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Clinical informatics solutions in COVID-19 pandemic: Scoping literature review

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ABSTRACT

Background: The global outbreak of COVID-19 (coronavirus disease 2019) disease has highlighted the importance of disease monitoring, diagnosing, treating, and screening. Technology-based instruments could efficiently assist healthcare systems during pandemics by allowing rapid and widespread transfer of information, real-time tracking of data transfer, and virtualization of meetings and patient visits. Therefore, this study was conducted to investigate the applications of clinical informatics (CI) during the COVID-19 outbreak.
Methods: A comprehensive search was performed on Medline and Scopus databases in September 2020. Eligible studies were selected based on the inclusion and exclusion criteria. The extracted data from the studies reviewed were about study sample, study type, objectives, clinical informatics domain, applied method, sample size, outcomes, findings, and conclusion. The risk of bias was evaluated in the studies using appropriate instruments based on the type of each study. The selected studies were then subjected to thematic synthesis.
Results: In this review study, 72 out of 2716 retrieved articles met the inclusion criteria for full-text analysis. Most of the articles reviewed were done in China and the United States of America. The majority of the studies were conducted in the following CI domains: prediction models (60%), telehealth (36%), and mobile health (4%). Most of the studies in telehealth domain used synchronous methods, such as online and phone- or video-call consultations. Mobile applications were developed as self-triage, self-scheduling, and information delivery tools during the COVID-19 pandemic. The most common types of prediction models among the reviewed studies were neural network (49%), classification (42%), and linear models (4.5%).
Conclusion: The present study showed clinical informatics applications during COVID-19 and identified current gaps in this field. Health information technology and clinical informatics seem to be useful in assisting clinicians and managers to combat COVID-19. The most common domains in clinical informatics for research on the COVID-19 crisis were prediction models and telehealth. It is suggested that future researchers conduct scoping reviews to describe and analyze other levels of medical informatics, including bioinformatics, imaging informatics, and public health informatics.

1. Introduction

In December 2019, the outbreak of COVID-19 (coronavirus disease 2019), caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), was started in China. The World Health Organization (WHO) declared the outbreak of COVID-19 as a public health emergency of international concern on January 30, 2020 [1]. The pandemic affected nearly all countries with more than 20 million infected patients and more than 756000 deaths worldwide during the first nine months [2,3]. The WHO declared that the best prevention strategies (especially in low- and middle-income countries) are education and social distancing [4,5].

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Information Technology (IT) tools have already been shown to be potentially useful in educating patients and providing remote clinical services to patients where applicable [6,7].

Medical informatics (MI) is an area concerned with managing and using the required information in the fields of health and biomedicine [8]. MI is a general term encompassing key theories, concepts, and techniques applied to manage and use information in health and biomedicine [9]. Clinical informatics (CI) is described as the application of MI techniques to manage patients by employing an interdisciplinary approach involving clinical and information sciences [10]. There are various methods used to classify CI applications; for example, one of these approaches is the classification based on the type of information used. Basically, two types of information are used in CI, including patient-based and knowledge-based. Patient-based information is provided by patients themselves and used in patient care in healthcare settings, while information based on scientific knowledge forms the basis of healthcare services [8]. Medical and biomedical informatics plays a vital role in response to the COVID-19 pandemic [11]. CI tools seem to be useful in distributing information about decisions and controlling patients during the pandemic. A review study provided evidence for different CI applications in clinical settings, which covered three themes, including CI systems and interventions for providers, CI systems for consumer health, and methods and guidance in CI [12]. During a pandemic, CI could be useful in assisting hospital leaders to virtualize medical care, make clinical decisions, coordinate communications, and define workflow and compliance [13]. One of the fundamental changes in healthcare systems is the widespread development of telemedicine to help patients continue their treatment while maintaining social distance [14]. The application of patient-specific and population-based forecasting models could lead to scientific classification of patients and execution of prevention and control strategies at the national and international levels [15].

The results of this study could help clinicians in using and implementing clinical informatics systems (CIS). Researchers and CI specialists could design CIS and apply the information collected to improve COVID-19 detection and control. Big data could be helpful in modelling viral mode of action and guiding healthcare policymakers.

This study aimed to investigate the literature to identify the CI applications used in previous studies during the COVID-19 pandemic. Therefore, the following objectives were pursued: 1) identifying published studies on the COVID-19 pandemic using CI, 2) identifying the most common methods used in published studies, and 3) recognizing research gaps in pandemic conditions.

2. Methods

The methods used in the present scoping review have already been described in detail in a review protocol study [16]. This research was performed based on Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for scoping reviews (PRISMA-ScR) criteria (see supplemental material 1) [17].

2.1. Data source and research strategy

A comprehensive search was done on Medline (via PubMed) and EMBASE (via Scopus) databases for articles published during 2019–2020. The search was conducted in the second week of September 2020 (9/19/2020) using a combination of keywords and MeSH terms related to medical informatics and COVID-19. Table 1 shows a combination of keywords and MeSH terms used in the present research. Supplemental Materials 2 represents the full search strategy used to select eligible articles.

2.2. Eligibility criteria

The inclusion criteria used during the article screening process were

Table 1
Keywords and Mesh terms used in the search strategy.

