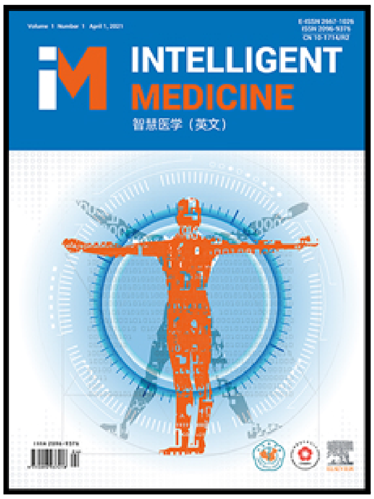
Journal Pre-proof



Practice of big data and artificial intelligence in epidemic surveillance and containment

Zengtao Jiao , Hanran Ji , Jun Yan , Xiaopeng Qi

PII: S2667-1026(22)00078-X
DOI: https://doi.org/10.1016/j.imed.2022.10.003
Reference: IMED 61

To appear in: *Intelligent Medicine*

Received date: 19 August 2022
Revised date: 12 October 2022
Accepted date: 13 October 2022

Please cite this article as: Zengtao Jiao , Hanran Ji , Jun Yan , Xiaopeng Qi , Practice of big data and artificial intelligence in epidemic surveillance and containment, *Intelligent Medicine* (2022), doi: https://doi.org/10.1016/j.imed.2022.10.003

Review

Practice of big data and artificial intelligence in epidemic surveillance and containment

Zengtao Jiao[1], Hanran Ji[2], Jun Yan[1], Xiaopeng Qi[2,*]

[1]AI lab, Yidu Cloud (Beijing) Technology Co., Ltd., Beijing 100083, China

[2] Center for Global Public Health, Chinese Center for Disease Control and Prevention, Beijing 102206, China

[*] Corresponding author: Xiaopeng Qi, Center for Global Public Health, Chinese Center for Disease Control and Prevention, Beijing 102206, China (Email: qixp@chinacdc.cn).

Abstract

Faced with the current time-sensitive COVID-19 pandemic, the overburdened healthcare systems resulted in a strong demand to develop newer methods to control the spread of the pandemic. Big data and artificial intelligence (AI) have been leveraged amid the COVID-19 pandemic; however, little is known about its use for supporting public health efforts. In epidemic surveillance and containment, efforts are needed to treat critical patients, track and manage the health status of residents, isolate suspected cases, develop vaccines and antiviral drugs. The applications of emerging practices of artificial intelligence and big data have become powerful "weapons" to fight against the pandemic and provide strong support in pandemic prevention and control, such as early warning, analysis and judgment, interruption and intervention of epidemic, to achieve goals of early detection, early report, early diagnosis, early isolation and early treatment, and these are the decisive factors to control the spread of the epidemic and reduce the mortality. This paper systematically summarizes the application of big data and AI in epidemic, and describes practical cases and challenges with emphasis in epidemic prevention and control. The included studies showed that big data and AI have the potential strength to fight against COVID-19. However, many of the proposed methods are not yet widely accepted. Thus, the most rewarding research will be on methods promising value beyond COVID-19. More efforts are needed for developing standardized reporting protocols or guidelines for practice.

Keywords

Epidemic prevention and control; Epidemiological investigation; Artificial intelligence; Big data; Early warning

1. Introduction

The coronavirus disease 2019 (COVID-19) pandemic, caused by the novel severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), has emerged in December, 2019 [1]. Up to this day, more than 500 million people worldwide have been infected with COVID-19 and more than 6 million people have died of COVID-19. The highly sudden onset, infectious and wide diffusion of COVID-19 and its variant such as Omicron variant made it a high-risk task to implement the prevention and control [2]. Although various strategies have been proposed and implemented such as vaccination, non-pharmaceutical intervention, etc., within strict containment, it is still arduous for the epidemic prevention and control [3].

With the vigorous developments of new generation in big data and artificial intelligence (AI) technology, the new era of data-driven 'Internet plus AI' is coming. The application value of AI is gradually released and AI has been applied more and more widely in various walks of life such as intelligent manufacturing, smart city and healthcare, telemedicine [4-7],etc. In this battle against the epidemic, the new generation of information technology including big data and AI has made a deep integration of transportation, medical treatment, education, and other fields [8-10]. AI has become a powerful and effective technology against the COVID-19 pandemic, making the prevention and control more efficient. With the development of the epidemic, data-driven epidemic prevention and control is rapidly unfolding, application scenarios for epidemic prevention and control are constantly emerging, and the scope of application continues to expand. In this context, the use of AI, big data and other new technologies has made considerable progress in improving the working methods, work efficiency and effectiveness. It has become the first choice of various government departments, aiming to further move towards a smart city. Therefore, with the more widely application of these scientific technologies, it is inevitable that higher requirements will be gradually put forward for emergency mobilization of government, grass-roots communities and civil society. There are also requirements for improving the ability of social governance.

