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Review

Big Data COVID-19 Systematic Literature Review: Pandemic Crisis

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Abstract: The COVID-19 pandemic has frightened people worldwide, and coronavirus has become the most commonly used phrase in recent years. Therefore, there is a need for a systematic literature review (SLR) related to Big Data applications in the COVID-19 pandemic crisis. The objective is to highlight recent technological advancements. Many studies emphasize the area of the COVID-19 pandemic crisis. Our study categorizes the many applications used to manage and control the pandemic. There is a very limited SLR prospective of COVID-19 with Big Data. Our SLR study picked five databases: Science direct, IEEE Xplore, Springer, ACM, and MDPI. Before the screening, following the recommendation, Preferred Reporting Items for Systematic Reviews and Meta Analyses (PRISMA) were reported for 893 studies from 2019, 2020 and until September 2021. After screening, 60 studies met the inclusion criteria through COVID-19 data statistics, and Big Data analysis was used as the search string. Our research's findings successfully dealt with COVID-19 healthcare with risk diagnosis, estimation or prevention, decision making, and drug Big Data applications problems. We believe that this review study will motivate the research community to perform expandable and transparent research against the pandemic crisis of COVID-19.

Keywords: Big Data applications; Big Data; pandemic crisis; machine learning; artificial intelligence; deep learning; COVID-19; environment; public health; crisis identification; pandemic

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1. Introduction

With the significant changes in social connections, health regulations, commerce, and work, the pandemic scenario COVID-19 affects billions people in every field. Researchers have found new means of combating a transnational digital pandemic that poses a significant danger to human civilization [1,2]. The beta coronavirus SARS-CoV-2 (SARS-CoV-2) produces COVID-19. A strange kind of pneumonia was initially identified in Wuhan, the Chinese capital of the Hubei Province, and reported to the WHO Wuhan office on 31 December 2019 [3,4]; since then, the virus has spread to 214 nations and territories [5].

As of 30 September 2021, there have been more than 262 million illnesses and 5.2 million deaths, and the World Health Organization has declared a pandemic. The breakout of COVID-19 is seen as the worst catastrophe globally since the World Wars. COVID-19 has infected 213 nations and territories with (confirmed) sick patients, and the total is growing steadily [6,7]. The COVID-19 pandemic was associated with a stressful effect. Multiple efforts have been undertaken to fight COVID-19 because of its broad dissemination. A partial quarantine zone in Dutch population in year 2020 has been established to limit the spread of the virus, and the healthcare system has been prepared to deal with a pandemic should it occur [8]. Although seasonal effects remain questionable, the initial infection rates decrease with hot temperatures. Figure 1 illustrates the percentage of patients with COVID-19 symptoms. The cough symptom was highest among affected people [9].

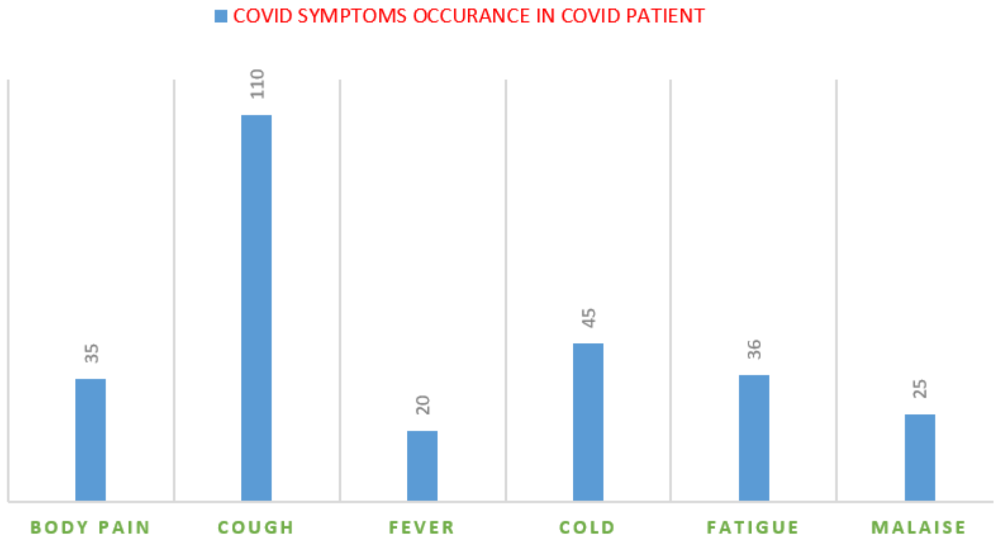

Figure 1. COVID-19 symptoms in COVID-19 patient [10].

Artificial Intelligence is based on machine learning, data mining, Big Data, deep learning [11]. The data mining models are now applied to identify and predict various tasks [12], specifically for disease prediction [13]. Big Data might be used to track outbreaks of diseases in real-time. The number of new infections in the country and COVID-19 differs from other pandemics [14]. The Big Data concept creates new meaning and value from a large amount of available data. The evaluation and utilization of sufficient data for many operations is critically significant [15]. Big Data are available in structured and unstructured form for information retrieval [16] and information extraction [17]. Recently, Big Data grew significantly, with exponential growth due to data gathered through machine learning used for applications such as sales analytics [18], stock market prediction Big Data [19], food reviews through sentiment analysis [20], cloud computing [21], recommendation systems for movies [22], deep learning regarding leukemia diseases [23], fake profiles [24], flight web search analytics [25], Cricket match winning prediction [26] and IoT threads for predicting Denial of services attacks [27] by using Big Data frameworks.

Big Data is characterized by high volume, speed, variety, value, and integrity of information known, as detailed in Table 1. Digital health technology can aid complex human pandemic-related tactics and reactions [28,29].

The expansion of the COVID-19 international pandemic has created a large amount of data that can substantially enhance our understanding of the Big Data research system. Big-data technology has been used to minimize pandemic dangers [30,31]. A COVID-19 cure could be further delayed due to potential viral genetic alterations. Acquisition of data in the medical sector raises the tendency to use Big Data analysis with machine learning algorithms as aids in early prediction [32], detection of schistosomiasis [33], osteoporosis prediction for trabecular bones [34], drug interaction diagnosis [35], ensemble techniques on detection of diabetic [36] and prediction of fake news [37].

Now, the massive quantity of information on the persons infected with this COVID-19 virus may be stored in the Big Data technologies. There are many different sources of Big Data. There are several sources that may be tapped into, including online social networks, mobile devices, Internet of Things-enabled devices, and publicly available data in various formats. Big Data technology has also been utilized to track contacts [38]. COVID-19 information on patients is contained inside Big Datasets [39]. A pandemic management multi-dimensional reference framework is meant to utilize massive data analytics regarding pandemics. The COVID-19 pandemic diffusion is challenging to model [40]. Figure 2 elaborates about Big Data and management of the COVID-19 pandemic.