	Mesh Terms	Other Terms
Clinical informatics	Telecommunications, telemedicine, computers, handheld, medical informatics hospital medication systems, adverse drug reaction reporting systems, radiology information systems, clinical laboratory information systems, electronic health records, electronic prescribing, computerized medical records systems, hospital information systems, medical informatics applications, expert systems medical order entry systems, clinical decision support systems, decision support system management, decision support techniques, point-of-care systems, information storage and retrieval software, patient portals, health information exchange and monitoring system, smartphone cellular phone mobile, cell phone mobile applications, web browser, internet web information technology, information systems	Telemetry, mobile health, m-health, telehealth, e-health, personal digital, assistant, PDA computer, handheld computer, palm-top computer, computer, tablet, health informatics, clinical informatics, health information technology, medical information science, hospital unit dose drug distribution systems, medication hospital systems, adverse drug reaction reporting systems, picture archiving and communication systems, system, X-ray information, clinical laboratory information systems, laboratory information system, electronic medical record, computerized medical record, electronic health record, E-prescribing, electronic prescription, E-prescription, automated medical records system, computerized medical records system, automated medical record system, multi-hospital information systems, informatics applications, medical, medical informatics application, expert systems, medication alert system, medication system*, medication alert/reminder system, computerized physician order entry system, computerized provider order entry system, CPOE, decision analyses, decision modeling, clinical prediction rule, prediction rule, clinical prediction, decision analysis, decision analyses, point of care technology, information extraction, computer program, software tool, computer software application, computer programs and programming, patient web portal, patient internet portals, patient portal, medical information exchange*, health information exchange*, screening system, surveillance system, smart phone*, cellular phone, mobile phone, transportable cellular phone, mobile app, portable electronic app, world wide web, ancillary information system, emergency care information system
Coronavirus	Severe acute respiratory syndrome coronavirus 2	Wuhan coronavirus, Wuhan seafood market pneumonia virus, COVID-19 disease, coronavirus disease 2019, SARS-CoV-2, SARS 2, 2019-nCoV, 2019 novel coronavirus

as follows: 1) studies aimed at improving at least one treatment or management outcome during the COVID-19 pandemic; 2) articles related to health information technology or medical informatics interventions; 3) randomized clinical trials, quasi-experimental studies (before-after interventions and interrupted time series), and observational studies (cross-sectional, cohort, case-control); 4) studies published in English; 5) studies published in scientific journals; and 6) studies published during 2019–2020.

Exclusion criteria were as follows: 1) articles whose title, abstract, or full text was not related to COVID-19; 2) thesis, book chapters, letters to editors, editorials, short briefs, reviews or meta-analyses, case studies, conference papers, and study protocols; 3) articles whose full-text was not available; and 4) studies on contact tracing tools.

2.3. Article screening and data extraction

After searching databases, articles were first selected independently by two reviewers based on the analysis of their titles and abstracts, and then studies were subjected into full-text evaluation to select them based on the eligibility criteria. Two reviewers independently extracted the required data from the eligible articles by employing a pre-specified data collection form. The extracted data were reviewed by a third reviewer to ensure the accuracy and completeness of the data extraction process. The extracted data from the studies reviewed were about study sample, study type, objectives, clinical informatics domain [18,19], applied method, sample size, outcomes, findings, and conclusion.

2.4. Risk of bias

The risk of bias was evaluated by two authors using appropriate instruments based on the type of each article. In case of disagreement, the consensus was sought by the third reviewer. The quality of observational articles (cohort, cross-sectional, and case-control) was evaluated using the STROBE tool [20]. In this tool, a higher score means a lower risk of bias (0–8: high risk, 8–16: intermediate risk, and 16–22: low risk). The quality of prediction studies was assessed using the Prediction model Risk of Bias Assessment Tool (PROBAST) [21], which is used to rate the applicability and risk of bias in diagnostic and prognostic studies.

The quality of quasi-experimental studies was evaluated by employing the Quality Assessment Tool developed by Brown based on the study of Estabrooks et al. (2001, 2009) for pre-post intervention study designs [22,23]. Finally, the Cochrane Collaboration tool was used to assess the risk of bias in clinical trials [24].

2.5. Synthesis and analysis

The selected studies were then subjected to thematic synthesis, which is a qualitative analysis used to generate new findings [25]. At first, the themes of the selected articles were identified through a series of meetings after summarizing and categorizing the results that seemed to be relevant into higher-order categories. Finally, the selected themes were arranged according to scientific domains in medical informatics to provide a comprehensive view [18,19]. The analysis was carried out by RG, MS, and SE with periodic input provided by a wider team.

3. Results

3.1. Included studies

In this review study, a total of 1882 and 1045 articles were retrieved from the MEDLINE and EMBASE databases, respectively (Fig. 1). After removing duplicates, 2716 articles remained. Among which 110 articles were selected for full-text evaluation based on their titles and abstracts. After full-text evaluation, 38 articles were removed as irrelevant, and the remaining 72 studies were included in qualitative synthesis.

