authors in this research field in terms of burst and betweenness centrality. This Table shows the author's name, burst, centrality value (Cent), and citation count (Freq). These are the reputed authors whose papers and ideas have received worthy attention in this field. The analysis shows that Wang L (436), Li L (355), and Wang X (348) are the most

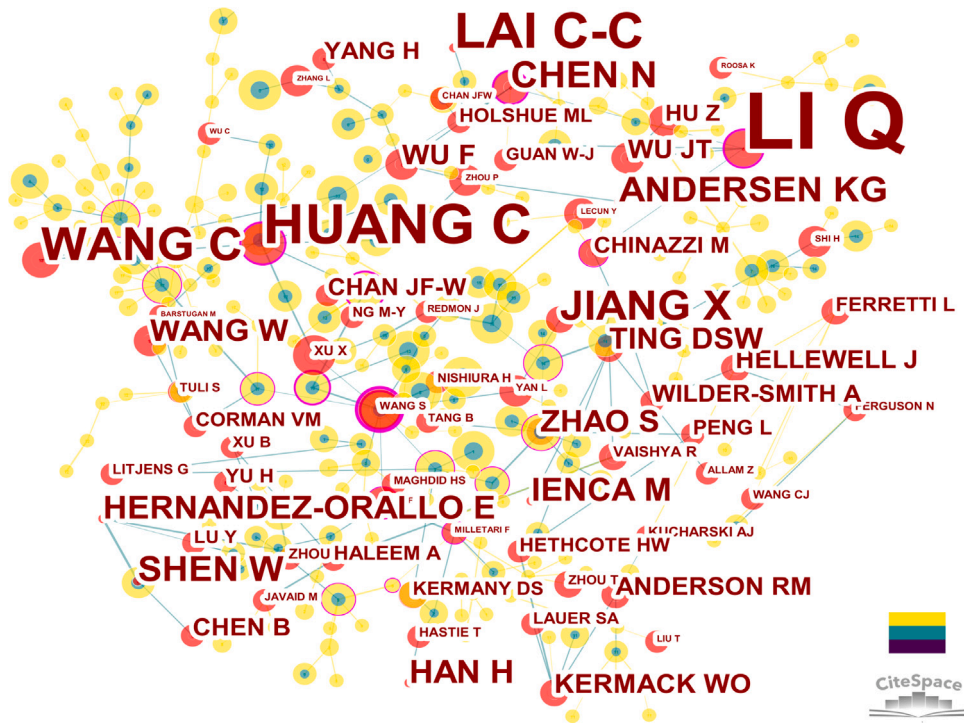


Fig. 5. Visualization of Author Co-citation Network by Bursts.



Fig. 6. Visualization of Author Co-citation Network by Centrality.

Table 5
Top Ranked Authors by Burst and Centrality.

Author	Burst	Centrality	Freq	Author	Burst	Centrality	Freq
Li Q	14.24	0.23	198	Wang S	2	0.41	310
Huang C	9.85	0.27	346	Narin A	0	0.34	234
Zhong L	8.9	0	17	Ai T	0	0.3	215
Lai C-C	8.9	0	17	Chen N	6.56	0.28	149
Wang C	8.25	0	184	Gozes O	0	0.28	151
Jiang X	7.33	0	67	Huang C	9.85	0.27	346
Sohrabi C	7.11	0	105	Li Q	14.24	0.23	198
Dong E	6.6	0	108	Shan F	1.41	0.19	118
Chen N	6.56	0.28	149	Milletari F	1.51	0.17	40

Table 6
Top-15 Keywords with High Frequency Values.

Frequency	Centrality	Keywords
777	0.28	Deep Learning
543	0.02	Diagnosis
509	0.06	Machine Learning
367	0.03	Convolutional Neural Network
349	0.21	Learning System
345	0.06	Computerized Tomography
336	0	Artificial Intelligence
311	0.05	Forecasting
295	0	Decision Making
175	0	Supply Chain
165	0.01	Internet of Things
162	0	Deep Neural Network
161	0.03	Transfer Learning
154	0	Medical Imaging
153	0	Social Networking

influential authors in terms of citations. Li Q (14.24), Huang C (9.85), and Zhong L (8.9) are the burst authors. This indicates that these authors have gained a sudden growth in the number of citations of their papers published in this field. In terms of centrality, Wang S (0.41), Narin A (0.34), and Ai T (0.3) have acquired certain positions in COVID-19 research. Furthermore, Haung C has received a high citation count (346) and obtained high burst and centrality values. It indicates Haung C is a core author in this knowledge domain.