Table 1. Description of Big Data characteristics.

Characteristics	Description
• Volume	• This feature shows the large amount of data saved in terabytes or Exabyte.
• Variety	• The impermissibility and complexity of huge data quantities. Text, images and videos may be used to format organized and unstructured material.
• Velocity	• As the name suggests, this term relates to the rate that may be measured during or in the frequency domain. This is crucial for time-sensitive applications, such as health monitoring and diagnosis.
• Value	• Value is perhaps the most crucial among the aspects of Big Data. Regardless of how quickly volume data are generated, they must be trustworthy and valuable. For treatment or analysis elsewhere, the data are not adequate.
• Veracity	• The data quality is necessary to predict any model. The trust level of the data is determined. Since most of the obtained data is arranged, extra information must be filtered and the remainder used for processing.

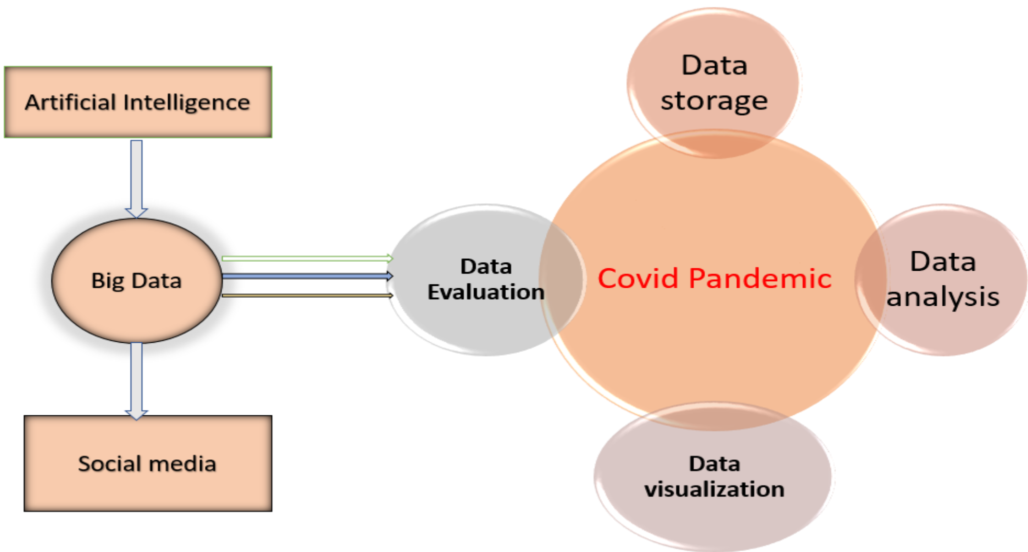

Figure 2. Role of Big Data in the COVID-19 pandemic.

The systematic literature review aims to address the COVID-19 research in the context of Big Data applications and frameworks, and to identify research gaps. Our study further provides guidelines for future work related to Big Data for COVID-19 through deep learning. We analyzed 60 papers from the top journals and conferences conducted between the year 2019 to 2021.This review paper's remaining sections are organized as follows. The research methodologies utilized in our study, including the research strategy, research objectives, and research questions, the processes used to conduct a systematic mapping, the findings of the preliminary research, and the quality evaluation and data extraction methods for each review topic are discussed in Section 2. Section 3 represent the results of each review question in detail. Section 4 contains the concluding remarks. In Section 5, suggestions are highlighted arising from this paper's findings.

2. SLR Research Methodology

The primary objective of a systematic mapping study is to identify an arena for research and the amount and types of research and discoveries inside it. A researcher could examine the frequency of publications over time to determine trends. The identification of published research on the issue might be an additional objective. This section includes the search for relevant articles, the design, and the mapping of publications. Mapping research summarizes the present knowledge and identifies essential topics through a thorough literature review. The qualities and values of the technical systemic literature review for particular research contexts are discussed in this section [41]. This is not the objective of systematic mapping research because the papers are not thoroughly examined. Its primary focus is on the categorization, thematic analysis, and publication identification process of the research methodology, as explained in Figure 3.

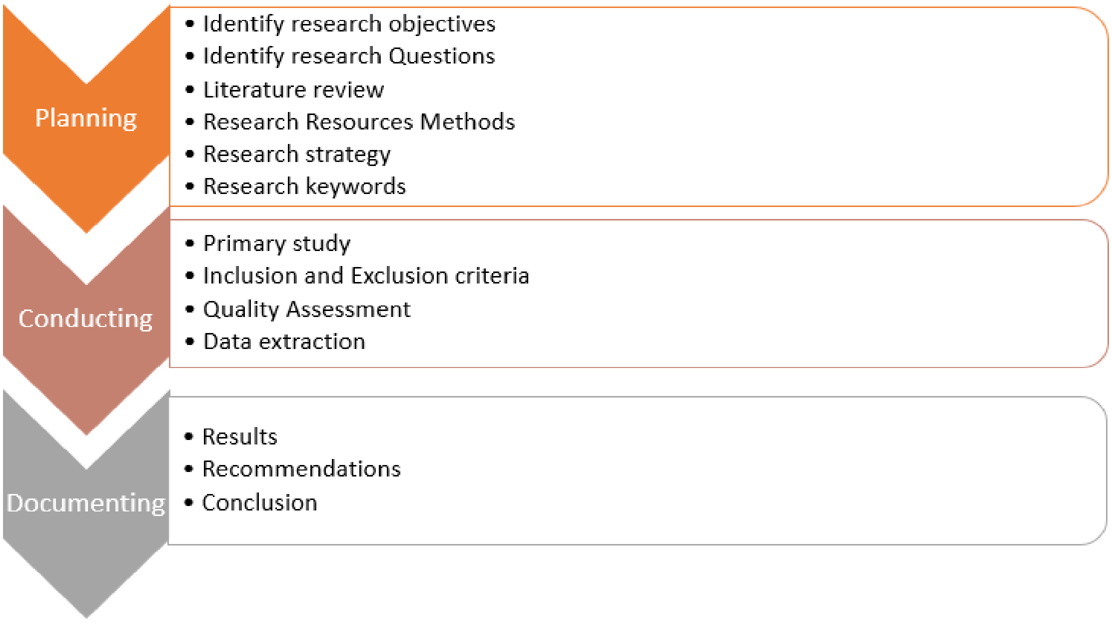

Figure 3. Systematic literature review research methodology.

2.1. Research Objectives

A research question is a specific subject that the study will address. It is the foundation of systematic research and assists in developing a clearly defined research path. Choosing a study subject is the first stage in every research endeavor. A compelling research question is required to begin a research paper or thesis. It pinpoints exactly what you want to study and guides your efforts in the proper direction. The objectives are used to produce the research questions. In an SLR, the importance of choosing study participants cannot be emphasized enough. These make it easier for the researcher to stay on track. The research questions and motivations are described in Table 2. The study subjects have an impact on how a research plan is developed. As a result, the study questions for the SLR were thoroughly planned. This section includes a collection of research questions as well as justifications for them.