3.2. Characteristics of studies

The general characteristics of the 72 studies included in this research are presented in Supplemental Materials 3 [26–40], [41–80], [81–109]. The reviewed articles were diverse in terms of study design. Out of the 72 studies reviewed, 57 studies were cross-sectional, 12 studies were cohort, one study was case-control, one study was performed as a before-after study design, and one study was performed as a randomized

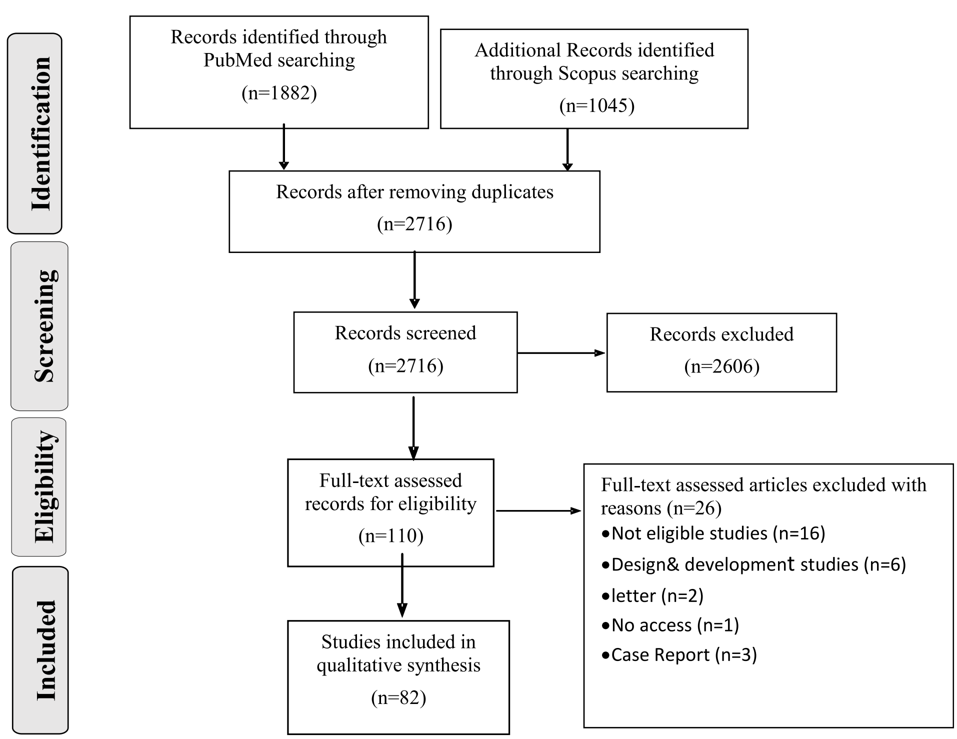

Fig. 1. Flow diagram of literature search and publication selection.

controlled trial (RCT). As shown in Fig. 2, 19 studies were conducted in China, 17 studies in the United States, six studies in Italy, five studies in the United Kingdom, and four studies in India.

3.3. Risk of bias assessment

In this study, the reporting quality of 27 analytical observational studies was assessed using the STROBE checklist (Table 2) [32,35–37,43,44,48–50,54–56,59–61,69,70,75,76,82,83,87,90,95,100,101,103]. The highest and lowest scores were related to the introduction and method sections, respectively. Also, 27% (10 cases) of the studies did not disclose their funding sources, resulting in a mean reporting quality score of 0.73 ± 0.4.

Most of the publications (n = 33) didn't report a bias determination (Item 9). The discussion section obtained a total quality score of 3.3 ± 0.7. Also, 31 (83.8%) studies obtained an intermediate quality score [32,35–37,40,44,48–50,54,56,59–61,63,69,70,75–77,79,81–83,87,89,90,95,100,101,103], and six (16.2%) studies obtained a good quality score [39,43,55,68,85,99].

Besides, in 12 and 7 studies, the risk of bias in data analysis was high [30,31,34,42,45,46,52,64,71,73,88,107] and unclear [26–28,62,80,86,98], respectively. Overall, the risk of bias was high and unclear in 16 (37.2%) [28,30,31,34,38,42,45,46,52,64,71,73,84,86,88,107] and five (11.6%) [26,27,57,92,96] studies, respectively. The risk of bias determined by Probast in other studies was low. One study was designed as a RCT [97]. This study had an overall good quality score. Only one quasi-experimental study was included in this review [53], which obtained an overall weak quality score.

3.4. Medical informatics domains

Out of the 72 studies reviewed, 26 studies aimed to design and implement telehealth [32,35–37,43,44,48–50,53,55,56,59–61,69,70,75,76,82,83,87,90,95,100,103], three studies used mobile-health (m-health) [54,101,110], and 43 studies developed prediction models [26–31,33,34,38,41,42,45–47,51,52,57,58,62,64–67,71–74,78,80,84,86,88,91–94,96,98,102,104–107] (see Fig. 3).

3.4.1. Telehealth domain

Among the reviewed studies, 26 studies were conducted in the telehealth domain. Of which 24 studies used synchronous methods, such as online and phone- or video-call consultations [35–37,43,44,49,50,53,55,56,59–61,69,70,75,76,82,83,87,90,95,100,103], while two studies used asynchronous approaches for communication and providing telehealth services [32,48]. Moreover, nine (35%) studies designed online consultations [43,49,50,55,56,59,69,90,100]. In the reviewed studies, video communication was considered as the most suitable type of patient-provider interaction. Also, six (24%) studies used video conferencing technology for creating communication [35,44,60,70,76,82]. Among the studies reviewed, 8 (31%) studies used the telephone as a telehealth technology [36,37,53,61,75,83,87,95]. Finally, one (3%) study employed a real-time telemetry system via Bluetooth to assess vital signs in isolation wards [103]. Telemetry system was shown in this study to be significantly safe and reliable in reducing the risk of nosocomial infections and the workload of medical personnel.