7. Keyword co-occurrence network analysis

This section presents the Keyword Co-occurrence Network (KCN) analysis. KCN analysis is a technique for swiftly assessing the research focus of the entire articles collection. In contrast, KCN quickly grasps the significant terms according to their frequency and burstiness values. Fig. 7 presents a total of 530 keywords 414 connection lines. The modularity (0.9102) and silhouette value (0.9851) indicate that the network structure is highly reliable. Keywords with high frequency and centrality (> 0.1) strongly influence the overall network. Such keywords represent research hotspots. High-frequency keywords appeared in most recent years indicating the emerging research areas. Table 6 shows the most frequently occurring keywords with centrality value. It should be noted that this research excludes irrelevant keywords such as “human”, “procedure” from this table. This study reveals that intelligent technologies are on the top of the table with high-frequency values such as Deep learning (777), machine learning (509), neural networks (367), and artificial intelligence (336). In contrast, computerized tomography (345), internet of things (165), medical technology, and social networking (153) are also frontline technologies used to combat COVID-19.

7.1. Research focus

Table 7 presents the high-frequency keywords with their co-cited terms. These terms have appeared together in the common literature. It reflects the core research content and recent research focus of an article. This research extracts Table 7 from the pennant diagram generated by CiteSpace. Pennant diagram used the weight of term frequency and inverse document frequency of the literature co-citation with the seed keywords. Deep learning is co-cited with X-ray imaging, transfer learning, convolution neural networks, and diagnosis. It indicates that deep learning is mainly used with the above-mentioned technologies to diagnose COVID-19. Similarly, machine learning is co-cited with machine learning models, learning algorithms, and forecasts. The majority of the machine learning-assisted frameworks are designed to forecast the pandemic. Computer tomography is strongly connected with the following co-cited keywords: polymerase chain reaction, Computer-aided diagnosis, and X-ray. Likewise, big data, contact tracing, and blockchain technology are co-cited with distinct influential terms mentioned in Table 7. Fig. 8 represents core research content in the literature of COVID-19 research. E-learning (121), contract tracing (79), forecasting (311), decision making (295), supply chain (175), medical imaging (154), risk assessment (127), social distancing (77), personal protective equipment (45), smart city (77), distance education (23), Industry 4.0 (23) and clinical features (22) are some of the top visualized terms as shown Fig. 8.

7.2. ICT trends

ICT trends represent the evolution of innovative technologies over the years. ICT trends illustrate the most recent technologies that authors significantly use in their research. Fig. 9 shows the ICT keywords with their frequencies. These keywords are organized chronologically by their first appearance in the entire literature. The analysis observed that e-learning, data analytics, and privacy are the main ICT keywords used in 2019. Similarly, researchers have used a surge of technologies to address various problems raised by this pandemic. Deep learning, machine learning, medical imaging, artificial intelligence, internet of things, and other technologies listed in 2020. Similarly, technologies introduced in 2021 are shown as the most recent ICT trends utilized to combat COVID-19. Text mining, fuzzy sets, face recognition techniques, 5G mobile network systems, medical computing, Industry 4.0 technology and other technologies listed under 2021 as shown in Fig. 9.