Table 2. Research Questions and their motivation.

Sr. No	Research Question	Main Motivations
RQ1	What is the role of Big Data applications in fighting the COVID-19 pandemic?	The main motivations for writing this question are to identify COVID-19 outbreaks and determine where considerable data research may be discovered as well as finding appropriate targets for future study.
RQ2	How is a Big Data application framework used for forecasting and monitoring the pandemic?	The aim is to examine the available data channels and determine the patterns in publishing data over time.
RQ3	What are popular Big Data applications during a pandemic?	The reason for writing this question is to identify what large-scale data efforts are being utilized to encourage the extension, validation, and cooperation of work in the global pandemic battle.

2.2. Research Resources and Methods

The IEEE Digital Library, ACM Digital Library, and Science Direct databases were used to locate the papers. Google Scholar was also used to find grey literature on the issue, such as white papers and technical studies. Google Scholar has been demonstrated to be a useful tool for carrying out bibliometric research. The Table 3 lists the research databases that we utilized to find literature for our research project.

Table 3. Research resources.

Sr.no	Research Resources	Sr.no	Research Resources
1	IEEE Xplore	4	Springer link
2	Science Direct	5	MDPI
3	ACM Digital library		

Methods of research or strategies, procedures, and techniques for collecting data or evidence for analysis to reveal new data or to gain a better knowledge of an issue are illustrated in Table 4. These research methodologies have been employed in this review article.

Table 4. Research methods.

Sr.no	Research Methods	Type of Data Used	Sr. No	Research Methods	Type of Data Used
1	Survey	Primary	5	Observations	Primary
2	Experiments	Primary	6	Interviews	Primary
3	Case study	Primary	7	Focus group	Primary
4	Action Research	Primary			

2.3. Search String

The third stage of SLR consists in searching for suitable research studies. A search string was established for gathering published papers relating to the study themes. We performed a pilot search using precise terms, and we chose to limit the search string only to Big Data applications. However, we also leveraged COVID-19 effects on Big Data in the pilot search. Multiple search engines and digital libraries were used to gather information during Internet researches. The acquired results were carefully assembled to obtain the best information sources to answer the given research topics [41]. It was decided to use specific search engines and digital libraries based on their scientific content and relevance to the paper's goals. As a result of the analysis, Science Direct and IEEE Xplore were employed, as well as the ACM, SL, and MDPI databases. Search engines and digital libraries may be used to find technical and scientific documents. The next step is to decide the strategies and search phrases to employ. A set of words was picked from the study questions to define the search string. Table 5 shows the terms selected from study questions to determine the search string.

Table 5. Search String.

Sources	Search String	Context
IEEE Xplore, Springer, ACM, MDPI, and Science direct	((“COVID pandemic” OR “COVID-19 crisis”) AND (“big data” OR “big data applications OR “big data Analytics”) OR “COVID big data”)	Big Data applications or Analytics

2.4. Search Keywords

We utilized an iterative technique to find keywords throughout the early phases of our study. To link our research questions to our research aims, we first gathered keywords from our research questions. The initial searches were meant to help us fine-tune our keyword selections. A list of keywords is stated in Table 6 may be found in the Keywords section.

Table 6. Keywords used in research paper.

Sr. No	Index Terms
1	Big data, artificial Intelligence, COVID-crisis, data analytics, COVID-outbreak
2	COVID-19 crisis, big data applications, deep learning, social distancing
3	Pandemic COVID-19, significant data analysis, open-source, datasets, COVID-19 impacts

2.5. Result of Primary Studies

Once the research method and topic are finalized, the keywords-based primary research is conducted. The following results of an introductory study are listed in the percentages of the pie chart shown in Figure 4.

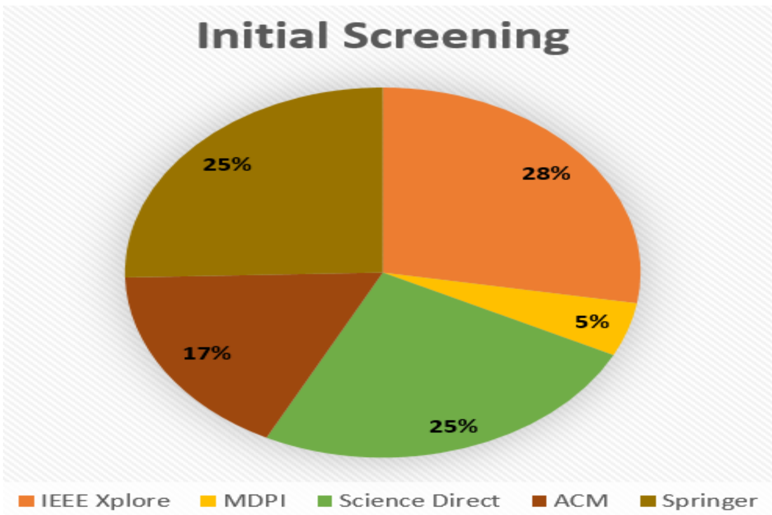

Figure 4. Selected research papers from various research databases.

2.6. Study Selection

The selection process aimed to determine the articles most linked to the aims of the mapping research. When there was a document in several places, we only reviewed it once, following our search order. We followed the recommendation of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [42]. A total of 893 studies were reported from years 2019, 2020, and till September 2021 after the initial screening shown in Figure 4. One author obtained every article, which was then assessed by two other authors to see if the title, abstract and keywords are to be included. The two writers who conducted the article assessment discussed the papers, which received different ratings until an agreement was achieved. The other writers examined the final choices. After the articles were found, the first step was to remove obvious duplicates. Many of the studies identified during the inquiry had nothing to do with our conditions and were vague. We have done a lot of research to filter out publications unrelated to our research topics through a study selection procedure. Figure 5 depicts the phases of study selection and the activities that occurred throughout each study period, which shows the number of records included and excluded in each selection step. The primary focus of the search was COVID-19, which is quickly gaining traction among government officials, researchers, and scientists.