Of the 26 studies conducted in the telehealth domain, two (6%) studies provided telehealth services through asynchronous communications [32,48] by employing an automated text-based active monitoring system [32] and sending photos [48], respectively. These studies showed that teleconsultation could enhance patient compliance and improve doctor-patient interaction. The most common outcomes in the studies evaluated were as follows: satisfaction in six studies [69,76,87,90,95], increased visit volume in three studies [43,60,61], and increased usage rate in two studies [44,70]. Other outcomes are shown in Table 3.

3.4.2. Mobile health domain

Among the reviewed studies, three (3.5%) studies designed and developed mobile health systems [54,97,101]. Judson et al. (2020) designed a self-triage and self-scheduling tool based on patients' portal to provide personalized recommendations and information about COVID-19 [54]. The other two studies applied a mobile platform to deliver information about COVID-19 [101] as well as a psychological health digital learning package to educate all healthcare staff [97], respectively.

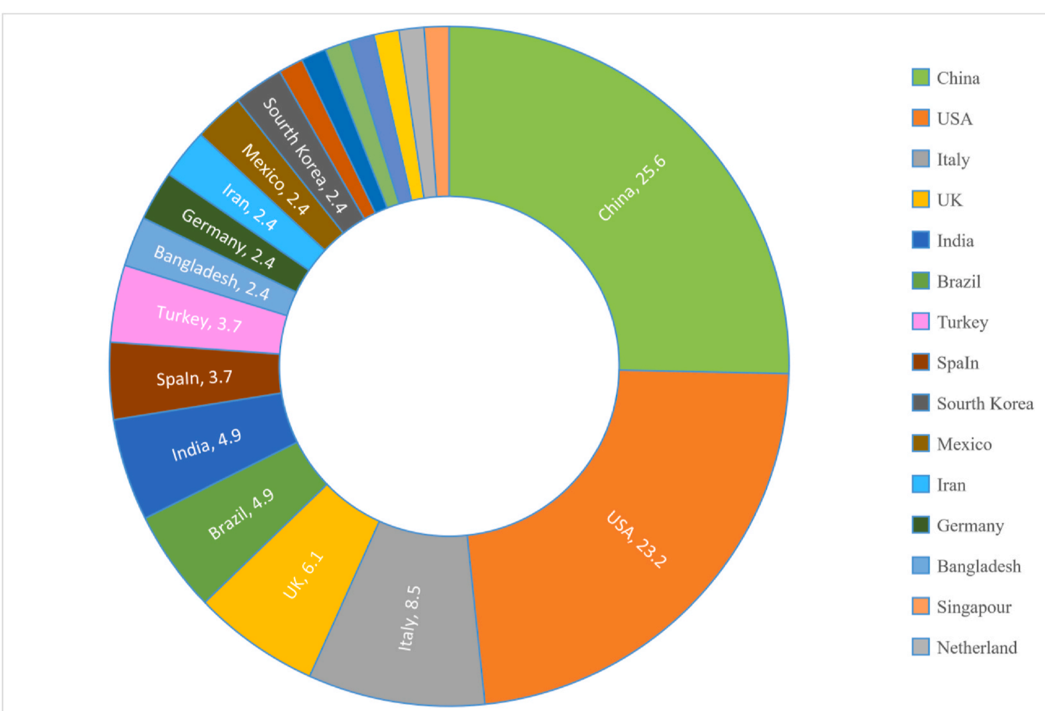

Fig. 2. Distribution of the reviewed studies based on country.

Table 2
STROBE complete reporting scores.

	CRS (ALL)	CRS (INTRODUCTION)	CRS (METHOD)	CRS (RESULT)	CRS (DISCUSSION)
ALL (N = 37)	14.6(1.9)	1.8(0.3)	5.2(1.3)	2.8(0.5)	3.3(0.7)
USA(N = 10)	14.9(1.8)	1.9(0.3)	4.9(1.4)	3(0.3)	3.6(0.6)
CHINA (N = 10)	14.5(1.7)	1.9(0.3)	5(1.4)	2.5(0.4)	3.4(0.3)
OTHER (N = 17)	14.5(2.1)	1.8(0.28)	5.4(1)	2.9(0.6)	3 (0.7)

CRS (complete reporting score) measures reported in means (SDs).

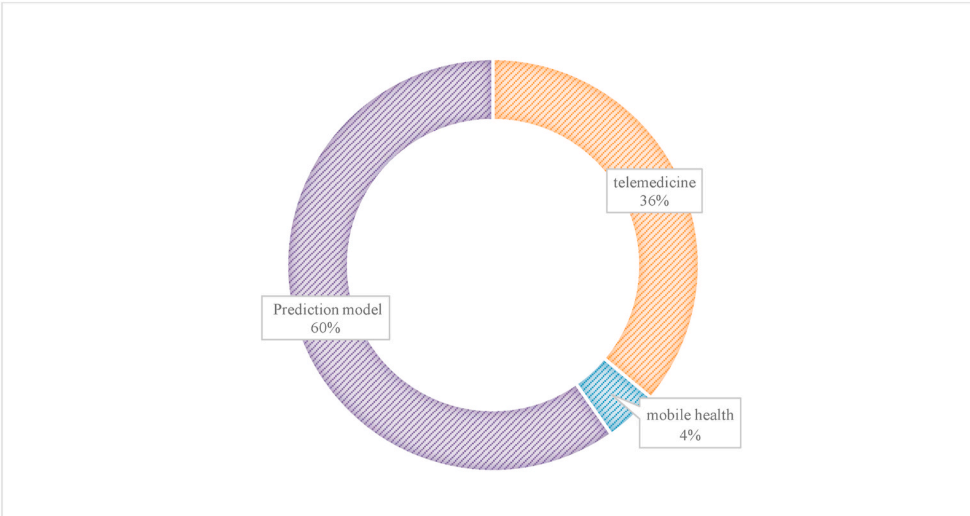

Fig. 3. Distribution of the studies based on medical informatics domains.