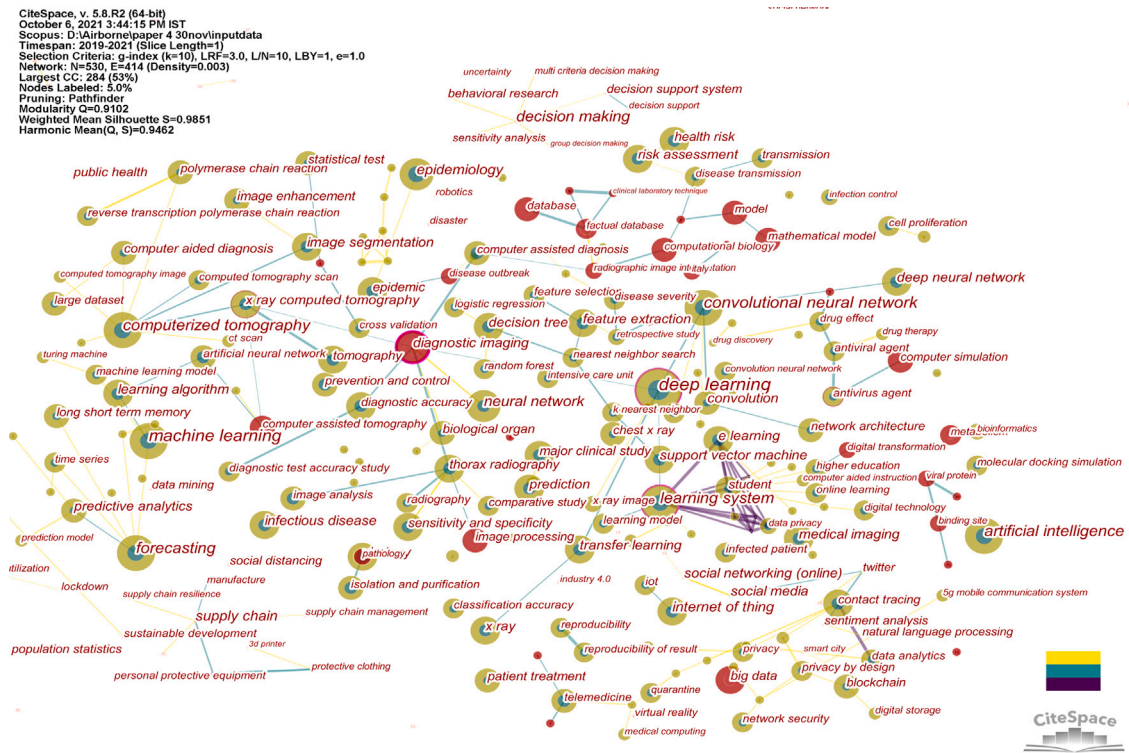


Table 7
 High-Frequency Keywords with Co-cited Terms.

Keywords	Co-cited Terms
Deep Learning	X ray image Diagnostic Imaging Transfer learning Convolution Neural network Diagnosis
Machine Learning	Machine learning model Learning Algorithm Forecasting
Computerized tomography	Polymerase chain reaction Computer aided diagnosis X ray
Big Data	Advance analytic Data analytics
Contact Tracing	Bluetooth Privacy preserving
Blockchain	Privacy by design Digital Storage

8. Conclusion and future work

The fourth industrial revolution has emerged in the healthcare domain as an area of growing interest in academia and industry discipline. This research is a manifestation of 4763 citation data points based on COVID-19 research published in the period 2019–2021 retrieved from the Scopus database. It explores the underlying knowledge structure of Industry 4.0 technologies in COVID-19 research. It provides an in-depth understanding of scientific relations of publications, evolutionary patterns, and technological trends using the analytical tool CiteSpace.

The results of analysis reveal that deep learning technology has been extensively used for COVID-19 diagnosis. The majority of scientific papers reflect the integration of deep learning and medical imaging techniques such as X-ray and computer tomography

