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A rapid review of machine learning approaches for telemedicine in the scope of COVID-19

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ABSTRACT

The COVID-19 pandemic has rapidly spread around the world. The rapid transmission of the virus is a threat that hinders the ability to contain the disease propagation. The pandemic forced widespread conversion of in-person to virtual care delivery through telemedicine. Given this gap, this article aims at providing a literature review of machine learning-based telemedicine applications to mitigate COVID-19. A rapid review of the literature was conducted in six electronic databases published from 2015 through 2020. The process of data extraction was documented using a PRISMA flowchart for inclusion and exclusion of studies. As a result, the literature search identified 1.733 articles, from which 16 articles were included in the review. We developed an updated taxonomy and identified challenges, open questions, and current data types. Our taxonomy and discussion contribute with a significant degree of coverage from subjects related to the use of machine learning to improve telemedicine in response to the COVID-19 pandemic. The evidence identified by this rapid review suggests that machine learning, in combination with telemedicine, can provide a strategy to control outbreaks by providing smart triage of patients and remote monitoring. Also, the use of telemedicine during future outbreaks could be further explored and refined.

1. Introduction

The COVID-19 pandemic of the novel coronavirus (SARS-CoV-2) has spread rapidly across the world. As of January 05, 2021, there were more than 86 million cases and almost 1.9 million deaths related to COVID-19, and the numbers are in growth [1]. The swift transmission of the virus is a threat to the world, hindering our ability to contain the spread of the damage. Many countries advise that infected patients presenting mild symptoms to remain isolated at home to avoid a collapse in the health care system [2].

Strategies reported as efficient for controlling or preventing outbreaks are screening or classifying patients before being admitted into health services. Virtual care can provide efficient triaging in countries with the highest COVID-19 cases [3]. Through telemedicine, patients receive supportive care without physically visiting a hospital, for example, using an artificial intelligence-based conversational agent that provides treatment advice. Artificial intelligence techniques are widely used in the medical domain [4]. Chatbots can help deliver telehealth to provide free primary health care education, information, advice to chronic patients, and enable virtual interaction while social distancing [5–7]. Similarly, a mobile clinical decision support system can provide a comprehensive model for disease detection and monitoring. By monitoring a person with COVID-19 in real time, physicians can guide patients with the right decisions [8,9].

The COVID-19 has become a severe global pandemic in the past few months, and it caused a vast loss to human society worldwide. For such a large-scale pandemic, early detection and isolation of the potential virus, carriers are essential to curb the spread of the pandemic [10].

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Telemedicine has a critical role in emergency responses, and it is an ideal model for managing infectious diseases [11]. Therefore it can support long-distance clinical care, education, and health administration, and its use has increased dramatically in the past decade [12]. Machine learning techniques were applied in telemedicine to improve patients' identification with COVID-19 and track for real-time use by health systems [6,8].

Analyzing all the articles found in this research, no one proposed a systematic literature review aiming to identify different telemedicine applications using machine learning in the scope of COVID-19 and related epidemics. The current article aims at presenting a literature review in which the selected papers bridge the gap between present technologies and health care systems in response to the COVID-19 pandemic. These solutions address various clinical challenges, facilitating a set of operations such as assessing risk as well as managing, predicting, diagnosing, tracking, and following up with patients during the COVID-19 outbreak. One of the biggest challenges that researchers face in analyzing medical data is the shortage of available datasets. Deep learning models applied in some works depend on the availability of comprehensive sets of labeled data.

The proposed work provides a set of contributions that can be used as directions for future research by the scientific community. As the main contributions, this article: (i) identifies machine learning contribution to improving telemedicine in the fight against COVID-19 and similar pandemics in the future; (ii) proposes a taxonomy emphasizing machine learning-based telemedicine applications in the mitigation of COVID-19; (iii) identifies opportunities and future research directions to contain the outbreaks, epidemics, or pandemics with a promising trend toward broader adoption of telemedicine. Thus, we set it into four major topics: machine learning methods, telemedicine applications, functionalities of telemedicine, and clinical data. We further sought to answer various questions related to telemedicine's goals and future challenges when applied to outbreaks, epidemics, or pandemics control. We conducted a systematic review, reported here following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [13] methodology to guarantee a transparent and comprehensive reporting of results.

The remaining of this article is organized into four sections. Section 2 details the materials and methods used in this literature review. Section 3 presents the results with a focus on the research questions. Finally, conclusions and final considerations of this review are presented in Section 4.

2. Materials and methods

Rapid reviews have emerged as a streamlined approach for synthesizing evidence quickly, typically for the purpose of helping decision-makers in health care and health services settings to respond in a timely manner to urgent and emerging needs [14]. Rapid reviews simplify systematic review methods by focusing the literature search while still aiming to produce valid conclusions [15]. The protocol of this review was registered in the international prospective register of systematic reviews (PROSPERO) under number CRD42020209670.

2.1. Planning the review

The presented rapid literature review method was carried out through the following activities:

1. Research questions: identify the research questions to guide the literature review;
2. Search strategy: define the strategy to collect the initial literature corpus, including keywords and research databases;
3. Selection criteria: explain the criteria for selecting the studies;
4. Quality assessment: describe the quality assessment of the selected studies;
5. Data extraction and synthesis: compare the selected studies and research questions.

2.2. Research questions

The proposed rapid review will answer two general (GQ) and four specific (SQ) research questions. The general research questions have been refined into more specific questions to provide better classification and thematic analysis. Table 1 describes the general and specific research questions.

2.3. Search strategy

A rapid review was conducted to synthesize evidence regarding the impact of telemedicine and machine learning techniques on the monitoring of COVID-19 victims. The database searches for the review were completed in September 2020. This rapid review followed the PRISMA guidelines [13]. The Participants, Intervention, Comparison, Outcome (PICO) that guided this review were as follows:

- (P) Participants: Infected people and with suspected infection from COVID-19.
- (I) Interventions: The application of telemedicine and machine learning techniques in outbreaks, epidemics or pandemics, particularly of COVID-19.
- (C) Comparators: To compare applications of telemedicine and machine learning techniques found in the scientific literature.
- (O) Outcomes: Telemedicine and machine learning innovative solutions noticed in scientific literature to help to reduce the global impact of COVID-19.