3.4.3. Prediction model domain

Prediction models applied in the reviewed studies were classified into five main types, which were derived and extended from the two studies [111,112]. Fig. 4 shows the most common types of prediction models examined in the reviewed studies and used to organize and describe the present study findings.

As shown in Table 4, among the reviewed studies, 43 articles developed prediction models [26–31,33,34,38,41],[42,45–47,51,52,57,58],[62,64–67,71–74,78],[80,84,86,88,91–94],[96,98,102,104–107]. It was found that two (4.6%) studies were performed on linear models [28,30], 18 (42%) articles were performed on classification models [33,34,38,41,45,46,52,58,64,78,80,88,94,96,98,105–107], and only one (2.22%) study was performed on cluster models [42]. Also, 21 studies developed neural networks, of which four (9%) studies implemented artificial neural networks [26,27,31,67], and 17 (39.5%) studies were based on deep neural networks [29,51,57,62,65,66,71–74,84,86,91–93,102,104]. Finally, one (2.3%) study used natural language processing (NLP) [47].

3.4.3.1. Linear models. Case fatality rate and case recovery rate were estimated in a study using time- and location-based data [28]. Moreover, Ayyoubzadeh et al. (2020) demonstrated that the linear regression based model could predict the incidence of COVID-19 [30].

3.4.3.2. Classification models. The most common classification algorithm used in the reviewed studies was logistic regression, applied in 77.8% (n = 14) of the studies [34,38,41,45,46,52,64,80,88,94,96,98,105,106]. Decision tree algorithm was used in three studies [38,78,94]. The other classification algorithms applied in these studies were Bayesian [33,38], SVM [78,94], random forests [38,94], and KNN [38,78]. Prediction models were developed in five studies to forecast death [41,46,98,105] and hospital mortality rates [80]. Moreover, four studies used these approaches to classify COVID-19 patients needing to ICU (intensive care unit) care [41,46,98,105]. Also, classification models were developed in three studies to predict the disease severity [34,64,106]. In addition, three studies used these methods to predict SARS-CoV-2 infection [45,58,88].

3.4.3.3. Cluster models. Only in one of the reviewed studies, cluster models were developed by applying K-Means to recognize patient clusters [42].

3.4.3.4. Artificial neural networks. Artificial neural network (ANN)-based models are other computational approaches used to efficiently solve classification problems. ANN prediction models developed in four of the reviewed studies were MLP (multilayer perceptron) neural networks with one, two, or three hidden layers [26,27,31,67]. Among which two studies used ANN to predict the recovery and mortality status of COVID-19 patients [26,27]. Banerjee et al. (2020) applied ANN to identify SARS-CoV-2 positive patients based on the results of their complete blood count tests [31]. Mollalo et al. (2020) employed multilayer perceptron (MLP) neural networks to model the COVID-19 incidence in the United States [67].

3.4.3.5. Deep neural networks. The second most common type of prediction models deployed in 17 reviewed studies was deep learning (DL)-based neural networks or DNNs (n = 17) [29,51,57,62,65,66,71–74,84,86,91–93,102,104]. All of which were convolution neural networks (CNN). Of the 17 CNN-based studies, eight (47%) and eight (47%) studies developed these models to classify chest radiography images [29,62,65,71–73,91,92] and chest computed tomography (CT) images [51,57,66,74,86,93,102,104], respectively. Only one (6%) study used these models to classify lung ultrasonography (US) images as the data source [84].

3.4.3.6. Natural language processing (NLP). Among the prediction

Table 3
Characteristics of telehealth studies.