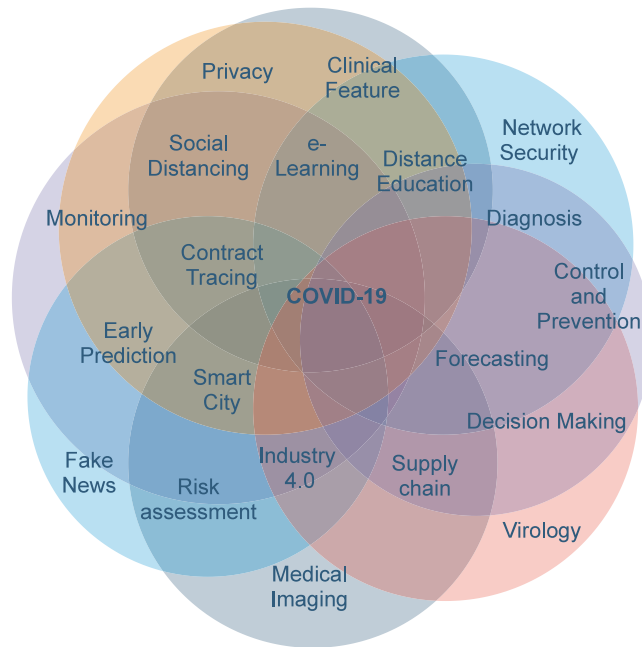


Fig. 8. Core Research Topics.

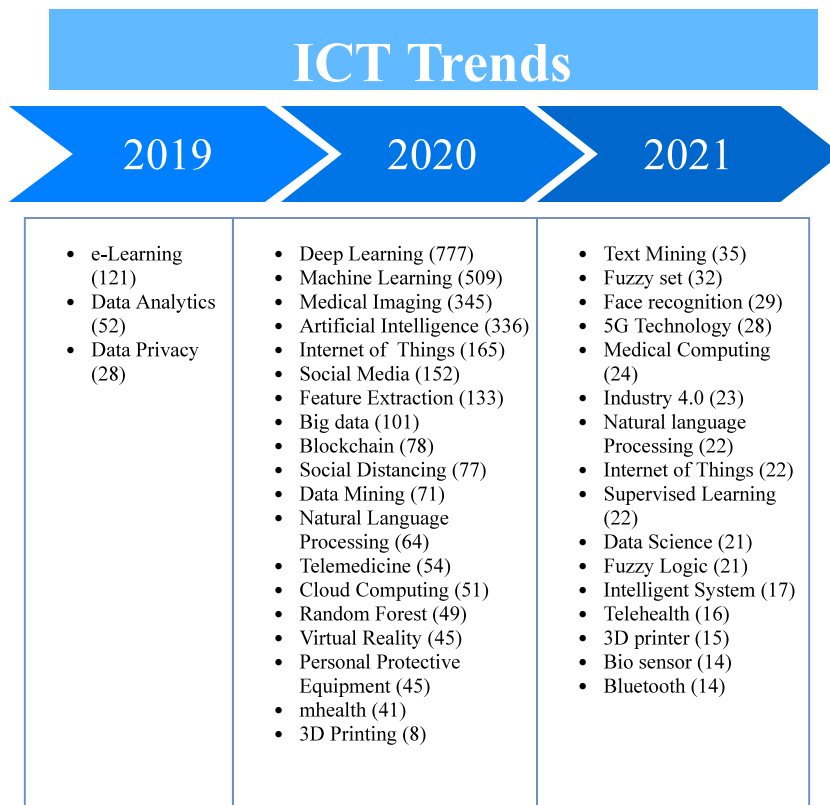


Fig. 9. Recent ICT Trends.

have been widely employed by researchers for testing and screening COVID-19 patients. Similarly, the integration of IoT-cloud and big data has been frequently used to monitor, surveillance, and forecast the COVID-19 curve. It indicates that researchers, policymakers, and academic fraternities should continuously increase the research collaborations and emphasize the emerging technologies (such as 5G, deep learning, machine learning, 4D printing, and IoT) in the healthcare domain.

Industry 4.0 is an important foundation for futuristic healthcare under the global profile of technological advancements. Early research contributions of Industry 4.0-assisted COVID-19 research have been primarily from China and the United States of America. Although, it is necessary for all countries to develop local strategies because each country has its own historical growth route and future dynamics. The sustainability of supply chain management has been a critical issue in healthcare during this pandemic. The main research topics that need to be addressed are disruption propagation, global propagation, global supply chain, and disruptive risks. In future work, this study will be further extended to focus on sub-themes of Industry 4.0 and COVID-19 research.

Declaration of competing interest

No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to <https://doi.org/10.1016/j.compeleceng.2022.107948>.

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