The literature search strategies were conducted in six databases: PubMed, IEEE Xplorer Library, Science Direct, ACM Digital Library, SpringerLink, and Google Scholar. These online databases cover the most influential journals and conferences within the computer science and health care area. The initial search was implemented on September 22, 2020. We conducted a review of the scientific literature published between 2015 and 2020, written in English, and excluding results from patents and citations. The data search involves keywords, related terms, variants, or the same meaning for the technologies. Therefore, the following search string in Fig. 1 was defined for the selection. The search string was generated and aimed to provide maximum coverage while maintaining manageability.

2.4. Selection criteria

As in PRISMA, there are two general categories of eligibility criteria: study characteristics and report characteristics [13]. Study eligibility criteria are the typical PICO elements, and they were explained in Subsection 2.4. Review eligibility criteria are those applied during the screening stages, and they are shown below:

Table 1
Research questions for rapid review. GQ: General question. SQ: Specific question.

GQ1.	How telemedicine and machine learning techniques can help to face outbreaks, epidemics or pandemics, particularly of COVID-19?
	SQ1. Which are the significant machine learning methods applied in telemedicine?
	SQ2. What are the applications of telemedicine in the scope of COVID-19 and related epidemics?
	SQ3. Which functionalities of telemedicine were employed to manage and to control COVID-19 and related epidemics?
	SQ4. What are the clinical data used by the telemedicine solutions in the scope of COVID-19 and related epidemics?
GQ2.	What are the challenges and open questions related to telemedicine when applied to outbreaks, epidemics or pandemics control?

Search String

("artificial intelligence" OR "machine learning" OR "deep learning") AND ("telemedicine" OR "telehealth" OR "remote monitoring" OR "telemonitoring") AND ("covid-19" OR "SARS-CoV-2" OR "coronavirus")

Fig. 1. Search string used for database queries.

- Inclusion criteria: All full length articles of telemedicine which employ machine learning methods in the management of patients with COVID-19 and related epidemics will be considered for inclusion. Furthermore, only articles published between 2015 and 2020 in academic journals, written in English and with full text accessible.
- Exclusion criteria: Books, editorials, letters, practice guidelines, papers without abstract, abstract only reports, dissertation, thesis, short papers (fewer than five pages), commentaries, preprints, articles not related to machine learning and health care fields of research will be excluded from this review.

After collecting the set of related articles in the databases, search results were uploaded to Parsifal [16]. Parsifal is an online tool designed to support researchers to carry out systematic reviews of the literature in the context of Software Engineering.

The steps of the filtering process are as follows:

1. Removal of duplicates: Some studies are indexed by more than one database, and in some cases, there are duplicate reports of the same research. In this first phase, the replicate items were automatically removed by the Parsifal system.
2. Impurity removal: In the second filtering step, the impurities of the search results were removed. For example, the names of conferences correlated to the search keywords were included in the search results because of the different electronic databases' characteristics.
3. Filter by title and abstract: We analyzed the title and abstract of the articles and excluded those that did not address telemedicine, machine learning, and COVID-19 as a subject according to the search string.
4. Filter by full text: In this stage, full-text articles of the remaining records will be downloaded and screened against based on the inclusion and exclusion criteria.
5. Snowballing strategy: To ensure including all the relevant sources as much as possible, we conducted forward, and backward snowballing method [17]. Snowballing refers to identifying papers using reference lists and citations, thus presenting reliable and efficient way of conducting systematic literature studies.

2.5. Quality assessment

Risk of bias assessment sometimes called quality assessment (QA) of studies included in a review, is an important component of any well planned or conducted systematic review [13]. Therefore, a set of questions was elaborated, used as criteria to evaluate the articles found. Quality assessment questions are listed in Table 2 and were proposed by [18]. The proposed questions with binary answers validate if the selected articles met the quality criteria are listed.

Table 2
The set of proposed questions for quality assessment proposed by [18].

Identifier	Question
QA1.	Does the article clearly show the purpose of the research?
QA2.	Does the article clearly show a methodology?
QA3.	Does the article present an evaluation of the obtained results?
QA4.	Does the article present a conclusion related to the research objectives?

2.6. Data extraction and synthesis

This rapid review aims to provide a comprehensive description of telemedicine and machine learning applications used to monitor and help manage COVID-19 and related epidemics. The process of data extraction is documented using a PRISMA flowchart of included and excluded studies. We provide a narrative synthesis of the studies from the literature corpus. Furthermore, we provide tables to summarize characteristics and main findings from articles. A narrative synthesis is conducted of the included studies. We answer each question of the research proposed through the synthesis of information elaborated. We proceed with the data extraction by reading the full text carefully from all selected articles and registering the main information into an electronic spreadsheet. The results of the synthesis are described in the subsequent sections.

3. Results

This section presents the results obtained from the 16 fully assessed studies related to the research topic. We seek to answer each proposed research question in the following subsections through elaborative information synthesis.

3.1. Performing article selection

The literature search identified 1.733 articles, from which 15 articles were included in the review. Additionally, we performed the snowballing technique, and as a result, one more paper was added. This stage was carried manually following the citation links provided by the publishing companies and Google Scholar. An overview of the selected articles is presented in Table 3, showing first author, reference, year of publication, publisher, and type. To find results of other similar pandemics, we prospect articles published between 2015 and 2020. However, only articles from 2020 were suitable and fitted our selection criteria.

The screening process and search results are provided in the PRISMA flow diagram [29]. Fig. 2 illustrates the PRISMA flow diagram of the evidences found in this rapid review. Sixteen articles passed through these stages and data were extracted into a spreadsheet. Section 2.6 explained each step of the selection criteria.