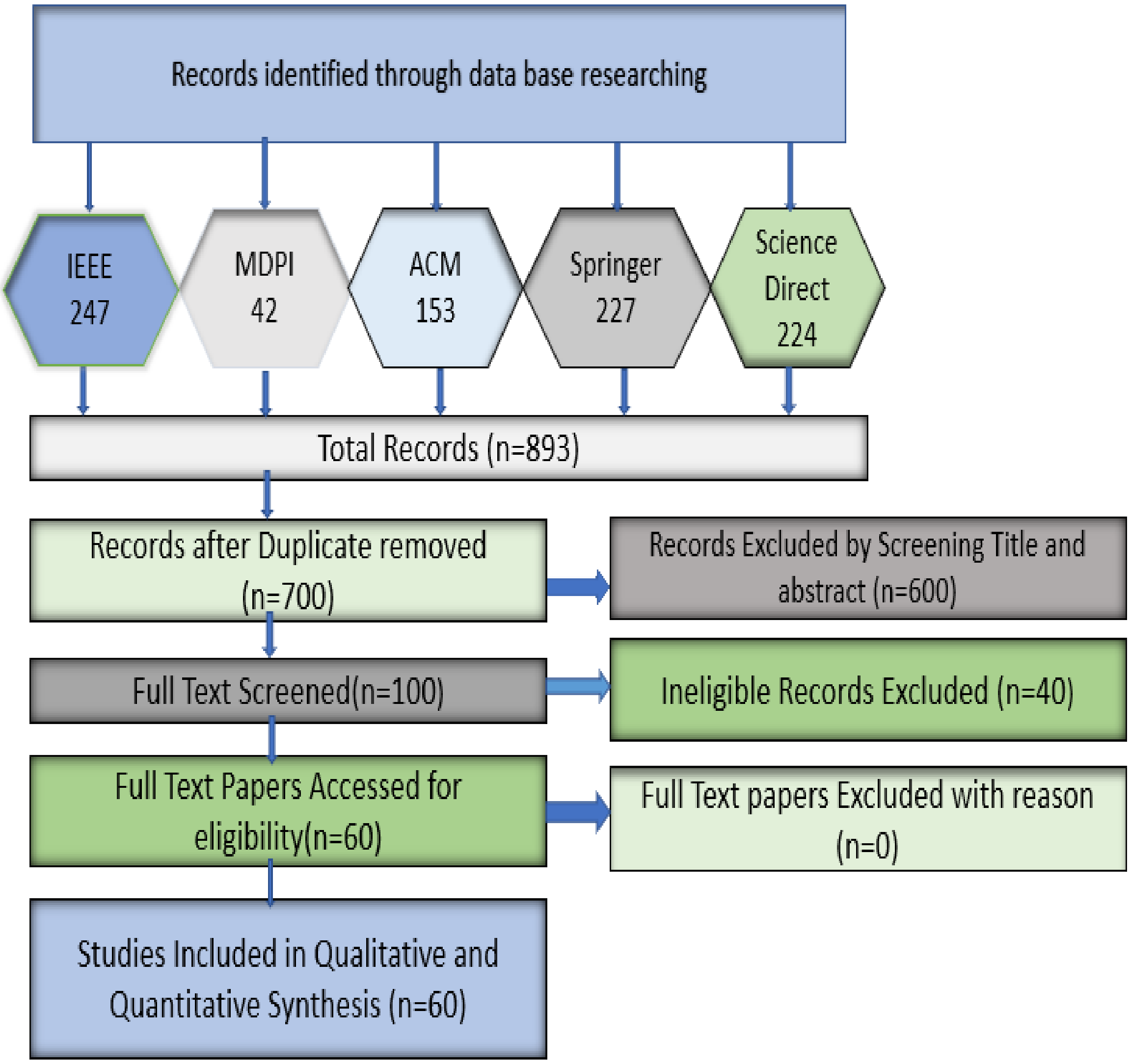

Figure 5. Study selection process for SLR through the PRISMA framework [42].

There were 43 papers from journals and 17 from conferences after qualitative and quantitative screening. The percentage ratio is shown in the Figure 6.

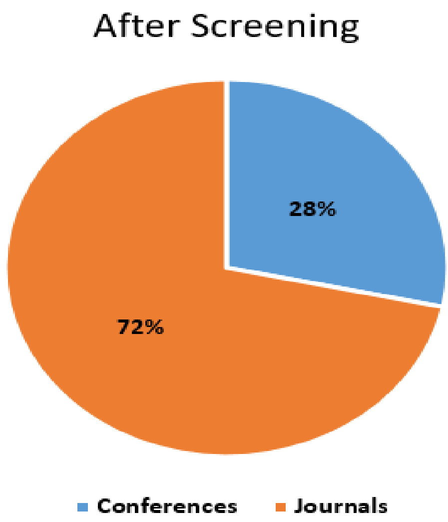

Figure 6. Graphic distribution of selected papers by type of publication.

Figure 7 shows a bar graph of each database for the years 2020 and 2021 with the number of conference and journal papers. ACM contained three conference papers, which was the lowest among the five databases searched.

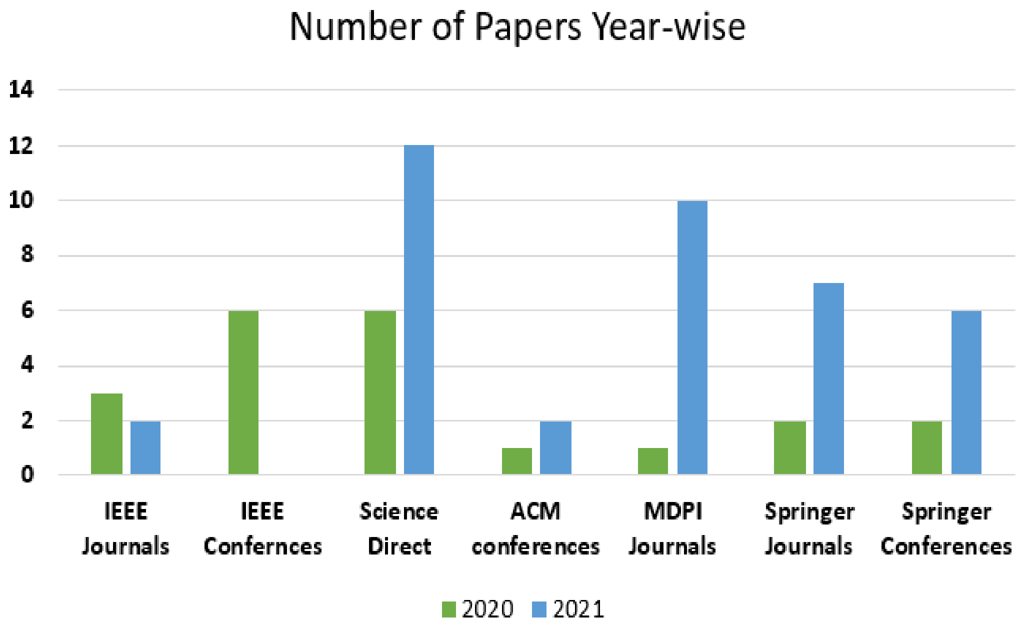

Figure 7. Number of selected papers included by year.

Figure 8 shows the distributions of five databases including journal and conference papers. The science direct database had the maximum number selected, with 18 papers. The IEEE Xplore database contained 17 papers from conferences and journals.