This paper summarized the overview of artificial intelligence in epidemic surveillance and containment in next section. Then the practice is separately elaborated on the tasks of infectious disease prevention and control including early warning of epidemic, analysis and judgment in epidemic, interruption of epidemic and treatment of patients. Finally, the paper summarized the exploration of AI in epidemic surveillance, containment and looking into the distance.

2. Overview of big data and artificial intelligence in epidemic

With the global spread of the COVID-19 epidemic, big data and AI technologies are widely used [11]. They not only play an important role in epidemic prevention and control and resumption of work and production in China, but also in Sino-foreign cooperation. In the process of assisting in curbing the spread of the epidemic and carrying out epidemic prevention and control, big data and AI play a vital role that cannot be ignored in the following aspects.

2.1 The dissemination of epidemic prevention and control knowledge

With the help of mobile Internet and smart phones, people can obtain various information such as the latest epidemic situation and scientific epidemic prevention knowledge at anytime and anywhere. Local governments regularly release the latest epidemic developments through e-government platforms, microblog, and official accounts. Various news clients, social platforms, search engines, and short video platforms have also actively cooperated with the release and dissemination of epidemic-related information.

Many digital health service platforms have launched online consultation service to offer necessary remote consultation and medical support. It is convenient to consult doctors about the prevention and treatment of COVID-19 online, effectively alleviating the difficulties of medical treatment caused by the shortage of medical resources during the epidemic. It can also prevent people with common diseases from flocking to the hospital, which may form the clustered cross-infection. It is useful to ensure social distancing and beneficial for medical care especially in rural areas to use telehealth [12]. AI powered chatbots such as conversational bot based on Natural Language Processing (NLP) and speech synthesis can play a principal role in

Telehealth. They can provide free primary healthcare education, information, and advice to people to carry out epidemic prevention knowledge popularization [13].

2.2 The flow of epidemic-related personnel tracking

Nowadays, big data analysis such as data mining has become a thrust area in tracking and controlling the spread of COVID-19 around the world. By integrating the information of telecom operators, Internet companies, transportation departments, etc., big data analysis can solve the problem such as the trajectories modeling and discovery of spatiotemporal pattern of COVID-19 [14-15]. Specifically, through data analysis and data mining, it is possible to simulate and draw the patient's movement trajectories through geographic location and timestamp information. Besides, contact tracing is recommended as a key component of COVID-19 control strategies [16]. According to the movement trajectory of the patient for a period of time before the date of diagnosis and the accompanying people who have been with him for a long time, the close contacts of the patient can be inferred based on big data analysis. Comprehensive analysis of the movement trajectories of confirmed patients, suspected patients and related contacts can accurately describe the flow of different types of people who enter and exit across regions. Mandatory home-based quarantine and isolation of these people, which are the epidemic control strategies in China have been followed successfully by many countries [17].

2.3 Prediction of epidemic development trend and origins tracing

AI plays a vital role in detecting the cluster of cases, and predicting the development trend of epidemic and likely reemergence [18]. Based on the data of high-risk groups, it is possible to identify the clusters and display the spatial distribution with the help of AI and big data analysis. Combined with the new cases, suspected cases, dead cases and cured cases in the epidemic, many techniques like transmission dynamics model [19-20], epidemic model [21] and regression model [22] use emerging AI technologies to predict the development trend or general situation such as the peak inflection point of the epidemic [21]. Finding the source of an infectious disease is critical and challenging. According to features like travel trajectory flow information, social information, consumption information, geographical location, etc., some methods based on machine learning (ML) or deep learning (DL) like spatio-temporal modeling can calculate the path of disease transmission and provide a theoretical basis for the traceability analysis of infectious diseases [23].

2.4 Scientific and precise policies implementation

AI can help governments with precise intervention policies. Models based on AI can forecast "how much" the disease has spread and "where" and to "what extent" it has spread to [24]. Besides, many countries are likely to operate beyond their maximum capacities [25], and it is a serious concern whether the capacity of the current healthcare system can keep pace with the pandemic. With the help of AI and big data analysis, they can provide an effective basis for dynamic monitoring, coordination of medical material reserves, the supply of civilian materials, and traffic control policies [26-27]. For example, during the period of mass migration for the annual Spring Festival in China, which is an epidemic high-incidence areas, epidemic monitoring and early warning can be used for precise prevention and control by tracking the trajectories of confirmed cases, suspected cases, and close contacts.