3.2. Performing the quality assessment

In this subsection, we present an analysis of quality articles based on our criteria defined in Section 2.5. Fig. 3 illustrates the quality criteria score (ranging from 0 to 4) of the selected articles based on the QA questions proposed in Table 2.

Table 3
Final list of selected article.

First author	Ref.	Year	Publisher	Type
Ying Liu et al.	[9]	2020	JMIR	Journal
Euchi et al.	[19]	2020	Springer	Journal
Lanza et al.	[20]	2020	Elsevier	Journal
Meinert et al.	[6]	2020	JMIR	Journal
Battineni et al.	[7]	2020	MDPI	Journal
Obeid et al.	[21]	2020	Oxford	Journal
Otoom et al.	[22]	2020	Elsevier	Journal
Rahman et al.	[23]	2020	IEEE	Journal
Jiang et al.	[10]	2020	IEEE	Journal
El-Rashidy et al.	[8]	2020	MDPI	Journal
Milenkovic et al.	[24]	2020	Elsevier	Journal
McRae et al.	[25]	2020	JMIR	Journal
Bharti et al.	[5]	2020	IEEE	Conference
Zeye Liu et al.	[26]	2020	Springer	Journal
Said et al.	[27]	2020	Elsevier	Journal
Hossain et al.	[28]	2020	IEEE	Journal

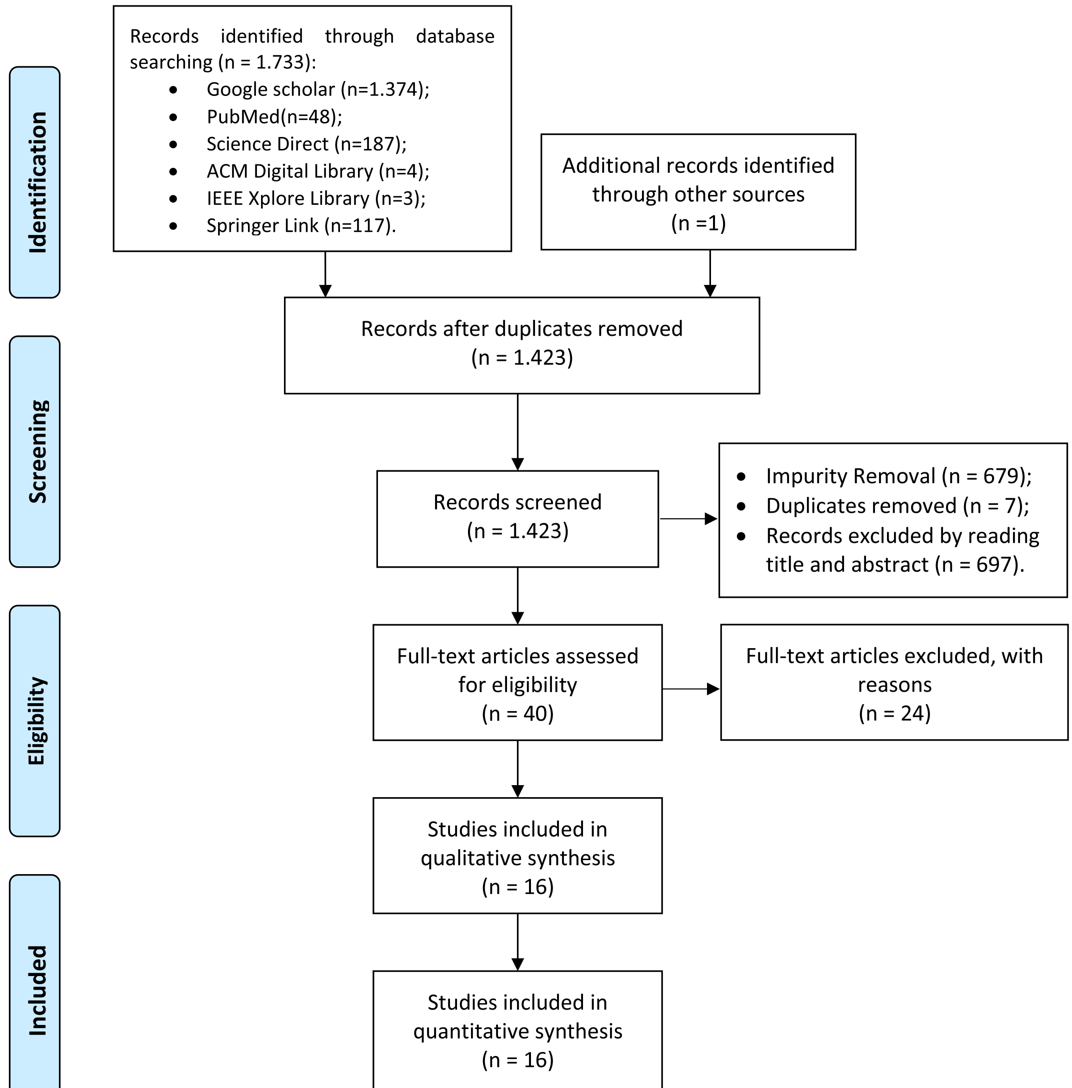

Fig. 2. Flow diagram showing the database search and article selection process using PRISMA guidelines.

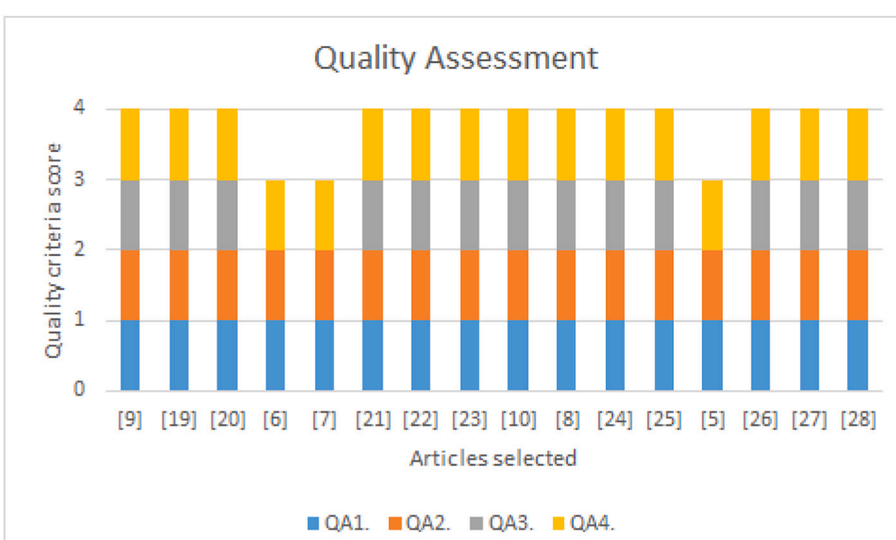

Fig. 3. Quality assessment of the articles.