NO	Author	care	Applied method	Outcomes
1	Kai Gong [43]	COVID-19 patients	Free online / synchronous	1) Medical-seeking behaviors 2) Risk factors for offline visit motivation
2	Yang Yang [94]	public tertiary dental clinics	online consultation / synchronous	Effectiveness of online professional consultations
3	Alex Borchert, [30]	urological inpatients	Telephone /synchronous	COVID-19 patients status
4	Katharina Boehm [105]	urological inpatients	Videoconference/ synchronous	1) Patients' perspective on telemedicine consultations 2) Risk factors of adverse COVID-19 consequences and unfavorable urological status
5	Peter M Barrett [26]	COVID-19 patients	automated text messaging/ Asynchronous	The rate of referral required based on reported symptoms
6	Hugo Bourdon [31]	eye emergencies	call/synchronous	The proficiency of teleconsultation in providing suitable physical consultations in eye emergencies
7	Anthony V Das [37]	multitier ophthalmology hospital network	Online phone or video call / synchronous	1) The rate of major directed departments 2) The rate of common advice 3) The rate of needed further evaluation 4) The rate of completely addressed issues
8	Lorenzo Giuseppe Lucian [55]	urology	Telephone / synchronous	1) The number of appointments overridden or confirmed 2) The outpatients load 3) The clinical signs in face-to-face visitations
9	Peter E Lonergan, [54]	cancer patients	Video conference/ synchronous	Variation in video visit volume
10	Luwen Liu [53]	COVID-19	Online consultation/ synchronous	Satisfaction
11	Lin Li [50]	T psychological load COVID-19 pandemic	Online consultation/ synchronous	1) Reducing psychological burden 2) Promoting disease knowledge
12	Gang Li [49]	fever health center	Online clinic/ synchronous	The most momentous anxieties and inquiries of patients
13	Morgan S. Jones [47]	inpatient diabetes	Virtual care by phone	1) Reduced patient-provider direct contact 2) Effective diabetes care
14	Jodie L Guest [44]	samples collected at home	Online video appointment/ synchronous	The biological adequacy of samples collected for testing
15	Amerigo Giudice [42]	dental operations	teleconsultations by sending photos/ Asynchronous	Adherence to the protocol
16	Ajinkya V Deshmukh [38]	pediatric ophthalmology and strabismus patients	Video call consultation/ synchronous	Teleconsultation usage rate
17	Jisong Zhang [97]	telemetry system in the isolation wards	Telemetry system in real-time via Bluetooth/ synchronous	1) Frequency of RW rounds (routine wards) 2) Frequency of TSW (telemetry system wards)
18	Vinidh Paleri [69]	cancer patients	Telephone triage / synchronous	1) Discharged directly 2) Triaged for immediate investigations and/or face-to-face consultations
19	Severin Rodle, [76]	urology	Video conference/ synchronous	Acceptance rate
20	Carol J. Peden [70]	Covid-19	Video consultation/ synchronous	Patient satisfaction
21	Adam S. Tenforde [84]	musculoskeletal conditions under non-surgical	Audio visual / synchronous	Satisfaction
22	Alannah Smrke, [81]	oncological care	Telephone / synchronous	Satisfaction
23	Nikolaos Mouchtouris [64]	neurosurgery patient	Videoconference/ synchronous	1) Usage of telemedicine 2) The number of patients examined through telemedicine per week
24	Tobias O. Wolthers [89]	pediatric patient	Telephone / synchronous	Satisfaction
25	Carlos Roncero[77]	mental diseases	telephone/ synchronous	The rate of activity
26	Susan L. Moore[63]	hospice in person	Video call / synchronous	1) Satisfaction

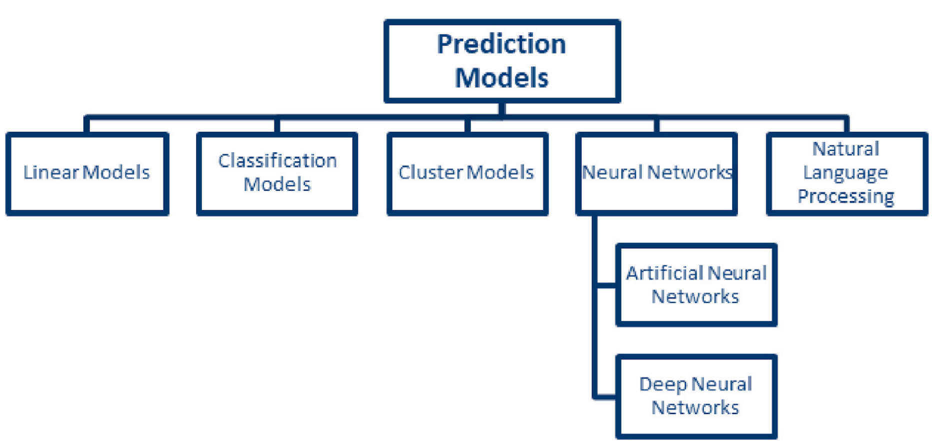

Fig. 4. Types of prediction models.

Table 4
Characteristics of prediction models studies.