2.5 Drug and vaccine discovery

AI can support COVID-19 at the molecular level as well. As there is no effective treatment for COVID-19, the application of AI in vaccine and drug discovery is the most critical part of the epidemic. An effective and safe vaccine against COVID-19 is a top priority for effective epidemic prevention. ML could be used to design the vaccine and predict the potential targets for effective and safe vaccine [28-29]. Some research focus on the drugs discovery based on data-driven AI framework [30-31]. DL is applied to predict the potential of drug repurposing such as the identification of commercially available drugs [32-33]. ML and DL can detect virus gene sequences, helping scientists better understand COVID-19 and to develop the vaccine and drugs.

2.6 Infectious disease diagnosis, treatment, and convenient life

The applications of AI relieve the pressure of hospital and government, and play a very important role in diagnosis and treatment, and provide a convenient life during the pandemic. NLP and Automatic Speech Recognition (ASR), which are the branches of AI, have been widely developed and adopted in numerous applications to organize and structure knowledge in recent years [5,34]. NLP and ASR can help medical staff and citizens complete telemedicine consultations safely and conveniently [35], making significant contribution to the process of early screening and diagnosing [36-37]. Many online meetings have been held during the COVID-19 pandemic, NLP and ASR also play a vital role in intelligent conference system [38] such as the remotely communication of Chinese and foreign experts. The applications of AI-based imaging and robots are important tools for diagnosis, treatment, and convenient life assistance either during the pandemic [39-40]. Imaging in AI plays a crucial role in the detection and management of COVID-19. Some techniques such as face detection have made some contributions in tracing COVID-19 cases and contacts such as masked face recognition and fever detection [41-42]. The homeschooling and telework have become normal situation during the pandemic and the demands of video conferencing surge. This resulted in unprecedented growth in the number of video conferencing users. Face detection and portrait segmentation have made great support for video conference, providing convenience for homeschooling and telework [43-45]. Robotic technologies, including examination robot [46], healthcare robot [47], monitoring robot [48], disinfection and cleaning robots [49], delivery and logistic robot [50] etc., leveraging face detection, voice recognition, and sensors, have been globally used to facilitate the diagnosis and treatment, reduce personnel contact and aid human daily life. Therefore, intelligent robot is a very important development direction in the future.

In summary, big data and artificial intelligence technologies can play a major role in the prevention and control of the epidemic. However, there are still many challenges in practice during the process of data-driven epidemic prevention and control. For example, due to the limitation of data sources, the backward of data collection, the lack of data governance, the poor data quality, the unification of data standard, the serious data island, the difficulty in analysis and judgment in epidemic, etc., there are still many problems to be solved in the process of anti-pandemic. The following part focuses on the challenges of big data and AI in the anti-pandemic process, including the early warning of epidemic, the analysis and judgment in epidemic, the interruption of epidemic and the treatment of patients.

3. Practice of big data and artificial intelligence in prevention and control of epidemic

In 2020, the epidemic of COVID-19 overwhelmed public health systems in many countries, exposing problems such as weak emergency response capabilities. Reforming and strengthening emergency response to public health events has become a global focus. For public health departments, we can quickly monitor infectious diseases and conduct comprehensive epidemic surveillance through the nationwide patient electronic case database, and quickly respond through the integration of disease monitoring and response procedures. Big data and artificial intelligence can play a role in normalization monitoring, epidemic warning and disposal, trend prediction and judgment, tracing the source of infection, resource allocation, prevention and treatment, vaccine and drug research and development. At the same time, there are many challenges in practice.

3.1 Early warning of epidemic

Early warning of epidemic is intrinsically data driven. Identifying early, accurate, and reliable signals of health anomalies and disease outbreaks from a heterogeneous collection of data sources has always been one of the main objective of public health surveillance, which is technically premised on the basis of the data sourcing task and the analytics task. The data sourcing task is concerned with determining easily operationalizable sources of data that contain useful signals. The analytics task is concerned with developing effective computational frameworks to extract such signals. Big data and AI provide a range of methods and techniques to help tackle both challenges.