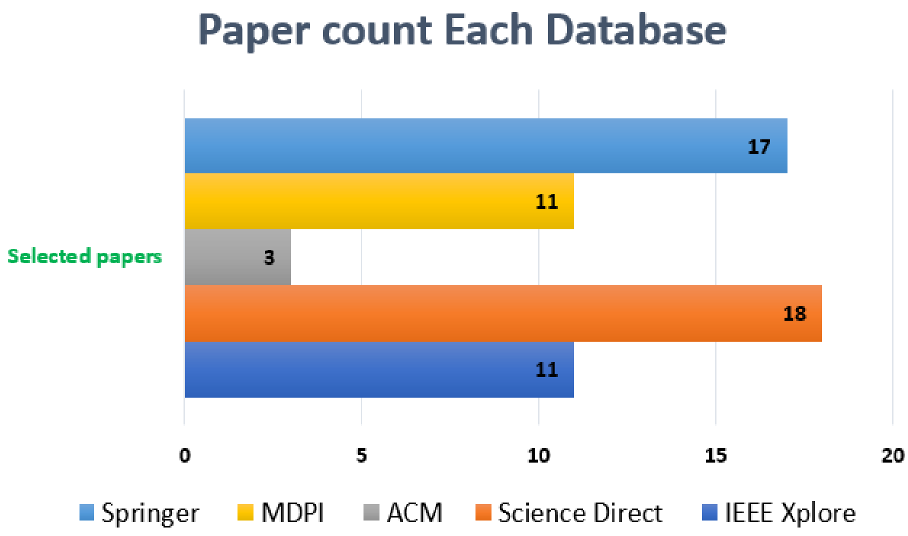

Figure 8. Five databases' paper count.

2.7. Inclusion Criteria

The inclusion criteria of study was based on five points as described in the Table 7.

Table 7. Inclusion criteria.

Sr No	Inclusion Criterion
1C1	All published research papers that can answer the research questions
1C2	All published papers, journals, and books that are written in the English language and have to do with Big Data analytics and the COVID-19 crisis
1C3	Studies that were subjected to peer review
1C4	Studies that provide more knowledge and prove helpful for finding answer of our research questions
IC5	Studies that describe the COVID-19 crisis and its impact on Big Data applications

2.8. Exclusion Criteria

The exclusion criteria for the current review paper are listed in Table 8.

Table 8. Exclusion criteria.

Sr. No	Exclusion Criterion
EC1	Papers that are not published in the English language
EC2	Duplicate papers
EC3	Literature works that are do not give a clear idea of the research objective
EC4	Papers that were publishes before 2019
EC5	Secondary data such as magazines, case studies, reviews

2.9. Quality Assessment

Quality evaluation (QA) is widespread in systematic literature reviews, but it is less typical in systematic mapping research. After reviewing our papers, we focused on determining the research's application for our outcomes. We looked at the scope of each inquiry to see if it aligned with our goals. This helped answer our research question. We examined each item to make sure it has clear instructions that clearly show what we need to accomplish. Table 9 depicts the quality assessment criteria of selected research papers. These criteria are based on four quality assessment questions (QAs):

I. Do the picked articles correspond to the query conference or journal?
II. Is there a blind review process for the selected study?
III. Were the selected research papers acceptable and had meaningful information?

Table 9. Quality assessment of selected research paper.

SRP#	QA1	QA2	QA3	QA4	SCORE
SRP1, [43]	2	2	0	1	5
SRP2, [44]	1	2	1	2	6
SRP3, [45]	1	2	0	2	5
SRP4, [46]	2	2	0	2	6
SRP5, [47]	2	2	1	1	6
SRP6, [48]	1	1	1	2	5
SRP7, [49]	2	2	2	2	8
SRP8, [50]	1	1	1	2	5
SRP9, [51]	1	2	2	2	7
SRP10, [52]	1	1	1	2	5
SRP11, [53]	1	2	1	1	4
SRP12, [54]	1	1	2	2	6
SRP13, [55]	1	1	0	1	3
SRP14, [56]	2	2	1	2	7
SRP15, [57]	1	1	0	0	2
SRP16, [58]	1	1	0	2	4
SRP17, [59]	2	2	2	2	8
SRP18, [60]	1	1	2	1	5
SRP19, [61]	1	1	0	1	3
SRP20, [62]	0	1	0	1	2
SRP21, [63]	1	1	0	0	2
SRP22, [64]	2	2	1	1	6
SRP23, [65]	1	1	1	1	4
SRP24, [66]	2	2	2	2	8
SRP25, [67]	1	2	1	1	5
SRP26, [68]	2	2	1	1	6
SRP27, [69]	1	1	0	1	3
SRP28, [70]	2	2	2	2	8
SRP29, [71]	1	2	0	1	4
SRP30, [72]	1	1	0	0	2
SRP31, [73]	1	2	1	1	5
SRP32, [74]	2	2	1	1	6
SRP33, [75]	2	2	1	2	7
SRP34, [76]	1	1	0	1	4
SRP35, [77]	2	1	0	1	4
SRP36, [78]	2	2	2	2	8
SRP37, [79]	1	1	1	1	4
SRP38, [80]	1	2	2	2	7
SRP39, [81]	2	2	2	2	8
SRP40, [82]	1	1	2	1	5
SRP41, [83]	2	2	0	2	6
SRP42, [84]	2	1	0	1	4
SRP43, [85]	2	2	1	2	7
SRP44, [86]	2	1	2	2	7
SRP45, [87]	1	2	1	2	6
SRP46, [40]	2	2	2	2	8
SRP47, [88]	2	2	1	2	7
SRP48, [89]	1	1	0	1	3
SRP49, [90]	1	1	1	1	4
SRP50, [91]	1	2	0	2	5
SRP51, [92]	1	1	1	2	5
SRP52, [93]	2	2	1	2	7
SRP53, [94]	2	2	2	2	8
SRP54, [95]	1	1	0	2	4
SRP55, [96]	2	2	1	1	6
SRP56, [97]	2	2	1	2	7
SRP57, [98]	1	1	0	1	3
SRP58, [99]	2	2	2	2	8
SRP59, [100]	1	1	1	1	4
SRP60, [101]	2	2	1	2	7

Queries for Quality Assurance (QA) must assess the nature of the investigation of each assertion and provide a quantifiable correlation between each proposition. Below are the scoring criteria.

- Acknowledge (A) = 2
- Some (S) = 1
- Conflict (C) = 0

2.10. Data Extraction

For data extraction, a variety of possible solutions to research questions were supplied. In fact, the type of data to be collected is mainly determined by the initial research subject. Important details include how the research's design and methodology, as well as the qualitative and quantitative results, were accomplished, as well as when, where, and by whom the primary study was conducted. The relevant information from each major research in the sample was then collected, extracted, and selected in the next stage. The following extraction technique is available for each study topic's extracted data.