As shown in Fig. 3, thirteen (81%) articles cover the four quality evaluation criteria and obtain the maximum possible quality score. Three (18%) articles cover three quality criteria. We found that three articles are in the design phase and did not obtain results.

3.3. Data extraction and answers to the research questions

As mentioned previously, we refine the general research question (GQ1) into four specific questions (SQ1–SQ4). We will discuss the answers to our research questions, starting with the general question, and then detailing some crucial issues in explaining the specific questions. Finally, we will answer our (GQ2) based on perspectives extracted by the selected articles.

3.3.1. GQ1. How telemedicine and machine learning techniques can help to face outbreaks, epidemics or pandemics, particularly of COVID-19?

We used the information found in the reviewed articles to classify the information and define our taxonomy. The main objective is to categorize information to increased theoretical understanding and predictive accuracy in empirical research. We decided to present our taxonomy as a network because it organizes content into hierarchical and associative categories. Fig. 4 shows our taxonomy. The taxonomy is organized based on the following central topics: telemedicine, machine learning, and COVID-19. We seek the answers to our specific questions (SQ1-SQ4) and classify them into classes and subclasses to better visualize the selected articles' information.

Telemedicine, also known as Telehealth, encompasses the use of technologies to facilitate remote patient monitoring. Researchers developed many different forms of telemedicine systems to meet the needs of fighting the pandemic. In Section 3.3.3, we discuss all telemedicine applications in the scope of COVID-19 that we identify in our corpus of review. The factor that slows the spread of the virus is physical distancing, which can directly reduce person-to-person contact. Telemedicine allows clinicians to evaluate, diagnose, and treat patients without needing any physical interaction with them.

The rapid development of automated diagnostic systems based on artificial intelligence techniques, particularly machine learning algorithms, can increase diagnostic accuracy and protect physicians and other health professionals by reducing their contact with infected patients. Researchers train the learning techniques and assess the obtained results against other studies or thresholds. In the next subsection, we mention the machine learning methods applied in telemedicine, which

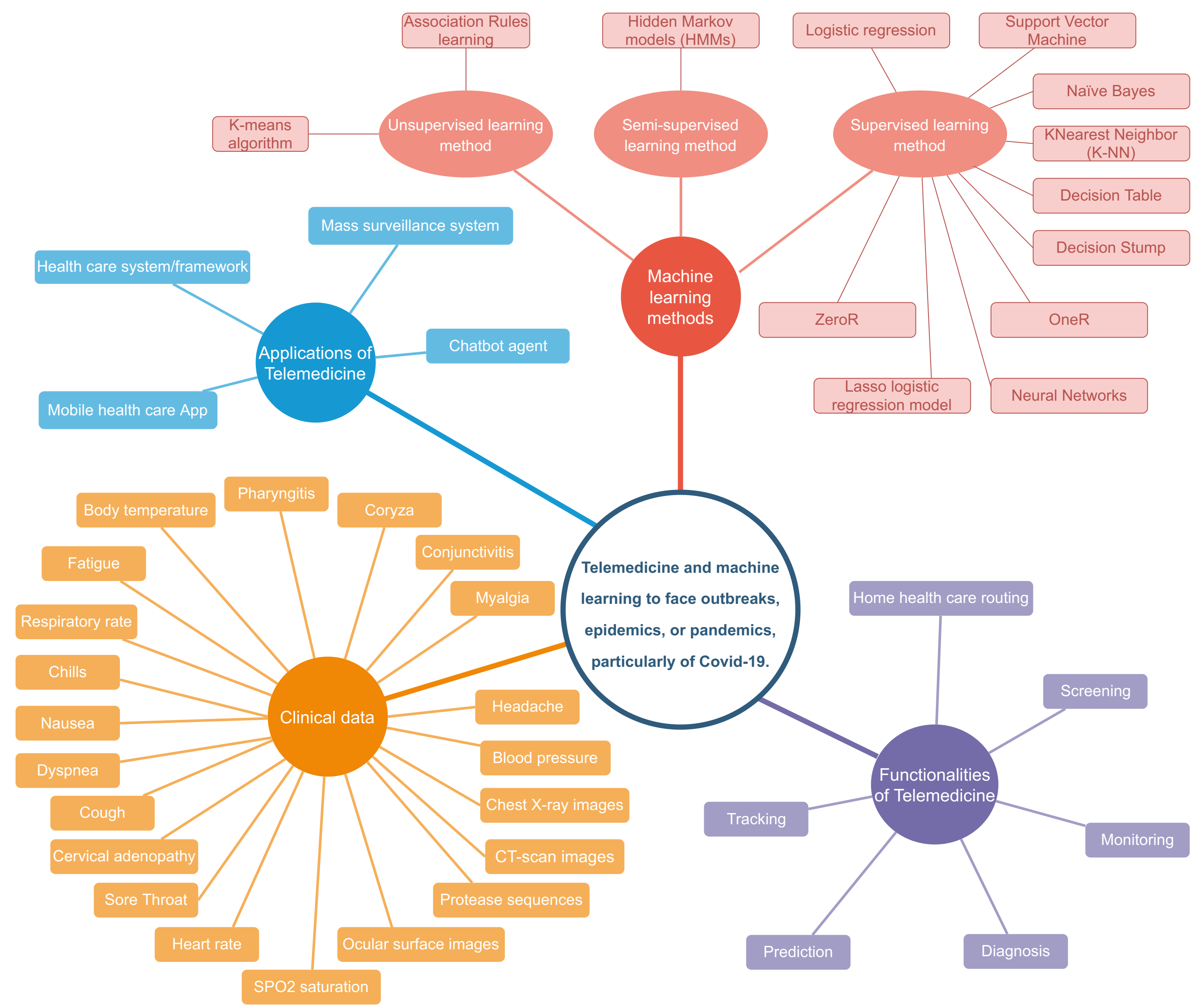

Fig. 4. Proposed taxonomy.

appear in our review corpus.