NO	Author	Type of model	Applied method	Outcomes
1	Mohammad Ayyoubzadeh [24]	linear model	Linear regression	Predicting the incidence of COVID-19
2	Cleo Anastassopoulou [22]	linear model	Linear regression	1) Case fatality 2) Case recovery ratios
2	James B Galloway [40]	classification	Logistic regression	1) Death 2) Critical care admission
4	Fredi A. Diaz-Quijano [39],	classification	Logistic regression	Prediction model for COVID-19 detection
5	Gang Wu [90]	classification	Logistic regression	Predicting consequences of SARS-CoV-2 pneumonia
6	Qiang Li [52]	classification	Logistic regression	Early detection of COVID-19
7	Zou, Xiaojing [101]	classification	Cox regression	1) Probability of death among patient 2) Comparing the predictive ability of APACHE II score, with SOFA and CURB65 scores
8	Yiwu Zho [100]	classification	Logistic regression	Predicting the risk of COVID-19 progression
9	Lara Jehi [46]	classification	Logistic regression	Hospitalization risk
10	Yinxiaohe Sun [82]	classification	Logistic regression	Recognizing persons at high risk of COVID-19
11	Anirban Basu [27]	classification	Bayesian mixed-effects nonlinear	Fatality rates
12	Zhi-jun Qin [74]	classification	Logistic regression	Prediction of in-hospital mortality
13	Salomón Wollenstein-Betech [88]	classification	1) Logistic regression 2) SVMs 3) Random forests	1) Admission to hospital 2) Death 3) Necessity of ICU 4) Necessity of ventilator
14	Omar Yaxmehen Bello-Chavolla [28]	classification	Logistic regression	COVID-19 lethality
15	Michael P McRae [58]	classification	Logistic regression	Classification of the disease severity
16	Davide Colombi [35]	classification	Logistic regression	1) Admission to ICU 2) Death
17	Qingxia Wu, June 2020, China [92]	classification	Logistic regression	Predicting mortality, necessity of mechanical ventilation and/or admission to ICU
18	Zirun Zhao, July 2020, USA [18,99,99,99]	classification	Logistic regression	1) ICU admission 2) Death
19	Davide Brinati [32]	classification	Decision tree, K-nearest neighbors, logistic regression, Näive Bayes, and random forest.	Prediction of SARS-CoV-2 infection
20	Rodolfo M. Pereira [72]	classification	1) Multi-class classification: kNN, SVM,MLP; DT, and RF′ 2) Hierarchical classification: Clus-HMC framework	Classification of many types of pneumonia including Covid-19
21	Wanting CUI [36]	clustering	K-means algorithm and the elbow method	Identification of latent clusters from patients
22	Ahmed Abdulaal [20]	ANN	Artificial neural network (ANN) with two densely connected hidden layers	Mortality risk
23	H. Al- Najjara [21]	ANN	Neural network	Classification of death and the status of recovered cases
24	Abhirup Banerjee [25]	ANN	Random forest, glmnet, and ANN	Predicting SARS-CoV-2 infection
25	Abolfazl Mollalo [61]	ANN	Multilayer perceptron (MLP) neural networks with one hidden layer	Modeling the COVID-19 incidence
26	Keelin Murph [65]	Deep Neural Network	CNN (convolutional neural network)	Grouping of chest radiographs as COVID-19 pneumonia
27	Xi Ouyang [68]	Deep Neural Network	1) A novel module with a 3D CNN. 2) The use of the 3D ResNet34 architecture as the backbone network.	Auto differentiation of COVID-19 from other forms of pneumonia.
28	Tanvir Mahmud [56]	Deep Neural Network	Deep CNN	Auto identification of Covid-19 based on chest radiography.
29	Stephanie A. Harmon [45],	Deep Neural Network	Multiple classification models, 3D classification,	Identification of COVID-19 pneumonia based on chest CT images
30	loannis D.postolopoulos [23]	Deep Neural Network	CNN	Classification of medical images (Covid-19, pneumonia, normal)
31	Dilbag Singh [80]	Deep Neural Network	Multi-objective differential evolution (MODE)–based CNN, ANN, and ANFIS models	Grouping of COVID-19 patients based on chest CT images
32	Lin Li [108]	Deep Neural Network	A 3D deep learning model	1) Detection of COVID-19 2) Differentiation of COVID-19 from CA pneumonia
33	Shervin Minaee [59]	Deep Neural Network	Four CNNs (ResNet18, ResNet50, SqueezeNet, and DenseNet-121)	Identification of COVID-19 disease
34	Arnab Kumar Mishra [60],	Deep Neural Network	Models including: VGG16, InceptionV3, ResNet50, DenseNet121, and DenseNet201	Detection of COVID-19
35	Yujin Oh [67]	Deep Neural Network	A local patch-based neural network architecture	Detection of COVID-19 pneumonia
36	Ali Narin [66]	Deep Neural Network	Five pre-trained models based on CNN	Detection of COVID-19 pneumonia
37	Subhankar Roy [78]	Deep Neural Network	CNN	Prediction of the disease severity score
38	Mesut Togaçar [85]	Deep Neural Network	DL models (MobileNetV2, SqueezeNet)	Detection of COVID-19 pneumonia
39	Ferhat Ucar [86]	Deep Neural Network	COVID diagnosis-Net model	Detection of COVID-19 pneumonia by CXR images
40	Xinggang Wang [109]	Deep Neural Network	A 3D deep CNN (DeCoVNet)	1) Forecasting the risk of COVID-19 2) Detection lesion areas in chest CT
41	Hai-tao Zhang [96]		3D CNN and a combined V-Net	1) Detection of COVID-19 pneumonia

(continued on next page)

Table 4 (*continued*)

NO	Author	Type of model	Applied method	Outcomes
		Deep Neural Network		2) Localization of COVID-19 3) Quantification of COVID-19
42	Kang Zhang [110]	Deep Neural Network	A lung-lesion segmentation model	Detection of NCP (novel coronavirus pneumonia)
43	Lyndsey E. Gates [41],	Natural language processing	NLP	1) Presenting the CovidX ranking algorithm 2) Listing medications identified in literature and using the derived CovidX ranking algorithm.

SARS-CoV-2: severe acute respiratory syndrome coronavirus 2; APACHE: acute physiology and chronic health wvaluation; SOFA: sequential organ failure assessment; CURB65: confusion, urea, respiratory rate, blood pressure, age 65; ICU: intensive care unit; CT: computed tomography; rRT-PCR: reverse transcriptase–polymerase chain reaction; kNN: K-nearest neighbors; SVM: support vectors machine; MLP: multilayer perceptron; DT: decision trees; ANN: artificial neural network; ML: machine learning; MLP: multilayer perceptron; CNN: convolutional neural network; CXR: chest X-ray; MODE: multi-objective differential evolution; ANFIS: adaptive neuro-fuzzy inference systems; LUS: lung ultrasonography; DeCoVNet: deep convolutional neural network; NCP: novel coronavirus pneumonia; NLP: natural language processing.

models examined, there was only one study using NLP [47] to detect off-label medications that may be beneficial for the COVID-19 pandemic.