3. Results

The findings of the systematic mapping questions are described in this section. Some papers were selected to serve as examples of each RQ's outcome. They are relevant and provide a significant contribution to the learning of Big Data applications.

3.1. Selection Result

Out of the 893 thoroughly examined items, 833 have been deleted and 60 have been picked. In order to answer RQs, the obtained data were analyzed. The Table 3 is described the list of the selected publications, overall categorization findings and their quality certification.

3.1.1. RQ1: Role of Big Data Applications for Fighting the COVID-19 Pandemic

Geospatial techniques have recently been a buzzword in the fields of technology and research. Fast action is critical when the world is confronted with a global pandemic as severe as COVID-19. Big Data technology's major purpose is to predict future trends based on present patterns, which involves substantial data collecting as well as technology to process and analyze large datasets [83].

Big Data applications assisted in strengthening the resistance to the global financial crisis's consequence [95]. Big Data applications play an important role in handling such pandemic situations as predicting COVID-19 outbreaks and diagnosing COVID-19 cases and spreading patterns, as described below [76].

The capacity of large-scale data analyzers to forecast the outbreak played an important role in the fight against COVID-19. The pandemic prediction we evaluated is based on public datasets that may be utilized to describe geographical areas with probable breakouts. In Wuhan there was a first attempt to track traffic from and into the city in order to prevent the spread of COVID-19. Predicting a viral outbreak is vital to take safety steps and manage more aggressive cases in this pandemic [47].

This allows simulations to predict the path of the COVID-19 pandemic, for example to identify hazardous pandemic areas. The pandemic is projected using accessible data points, which puts the accuracy of the prediction into question owing to the uncertainty of the fitting due to lack of thorough inquiry [49]. Accuracy may be affected by various circumstances, including diseased cases, population, living situations, surroundings, and so on. During the current Big Data period, a large volume of data was created and collected from various rich data sources [60].

Real-time data intelligence facilitates COVID-19 surveillance. The need for Big Data was highlighted in real-time illness monitoring, including the creation of visuals for an outbreak, medical services, and hospital and contact screening [97].

Big Data is important for creating pandemic models that can precisely forecast and aid governments in evaluating the path of an outbreak. Due to the global economic slowdown, the COVID-19 pandemic exacerbated the plight of people. Impacts on the economy, the environment, and society are significant. The Figure 9 shows that COVID-19 is impacting different age groups. The aging profiles of a population of patients have been substantially and reveal unique levels of recovery and mortality [65].

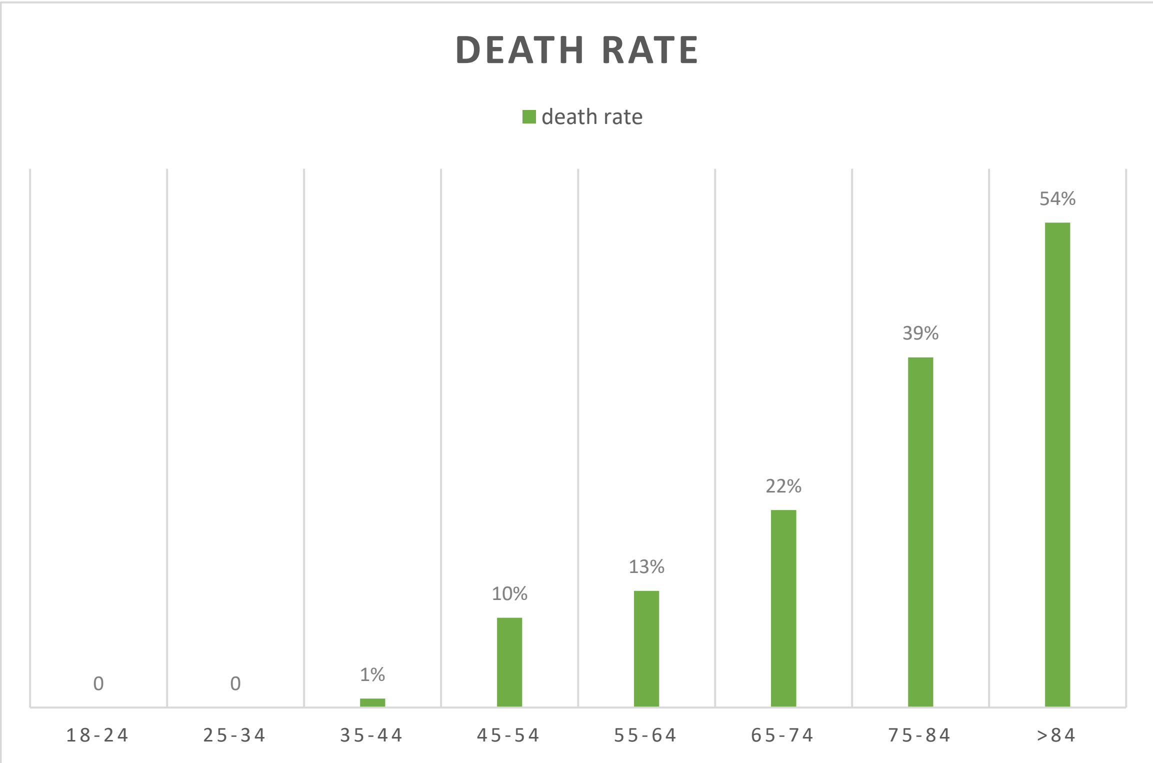

Figure 9. COVID-19 death rate by age group.

Diagnosis of COVID-19 Cases by Big Data

Big Data can be used on the internet to track progress and public pandemic concerns, foresee the trend in pandemics, and warn early on in circumstances of public health in general. COVID-19 symptoms vary, but research focusing on the medical characteristics and signs of positive patients of COVID-19 are not fully identified. One of COVID-19′s most significant problems was to provide sufficient safety amid a pandemic crisis in the transport business [89]. As part the five significant technological contributions, Big Data technology relevance was examined as a tool to locate virus-prone areas. When COVID-19 is suspected, RT PCR is utilized to make the diagnosis. Depending on the conditions, the test results may take 24 h to several days [92]. Therefore, the number of cases suspected of COVID-19 has risen above the current test capacity in numerous countries. In response, a number of researchers have devised alternative techniques for identifying COVID-19 infection. A variety of clinical symptoms and signs, including chest computer tomography, therapeutic measures and medical records, have been obtained and tested in the clinic. The statistics were analyzed and the results were similar to those with the most frequent fever and dry cough symptoms reported by reference [70].