3.3.2. SQ1. Which are the significant machine learning methods applied in telemedicine?

Machine learning methods usually are divided into categories according to their purpose. The main types are the following: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning [30]. In supervised learning, an algorithm learns to map an input to a particular output. The data collected in unsupervised learning has no labels and the output is unknown. Semi-supervised learning falls between these two, exploiting the idea that even though the group memberships of the unlabeled data are unknown, this data carries important information about the group parameters. Reinforcement learning algorithms learn how to behave within an environment from reward and punishment, thus being useful for sequential decision making problems.

The literature corpus describes more than 25 different machine learning techniques used for processing clinical data. Table 4 presents the most-cited algorithms and the reference articles which used them to produce the best results. The supervised learning method was the category of machine learning methods most applied by the selected research articles, accounting for 68% of the cases. Over a half of the articles (62%) used neural networks methods. Only two articles did not indicate the machine learning method applied. We did not find articles in the reinforcement learning category.

Artificial Neural Network (ANN), or simply neural network, is a supervised learning method. The learning process tries to mimic the learning that takes place inside the human brain. Thus, multiple layers of nodes are connected through edges. The edges connecting between the nodes represent numerical weights. Each node's output is computed as a weighted sum of its inputs. The neural network learns the numerical weights that best classify the instances from each class. This learned model is then used to predict a class label for any given test instance. The work of [22] proposes identifying potential COVID-19 cases from real-time symptom data quickly. The results suggest that the models built using neural networks and four additional machine learning algorithms provide useful and accurate identification of potential cases of COVID-19. Additionally, Zeye Liu et al. [26] used the neural network to refine the fitting at specific time points to achieve accurate prediction. The model was used to predict the epidemic's long-term trends and estimate the accumulated demands for local hospitalization during the epidemic period in Beijing.

The system DDC19 proposed by [9] is a mobile decision support system based on a multiclass logistic regression algorithm, designed and developed to assist general practitioners in providing dynamic risk assessments for potential patients during the COVID-19 outbreak. Their results show that logistic regression has good classification ability and interpretability, widely used in machine learning. In the same line, the results from [21] describe the increasing use of artificial intelligence methods to improve the efficiency of COVID-19 testing. They developed a word embedding–based convolutional neural network(CNN) for predicting COVID-19 test results based on patients' self-reported symptoms. A logistic regression model was used as baseline. The CNN outperformed the logistic regression model on all the metrics except for one item.

Table 4
Machine learning methods most used.

Category	Method	Reference articles
Supervised learning method	Logistic regression	[9,21]
	Neural Networks	[6,8,10,20–24,26,28]
	Support Vector Machine	[22,23]
	NaÃ¯ve Bayes	[22]
	KNearest Neighbor (K−NN)	[22,23]
	Decision Table	[22]
	Decision Stump	[22]
	OneR	[22]
	ZeroR	[22]
	Lasso logistic regression model	[25]
Unsupervised learning method	K-means algorithm	[19]
	Association Rules learning	[5]
Semi-supervised learning method	Hidden Markov models (HMMs)	[23]

3.3.3. SQ2. What are the applications of telemedicine in the scope of COVID-19 and related epidemics?

We summarize telemedicine applications found in this systematic review in Table 5. One of the most popular applications of telemedicine in our study is the health care system/framework. The suggested works propose functionalities to detect and monitor COVID-19. Some of them employ the Internet of Things (IoT) framework to collect real-time symptom data from users to identify suspected coronavirus cases early and to monitor the treatment response of those who have already recovered from the virus [22,28]. With the main objective of reducing the COVID-19 pandemic spread, some existing health care systems have been adapted and further developed by increasing the degree of social distancing. Online services for the communication between patients and the chosen physicians are provided. The social distancing of patients and physicians is also established by sending laboratory analyses per email, or SMS [24].

Mobile health is a broad field that includes applications that encompasses book medical appointments, track symptoms of a condition, educate users by having useful information on how they can avoid illness, and avoid being exposed to the virus. Mobile apps are designed to support decisions made in multiple settings, including home care, primary care or urgent care clinics, emergency departments, and hospital and intensive care [25,26]. A mobile digital health app was also proposed by [6], which provides older people, their families, and peers with a structured medium for social interaction. That work also implements a simple-to-use interface with built-in accessibility functions such as font size adjustment, a chatbot (text and voice), a voice control assistant, and voice messaging with family members.

Virtual chatbot applications are well known for automatic conversational agents that run on computer programming or artificial intelligence interactions between the users and machines with natural language processing [7]. Thus, it becomes evident that if effectively designed and deployed, a chatbot can help patients living in remote areas by promoting preventive measures, healthcare tips, virus updates, and reducing psychological damage caused by isolation and fear [5].

Many governments have begun tracking all residents' movement and behavior by installing mass surveillance system points in towns, villages, streets, and public spaces to track and monitor suspects and detect suspicious patterns. Installed in significant entryways, checkpoints, or other crowded venues, it can provide mass screenings, as well as recurrent temperature monitoring for potentially infected individuals [27]. A mass surveillance system proposed by [28] can identify, locate, and specify individuals' identity for safety or health reasons. Therefore, this function can be called upon to monitor the previous movement behavior of confirmed COVID-19 cases to detect the set of individuals who may have been in close contact with the infected case and locations recently accessed by the COVID-19 patients.