4. Discussion

This review study showed the applications of CI during the COVID-19 outbreak and identified current gaps in this field. Numerous studies have been conducted to demonstrate the applications of clinical informatics in the treatment, detection, and control of COVID-19.

The literature search for published scientific papers helped us identify a total of 72 relevant studies in this field. It was found that different domains of CI are potentially useful in promoting the management and control of the current COVID-19 pandemic.

Prediction models were the most helpful area for research on this novel universal pandemic. To reduce the consequences of an epidemic, it is necessary to appropriately control the epidemic in the early stages of its emergence and take appropriate measures to prevent its transmission to other countries in order to save many lives. Moreover, accurate prediction and monitoring of the disease transmission pattern could assist officials in designing and implementing the required control programs [113,114].

The second most popular area for research on COVID-19 was telehealth. Since the most distinctive feature of COVID-19 is its highly communicable nature and rapid transmission, teleconsultation could play a crucial role in preventing and controlling infection by creating social distance. To prevent the transmission of COVID-19 to high-risk patients requiring clinical follow-ups, routine healthcare interactions could be performed via available teleconsultation platforms [115]. During the COVID-19 pandemic, the use of telehealth has increased and expanded to reduce the risk of the disease transfer by increasing social distance and reducing direct contact. Moreover, it helps providers use limited supplies for the most urgent cases [116–118]. Therefore, it is necessary to discover the important applications of telehealth in pandemics.

The last popular domain for research on COVID-19 was m-health, which is one of the most appropriate methods that could be used to manage COVID-19 by providing health services through tele-visit instead of patient-physician direct contact as well as by fever coaching and providing real-time information about COVID-19. Due to the advantages of using smart mobiles, such as cost-effectiveness, simplicity, availability, and accessibility, the use of mHealth is recommended for information exchange [119].

Collecting information and data about COVID-19 plays an important role in reducing the risk of its occurrence [120]. The information gathered could be useful for possible outbreaks that may occur in the future because the results of works done on previous pandemics are useful for confronting the recent pandemic. Although clinical decision support systems (CDSS) have become popular among healthcare providers and clinical researchers [121], none of the included articles evaluated the use of CDSSs. Since the integration of CDSSs into clinical practice is complex [122], it seems that the use of CDSS for COVID-19 requires more time.

Many of the reviewed studies had no risk of bias. The quality of the methodology section varied significantly among the included studies. Limited information on study design, main results, statistical analysis, and interpretation was the most important factor contributing to the low scores of observational studies on the risk of bias. Only 25 studies obtained good quality scores in the methodology section, including five observational studies and 22 prediction model studies. Lack of information on analysis, outcomes, and predictors was the most important factor contributing to the low scores of this category on the risk of bias. A remarkable risk of bias may affect the outcomes.

Strengths and Limitations: This review study examined the applications of CI in the management and treatment of COVID-19. The present review addressed nearly all aspects of CI due to the use of the most popular databases in medicine. Moreover, the quality of all studies was thoroughly investigated using appropriate instruments based on the type of each study. Finally, this study provided a comprehensive and clear summary of observational and interventional studies.

This review study has several limitations. First, like all reviews, the present review had limitations due to publication bias; for example, studies with significant results are more likely to be published than those with insignificant results. Second, given that several studies have been conducted and published over time on the COVID-19 pandemic, the findings of this review could be considered as temporal effects of medical informatics tools. Third, other clinical informatics tools investigated in unpublished studies were naturally excluded from this review. Fourth, the results of some studies published in the form of letters to the editor, editorials, short briefs, etc. were not included in this review.

The present research proposes some momentous directions for future research. First, many of the reviewed articles on the topic provided no qualitative and descriptive statistics. To promote the use of clinical informatics, the exchange of experiences with others through providing accurate qualitative and descriptive statistics is necessary and valuable. Given that there was only one randomized controlled trial among the reviewed studies, it is suggested that future investigators employ this study design in their research and also take a step forward in applying these tools in clinical practice (e.g. clinical decision support systems, computerized order entries, etc.). To improve patient care in crisis conditions, it is necessary to develop clinical information systems that are able to collect real-time patient data. Furthermore, scoping reviews could be conducted to describe and analyze other levels of medical informatics, including bioinformatics, imaging informatics, and public health informatics.

5. Conclusion

The present study showed CI applications during COVID-19 and identified current gaps in this field. Health information technology and

CI appear to be useful in assisting clinicians and managers to combat COVID-19. The most common domains in CI for research on the COVID-19 crisis were prediction models and telehealth. It is suggested that future researchers conduct scoping reviews to describe and analyze other levels of medical informatics, including bioinformatics, imaging informatics, and public health informatics.

Disclosure statement

The authors declare that they have no conflict of interest.

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Authors' contributions

S. Eslami and R. Ganjali designed the scoping review and search strategy and also searched databases. R. Ganjali, T.Samimi, N.Firouraghi, S. MohammadEbrahimi, F.khoshrounejad and A. Kheirdoust conducted articles screening. R. Ganjali, and M.Sargolzaei conducted the analysis and interpretation under S. Eslami's supervision. R. Ganjali and M.Sargolzaei drafted the manuscript. All authors reviewed and approved it.

Ethical approval

The research ethics committee of Mashhad University of Medical Sciences approved this study (IR.MUMS.MEDICAL.REC.1399.264).

Availability of data

All data generated or analyzed during this review are included in this published article [and its supplementary information files].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Not applicable.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.imu.2022.100929.

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