Health Care Decision Making

Big Data can help doctors make better decisions. Big Data is mainly aimed at the ability to find, and turn a huge quantity of data into usable information for clinicians and decision-makers. Using large-scale data in healthcare, patient care enhancement in healthcare organizations and the production of value for patients and value-building in medical organizations has come about in a wide range of areas. An efficient administration, analysis and interpretation of large amounts of data can offer new game-changing approaches for medical care. Data on this automatic detection challenge are extensive in view of the great number of COVID-19 occurrences and the lung photographs [54]. Big Data applications can aid physicians, patients, and pharmaceutical and health workers. Big Data analysis methods allow for four types of extraction: volume, variety, speed, and truthfulness. Advanced prediction and diagnostic technology have been created together with rapid developments in medical imaging [87].

3.1.2. RQ2 Big Data Application Framework for Forecasting and Monitoring the Pandemic

The main objective of the proposed framework is to bridge the gap between present healthcare and technology, by creating a COVID-19 model employing unique Big Data analysis approaches and tools. The model's outcomes can be utilized to develop possible health system improvement initiatives elsewhere to improve the management of infected persons. Big Data has been used for corporate applications for a long time. Still, the technology quickly expands to other sectors, such as health care equipment, social media, and satellite imagery [102]. Computers have used numerous computer algorithms and techniques to tackle our problems throughout the years. Data are analyzed using Big Data approaches with spark and deep learning [78].

Proposed COVID-19 Framework

COVID-QF offers to improve injection and query efficiency for COVID-19 datasets. The COVID-QF includes three steps of input, index, stock and query. The suggested COVID-QF approach describes how many datasets can be used to perform complicated questions. COVID-QF uses the basic Apache Spark architecture to optimize and reduce processes [103]. Apache Spark is a data processing system with memory distribution that accomplishes jobs 100 times faster than other systems in a few steps; as shown in Figure 10 [31]. The CSS-COVID-19 use of Apache Spark improves the effectiveness of the regularly enhanced management of enormous corona viral disease data [104].

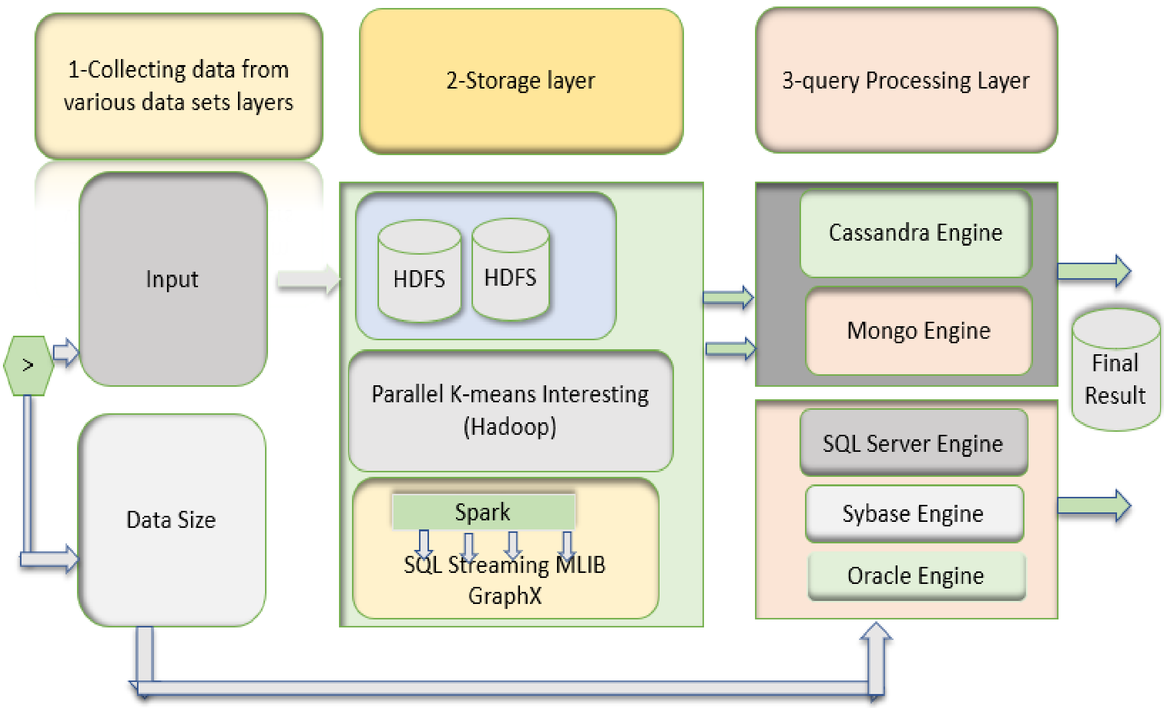

Figure 10. COVID QF Framework.

Hadoop Distributed File System (HDFS)

In Hadoop the Hadoop Distributed File System manages enormous data collections efficiently. After dividing the data into small chunks, you can save your data in various tubes with the Google 2File System. It is a dispersed structure of documents that continuously runs in all the district record structures and can store vast amounts of data. In Figure 11, the HDFS architecture is described clearly. There are two nodes in HDFS—Data Nodes and Name Node of Specialist. These hubs inspect, compose, manufacture, and omit tasks [40]. OpenSource includes a name, domain, the author's name, source quotation (if applicable), writing style, website features, and the source's presence on social media [56].

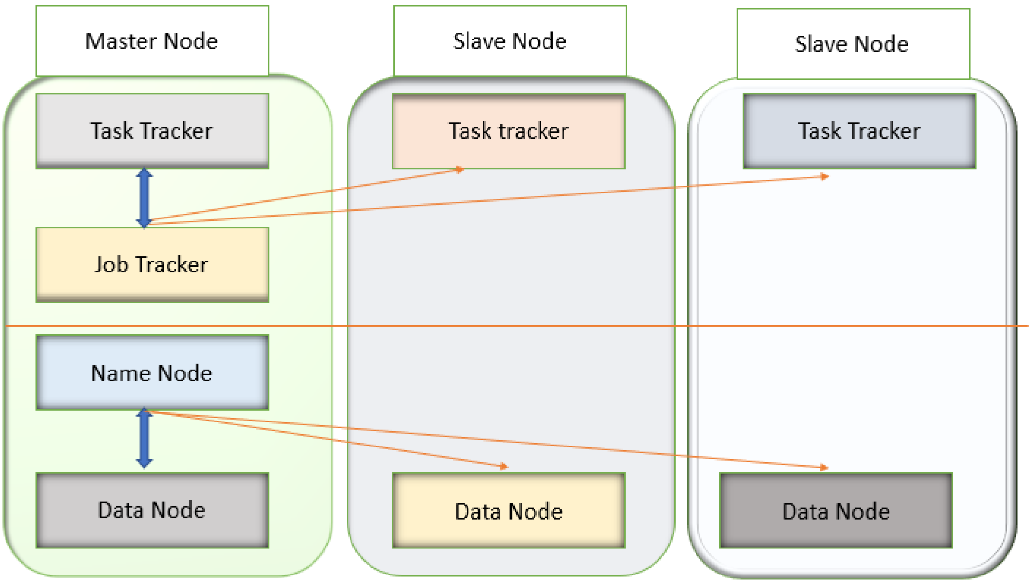

Figure 11. Structure of Hadoop [28].