Table 5
Articles for each application of telemedicine in the scope of COVID-19.

Subclasses	Reference articles
Health care system/framework	[8,19–26,28]
Mobile health care App	[6,9,10,22,25,28]
Chatbot agent	[5–7]
Mass surveillance system	[27,28]

3.3.4. SQ3. Which functionalities of telemedicine were employed to manage and to control COVID-19 and related epidemics?

We call functionalities the service line addressed, and these are the aspects of the medical care process. These aspects are grouped into six parts. Table 6 provides a list of functionalities subclasses. Screening is the functionality most found in the review. Fifty percent of the articles were assigned to identify patients with COVID-19 and significantly reduce contagion risk.

Screening determines whether an immediate emergency response is required and can provide the most appropriate service response. Therefore, to evaluate patients with COVID-19, suspected cases, and other patients with similar symptoms, and effectively triage under the condition of medical resource shortages is of great significance to protect the susceptible population, reduce hospital cross-infection, and decrease the burden on medical resources [9]. Additionally, [20] employs a multi-agent architecture that gives intelligent support to the physician and helps in all the early triage phases, reducing the risk of contagion.

Home hospitalization structures are growing around the world. A new technique for home healthcare routing and scheduling problems purely based on an artificial intelligence technique to optimize the offered services within a distributed environment was proposed by [19]. Establishments of Hospitalization at Home (EHH) is a complex and challenging system to manage from a human and material point of view. The objective is to considerably minimize costs while respecting priorities according to cases that will be facing. The automatic learning and search method seem to be interesting to optimize the allocation of visits to beneficiaries.

COVID-19 detection and monitoring systems employing Internet of Things (IoT) devices were proposed by [8,22]. To quickly identify potential coronavirus cases, they collect real-time symptoms data from wearable sensor technologies. By monitoring a person with COVID-19 in real time, physicians can guide patients with the right decisions.

Remotely monitoring public spaces for early signs of disease and tracking identified cases could prove beneficial in protecting the public and taking some of the load off health care workers [27]. This kind of application can help speed up the tracking rate of COVID-19 cases that are unknown. Placing the thermal imaging sensor at several locations like malls, schools, airports, etc. The application can help identify people with high body temperature and isolate them, and their data can help keep others safe.

Prediction models for early detection of severe coronavirus disease can help clinical decision-making and inform policymakers and public health officials to devise prevention plans. A clinical decision support system and mobile app for managing COVID-19 care were provided by [25]. The algorithm, which is directly related to mortality risk, predicts disease severity using biomarker measurements and age. To estimate the epidemic situation of large medical centers and predict the time to restore the functions of daily medical service [26] constructed a specific model to estimate the impact of community containment and construction of makeshift hospitals on the epidemic situation in China.

Rapid and early diagnosis of COVID-19 is essential for pandemic control and for finding potential patients as early as possible. An artificial intelligence chatbot for diagnostic evaluation and recommended immediate measures when patients are exposed to COVID-19 were proposed by [7]. The idea was to identify initial symptoms of COVID-19 from the user location. The designed bot can handle user requests and identify message patterns with an artificial intelligence markup language. Also, to diagnose respiratory diseases, [10] suggests a remote, portable, and intelligent health screening system based on respiratory data. The results provide a theoretical basis to encourage controlled clinical trials and thus helps fight the current COVID-19 pandemic.

Table 6
Articles for each functionalities of telemedicine in the scope of COVID-19.

Subclasses	Reference articles
Screening	[5,6,9,10,20–22,24]
Diagnosis	[7,8,10,23,28]
Monitoring	[8,22,27]
Tracking	[6,23,27]
Prediction	[25,26]
Home health care routing	[19]

3.3.5. SQ4. What are the clinical data used by the telemedicine solutions in the scope of COVID-19 and related epidemics?

There are many different ways that COVID-19 can show up in a person, and many symptoms overlap with those of other illnesses. Like the other respiratory viral infections, the most common symptoms at the onset of COVID-19 were fever and cough. Most people infected with the coronavirus will experience mild symptoms and in some cases remain asymptomatic, but even asymptomatic people can spread the virus to others.

COVID-19 non-invasive body temperature module was implemented by [23]. They find the face's location and identify the deep learning algorithm where the temperature value is augmented. Thus, they monitor the patient's body temperature in real-time and issue alerts on abnormal temperatures. Similarly, [27] propose a vision-based thermal tracking application. The application can scan as many as 30 people simultaneously at a distance of 3 m or nearly 10 ft, with a temperature accuracy of roughly 0.6 degrees Fahrenheit (0.3 °C). The key feature of this application is thermal camera sensors and an artificial intelligence-driven algorithm for temperature analysis.

The authors [28] propose a B5G framework that utilizes the 5G network's low-latency, high-bandwidth functionality to detect COVID-19. For this, they use chest X-ray or CT scan images. They also develop a mass surveillance system to monitor social distancing, mask-wearing, and body temperature. For the same purpose of detecting COVID-19, [8] propose a convolutional neural network-based deep learning model based on the patient's X-ray scan images and transfer learning.

The clinical data most commonly reported by the articles was body temperature, 68% consider this symptom for early diagnosis of COVID-19. Cough is also a symptom as the most widely observed. This information matches with the World Health Organization statistics [2]. Table 7 provides a list of clinical data for each article. Many studies collect real-time symptom data through a set of wearable sensors on the user's body or through information provided by users on health care systems. The most relevant COVID-19 symptoms were identified based

Table 7
Articles for each clinical data in the scope of COVID-19.

Subclasses	Reference articles
Body temperature	[7–9,20–25,28]
Cough	[7,9,21,22,24,25,28]
Respiratory rate	[7–10,21,22]
CT-scan images	[9,23,28]
Fatigue	[22,24]
Blood pressure	[8,28]
Headache	[24,25]
Myalgia	[24,25]
Sore Throat	[22]
Heart rate	[8]
SPO2 saturation	[8]
Conjunctivitis	[24]
Coryza	[24]
Pharyngitis	[24]
Cervical adenopathy	[24]
Dyspnea	[24]
Chills	[25]
Nausea	[25]
Chest X-ray images	[28]
Protease sequences	[28]
Ocular surface images	[28]

on a real COVID-19 patient dataset.

3.3.6. GQ2. What are the challenges and open questions related to telemedicine when applied to outbreaks, epidemics or pandemics control?

Since the pandemic started, the popularity of telemedicine is rising. Such a popularity facilitated the provision of various remote care types by medical professionals. Disasters and pandemics pose unique challenges to health care delivery [11]. We have made a study of main challenges, open questions, aspects, and common concerns related to the use of machine learning techniques intersected with telemedicine when applied to control outbreaks, epidemics, or pandemics. We will present this information, grouping the related topics according to the categories: assessing risk, managing, predicting, diagnosing, tracking, and COVID-19 datasets.

3.3.6.1. Assessing risk, managing and predicting. General practitioners are facing unique challenges from disasters and pandemics in delivering health care. Based on the actual scenarios and the process of patients using health care, the key issues that need to be resolved are: how to fully grasp and effectively manage the residents' status in real-time without increasing the general practitioners working burden and, without omitting potential patients with COVID-19; how to effectively use medical knowledge and risk stratification models to achieve effective evaluation and classification, as well as the patients' scientific stratification [9].

A clinical decision support system and mobile app to assist in COVID-19 were proposed by [9,25]. Physicians are tasked with evaluating large amounts of rapidly changing patient data and making critical decisions in a short amount of time. The system aims to deliver pertinent knowledge and individualized patient information to health care providers and assist in COVID-19 severity assessment, management, and care. They use supervised learning methods to dynamically predict and stratify the risk of COVID-19 infection based on different patient clinical data levels. COVID-19 dynamic risk stratification model constructed by [9] constructed is based on a multiclass logistic regression algorithm. They used low risk, moderate risk, and increased risk as labels. The model had an excellent ability to predict risk levels in any scenario it covered.

3.3.6.2. Diagnosis. Physicians have used CT scans and X-ray imaging to assess patients' lung health. One of the constraints of CT scanning and X-ray image processing is that they require radiology experts and are time-consuming, which is a problem for patients who require an immediate COVID-19 diagnosis. An automated assessment model is necessary to save time for health care experts. B5G network architecture suitable for COVID-19 diagnosis was proposed by [23,28]. By leveraging edge computing with the 5G RAN, the management of epidemic diseases such as COVID-19 can be conducted efficiently. Implementing a hierarchical edge computing system provides many advantages, such as low latency, scalability, and application and training model data protection, enabling COVID-19 to be evaluated by a dependable local edge server. They have introduced a COVID-19 management framework based on deep learning algorithms at the edge. The smart health care framework proposed for COVID-19 diagnostic may be extended to any infectious disease.

3.3.6.3. Tracking. The ability and accuracy of thermal imaging over conventional image cameras have led to the implementation of thermal cameras in people counting/tracking applications. To minimizing the spread of the infection [27] presents a thermal people counting/tracking application. It helps to ensure that preventive measures are appropriately made, reducing the burden on the medical staff. Although most of this method seems simple though, there are some situations difficult to solve, even with today's computer speeds, one of such difficulties is people occlusions. For example, the algorithm has to operate in real-time, so it makes limits for the complexity of methods for detection and tracking. Other issues with visual counting system is the cost. High spatial resolution visual camera and a frame grabber are required which makes the system expensive.

3.3.6.4. COVID-19 datasets. In References [23,28], the authors have developed a COVID-19 epidemic management system. It uses the local X-Ray dataset available from COVID-19 patients and non-infected patients. However, they highlight that existing deep learning algorithms suffer from two crucial drawbacks: first, the training requires a sizeable COVID-19 dataset on various dimensions, which is difficult for any local authority to manage. Second, the deep learning results need ethical approval and explanations from healthcare providers and other stakeholders to be accepted.

Most countries find that home isolation is the best practice to limit the spread of the virus. Current technologies and healthcare systems to provide flexible real-time clinical solutions. These solutions addressed various clinical challenges by facilitating operations such as sensing, processing, and communications. COVID-19 has caused rapid expansion in telemedicine. Experts are using machine learning to study the virus, test potential treatments, diagnose individuals, analyze the public health impacts, and more. Machine learning and artificial intelligence have many exciting applications in the medical field in general. Telemedicine, in particular, has emerged as an essential component of healthcare during the COVID-19 crisis.

4. Discussion and future directions

In recent years, the healthcare domain has received significant attention from artificial intelligence, especially machine learning, such as recent research exploring medical imaging [28], conversational agents to interact with the patients [4], chatbots to provide specific information and advice [5–7], besides the clinical decision support systems (CDSS) [8,9] to support the physician's side. This scenario reflects the growing transformation from paper-based to digital-based within healthcare institutions by adopting electronic record systems (EHR) and device adoption for monitoring and tracking patients remotely. In this sense, the effects of using machine learning for telemedicine are still incipient and even subjective to apply metrics. At the same time, telemedicine technologies adoption represents an increase in the availability of healthcare services [31,32], evaluating the growth effects of IA in healthcare domain still represent a challenge [33,34].

On the one hand, the telehealth and telemedicine adoption showed promised outcomes in medical error reduction [35], and assertiveness in the medical conduct [36], as well as using CDSS to help predict prognosis and assist clinicians in screening [37] become positive impacts to promptness response and resolve complex cases by consulting remotely specialized professionals. This scenario became positive when compared with traditional attendance approaches. On the other hand, to measure the impact of these advances, it is necessary to consider the straight beneficiaries, the patients.