Apache Spark

Apache Spark is a fast processing open-source structure used for data review, as shown in Figure 12. Apache Spark has been developed by Apache as the de facto framework for Big Data analysis, increased memory programming and high-level libraries for machine-level study, Graph analytics, streaming and structured data processing. Over the past few decades, frameworks such as Apache Hadoop and Apache Spark through google Colab [105]. If an application has been installed in a Spark cluster, the program has all resources, except when users limit the accessible resources. The programming model is based on Hadoop Map Reduce and expands the Map-Reduce model effectively to more computations. The critical character of Spark is that the data are put in memory cluster computing, which increases the processing speed and makes it very useful for interactive programs and interactive queries with standard parallel techniques such as join and match. Apache Spark MLlib package provides machine learning algorithms [65].

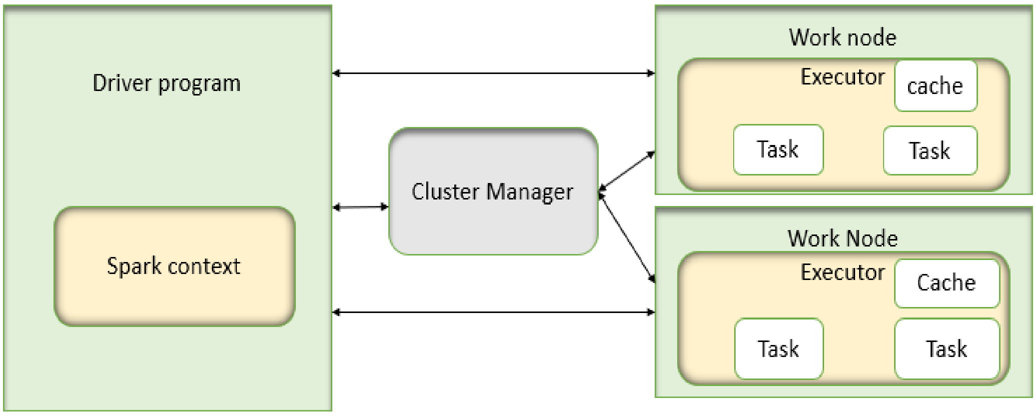

Figure 12. Apache Spark Architecture [23].

3.1.3. RQ3 Big Data Application to Popular Issues during the Pandemic

Big Data can potentially combat the COVID-19 pandemic, as is clearly described in Table 10. However, it still faces several obstacles.

Table 10. Popular Big Data applications in the pandemic.

Issues	Description	Reference
Accuracy of Data	Precision in collecting, assessing, organizing, and analyzing data is the biggest issue. Due to the continuous spread of the disease, massive amounts of data are produced online, leading to discussions on questions such as the correct distance between people, heat-prone viruses, the air-transmissibility of the virus and the persistence of the virus on various surfaces.	[64,68,86,92,95]
Business Operations	It is not easy to make the datasets effective and harmonize data from many sources. For example, several business organizations can use various codes to show the same item. There might also be more variety in each article for some stock market, market basket analysis and retail data.	[75,89,98,101]
Privacy and security	In the pandemic, authorities can demand information from their people, adopt rules and decide on immediate measures. These include GPS position, CT scans, report diagnostics, travel, and day-to-day activities. Data are required to enable the success of any AI and Big Data platform, if not officially requested, yet people frequently do not want to disclose their data.	[66,73,92,96,106]
Stimulus mechanism	A vast, trustworthy dataset is the foundation of AI and large-scale COVID-19 data systems. Therefore, incentives must be devised to encourage more people and organizations to provide their information. Data quality should be guaranteed to increase the exactness and efficiency of learning patterns. Such systems can be found in settings such as medical, telecommunication, Hajj, transit.	[63,77,94,97]
Integration and rapid analysis of huge datasets	For efficient pandemic prevention and control, data utilization is of great importance. With the advent of Big Data, it will be possible to identify the spatiotemporal process of pandemic development and the efficacy of preventative or control measures. Strategies for obtaining and integrating enormous volumes of geographic and social–spatial information are the most fundamental problem for the future, and spatial mining and analysis has to be overcome. As a result of its geographic structure, this research was able to quickly absorb and integrate massive geographic data, including the WHO.	[71,79,81,82,85,87]

4. Conclusions

The amount of data gathered from the international COVID-19 pandemic is growing significantly. After screening 60 articles included in the systematic review, our first question addressed the application of Big Data to fight the pandemic crisis of COVID-19 through diagnosis and health care decision-making systems. The second question had to do with risk diagnosis, estimation or prevention, decision-making, and drug applications for fighting COVID-19 efficiently. The study showed many analytical techniques and critical features. The third research question highlights some issues that might hinder COVID-19 data analysis technology. One hurdle is the safety of health data and the problems of patient safety, the problems of sharing data in business organizations, privacy and security, stimulus mechanism and integration, and rapid analysis of enormous datasets. Twenty-four papers were selected which addressed the third question and evaluated and identified some forward-looking themes in future studies and applications for assistance to stakeholders, such as government agencies, hospitals, patients, and autonomous employees. Finally, we analyzed and identified many prospective areas in future research and requests to help stakeholders such as governments, hospitals, patients, and responsible authorities make decisions and forecasts for the future.

5. Future Directions and Recommendations

Big Data technologies are a vital tool for battling COVID-19 in several appealing applications, ranging from pandemic monitoring, viral sensing and therapy, to diagnostic assistance. On the one hand, AI can provide a genuine range of COVID-19 treatments. COVID-19 has given several natural and typical test sites to estimate and minimize air pollution management possibilities. Because of various obstacles, including expenses and diminished COVID-19 test capacity, multiple countries have taken steps to prevent and reduce the spread of COVID-19. A vast and rising volume of data is described as Big Data, making it necessary to provide policy proposals for countries employing digital technology in combating COVID-19. Constant updates and modifications are essential to forecast and simulate the pandemic and post-pandemic era successfully, as well as developing COVID-19′s associated keywords and language. Ground measurements from meteorological stations are diurnally accurate. Rehabilitation rules can survive healthier recommendations if schistosomiasis has been employed and affected. Detecting vulnerabilities in current approaches is also needed. This systemic literature review provides a full report on research and studies. Deep learning has tackled the COVID-19 pandemic and is guided by future developments in COVID-19. Recent work inspired by deep learning models such as convolutional neural networks [107–112] could be applied to COVID-19 X Rays, CT Scan and MR images.

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