Telemedicine can promote a more democratic service, making viable access for healthcare professionals to take care of patients over long distances [38,39]. However, the technology and internet social inequality represents another challenge in Brazil's reality. On the healthcare professionals' side, telehealth systems availability allows more assertiveness to patients' continuous monitoring, using tools to enable patients actively communicate, providing up-to-date information to the hospital and healthcare professionals themselves. Moreover, it enables more autonomy for healthcare professionals to interact with patient data anytime when needed. Furthermore, a final evaluation represents the gradual transformation from the traditional scenario (less technology) to the initial digital and technology adoption during shifts, consults, and clinical decision support, including integrated national programs, [31]. For instance, the tele-ICU program for monitoring ICU COVID-19 patients was a real improvement by combining evidence-based practices and training project [40] in some SÃ£o Paulo city hospitals.

In parallel view, concerning the Brazilian reality, where the Unified Health System (Sistema Único de Saúde, SUS) is the Brazilian public universal healthcare system, and it covers approximately 75% of the population exclusively [41] is the front-line to attend the population. While Europe reality, the general practitioners (GP) are considered crucial 'gate-keepers,' the front-line professionals. Although their costs are mainly covered by public services or social insurance in all European nations, they are still self-employed physicians [42] everywhere. Nevertheless, although these few differences, in the Europe healthcare sector, during the pandemic, the primary care service also changed the face-to-face patient-physician relationship significantly on a scale never seen before [42], telemedicine had widespread adoption. There was a broad acceptance of using telemedicine in the Brazilian Unified Health System (SUS) and the national health systems in Europe, both representing a cost-effective with lower direct costs (clinical) and indirect (travel and work loss) costs.

In this sense, the Brazilian government promoted initiatives to allow the population to interact with healthcare professionals through digital resources by Law No 13989 of April 15, 2020 – operative during the pandemic emergence situation – which fostered the digital adoption of telemedicine and telehealth solutions in a national scale. Although the Brazilian government promoted a contingency plan [38], proposing initiatives aimed at adopting technologies to optimize healthcare action, implementing a system to track back diagnosis, and patients' monitoring (Tele-SUS system), implementation of telehealth guidance (Tele-ICU) for severe and critical cases of COVID-19, a telemedicine platform for multi-professional care, and a teleconsulting platform with psychiatrist and psychologists [31]. The significant proportions of the country represented challenges to combat the pandemic scenario equally because of many factors, such as availability of resources (such as equipment, masks, medicine), and hospitals infrastructure. Also, the distance from city centers (better prepared to support severe cases) made it harder for some Brazilian states to manage the pandemic.

This systematic review highlighted the growing research field in telemedicine combining machine learning and digital approaches to improve the healthcare scenario, such as monitoring, home healthcare, screening, and supporting prediction and diagnostic decisions systems. Although these approaches represent a significant advance, we reinforce machine learning as a promising field to explore novel proposes such as AutoML to automate the design and create algorithms in Machine Learning (ML) to improve the actual scenario in healthcare [43,44]. Besides the use of AI to enhance experiences of both clinicians and patients [33] in healthcare. Furthermore, the growth of AI explainable learning has made the AI understandable, providing explanations catered to humans, promoting transparency about the decisions and consequently reliability, [37,45]. Once the healthcare professionals and patients do not accept decisions without understanding and trusting the explanations, or at least how the decisions are made [46].

On the on hand, blockchain technology combined with the healthcare field has demonstrated a viable approach to ensure security to manage sensitive information [47,48], as exists in the healthcare domain data focusing on a patient-centered approach [49]. That scenario promotes a trustful network to represent patients' information and clinical and medical history data throughout their lives. On the other hand, concerning data decentralization to achieve security, Federated Learning (FL) has recently emerged as an approach to enable distributed data processing and reduce the risks of cyber-attacks [50], also improve the digital health workflow through decentralized artificial system [51].

Although these stimulating scenarios of ML and technologies, and the rich environment for digital transformation, we emphasize data limitations access and the hardship to get quality data besides the few available data to promote exploring and research. There are global efforts to publish data and enable new research since the more available data, the more research and better outcomes we can expect. However, as presented by the Brazilian government and abroad during the COVID-19 pandemic, the low integrated health system difficult rapid actions.

5. Conclusion

This rapid literature review provided an overview of machine learning-based Telemedicine systems and applications that can help manage COVID-19 and related epidemics. We list research questions to obtain specific answers regarding our subject, thus qualifying this survey's information. With the analysis of data extracted from selected articles, we proposed a taxonomy to classify the findings. We summarize the functionalities available in telemedicine applications for epidemics control, the employed machine learning methods, and their respective performance. We also described the clinical data required by telemedicine solutions in the scope of COVID-19 and related epidemics.

As with any other literature review, this study presents limitations that may affect the results' scope. However, the decisions taken during the planning and execution try to mitigate them. This review focuses on scientific articles and does not consider thesis, books, dissertations, commercial tools, patents, or software. We did not include gray literature and excluded articles not written in English. Another limiting issue is the search string. The words and phrases applied possibly to restrict the field of results. Our approach evaluated articles published in the last five years, seeking the latest methodologies and architectures. We did not find articles related to other epidemics or pandemics different from the current COVID-19.

The threat of COVID-19 has become an opportunity for various technologies to test themselves in real conditions. With the rapid development of the internet and smartphone apps, telemedicine has transitioned to a multimodal paradigm, offering greater possibilities and convenience [12]. Community paramedicine or mobile integrated health care programs allow patients to be treated in their homes, with higher-level medical support provided virtually [11].

In rapidly adopting telemedicine, the goal is to minimizing the number of patients who come into central care. In the future, with advancements in technology, for example, the application of 5G networks to improve the effect of video transmission and improvement in the management experience of telemedicine by policymakers, telemedicine may become a sustainable and mainstream solution for both public health emergencies and routine medicine.

Declaration of competing interest

We wish to confirm that there are no known conflicts of interest associated with the article "A Rapid Review of Machine Learning Approaches for Telemedicine in the Scope of COVID-19" sent to possible publication in the Artificial Intelligence in Medicine and there has been no significant financial support for this work that could have influenced its outcome.

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

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