In order to improve the timeliness and accuracy of outbreak detection and early warning approaches, public health researchers continue to investigate and explore sensor data and indicators from the physical world and the cyberspace. Based on the data collected from the physical world, AI methods have been successfully applied to estimate the high-risk regions and outbreak periods. The global distribution were simulated for Aedes aegypti and Aedes albopictus to fight against mosquito-borne infectious diseases such as ZIKV, dengue, and chikungunya [51-52]. A dynamic neural network model was developed to predict the outbreak risk of ZIKV in the Americas [53]. Significant efforts have been expended to make use of data from the cyberspace. Shah and Dunn proposed a machine learning method to generate a model to detect the magnitude of unexpected changes in terms of usage with spatiotemporal patterns from social media data streams [54]. Chen and Neill analyzed the heterogeneous network structure of Twitter using a nonparametric graph scan, and applied this approach to detection of hantavirus outbreaks in Chile [55]. Dai reported a clustering method based on word embedding for public health monitoring [56]. The objective of syndromic surveillance is early detection of disease outbreaks by identifying emerging clusters of cases in space and time. A variety of public health data sources, such as hospital emergency department visits, over-the-counter medication sales [57], and more recently online data sources such as search queries [58] and social media [55], have been employed for this task.

Time series of epidemiological data feature seasonality, non-stationarity, and sparsity. Predicting such time series has major public health implications and has attracted a lot of attention from the research and practitioner communities. Researchers have been proposing complex models for univariate prediction to extract useful patterns. In additional, efforts have been expended to develop multivariate prediction models. AI plays an important role in both research streams. Researchers have worked to extract long-term dependencies from one or more correlated incidence curves, without complex exogenous variables [59-60]. Past research has also explored external variables that are highly correlated with the outbreak of infectious diseases to make multivariate predictions [61-62]. The prediction performance of such methods has a lot to do with the selection of external variables.

However, the practice of big data and AI in early warning of epidemic has several limitations. First, data is the cornerstone of these tasks. Special attention is in use essential for the safety, confidentiality, sharing, openness and other medical ethics issues of infectious disease related health big data. Health big data inevitably involves the privacy information of people, including physical status, health history, personal information, and even gene and protein data. These confidential data of patient puts forward higher requirements for privacy protection and system security. Besides, there is a high probability of human error in diagnosing infectious disease, even if the diagnosis was done by highly qualified medical doctors. For instance, research has shown that a substantial portion of TB patients had been diagnosed with a non-TB respiratory-related diagnosis in hospitals [63]. In low resource healthcare settings, physicians may sometimes misdiagnose dengue fever patients and treat them as having a common upper respiratory tract infection. The inaccuracy of traditional diagnosis methods would be magnified if hospitals and clinics are overwhelmed with a sudden surge in cases.

Second, while forecast modelling using a variety of data sources can potentially aid public health organizations to preempt the spread of infectious diseases, these models have several limitations that inhibit their effectiveness. There are problems in modelling associated with data deluge, resulting in over or underestimation of statistical models [64]. On the other hand, in areas that are rural and do not have Internet broadband access, there may be problems associated with a lack of quality data [65], where data from underserved communities are not represented, severely compromising the quality of forecasting models.

Third, top-level design of the health big data framework is inadequate. It is a basic and long-term work to quickly obtain effective information through analysis from the scattered big data and provide a basis for public health decision-making in a timely manner, which requires long-term support from the government. The health big data framework needs top-level design at the national level and bears corresponding responsibilities.

3.2 Analysis and judgment in epidemic

Epidemiological investigation is a critical task to study the distribution, pathogenesis, transmission characteristics and determinants of epidemic diseases [66-67], putting forward reasonable preventive health care countermeasures and health service measures. Through epidemiological investigation, the infection pathway of each patient can be clarified, which will play an important role in the prevention and control of future epidemics. It is also possible for the public to know how to avoid infection and how to solve the problem after infection. This work has played a very important role in China's success in controlling the spread of COVID-19. In these tasks, investigators need to document case reports, including demographic data and clinical manifestations of confirmed cases. Those travel trajectories before the disease onset are especially important to be logged, plus the close contacts of confirmed cases. Additionally, investigators are responsible for analyzing and tracing all possible infection modes, pathways and sources, which triggers further follow-up records of close contacts. However, facing hundreds of patients diagnosed as COVID-19, it becomes extremely time-consuming and labor-intensive to do epidemiological investigation and trace the close contacts for each confirmed case in a typically manual way. Such investigation work is quite tedious and complicated and requires a lot of information searching, comparing, inductive and deductive reasoning.

Big data and AI can speed up the previous process. During the investigation, the dialogue recordings between epidemiological investigators and respondents are automatically collected, and the voice is dynamically converted into text in real time. The system supports full transcription or fragment transcription, and synchronously uploaded to the cloud [68]. Other epidemiological survey staff can cooperate with field epidemiological investigators to sort out the text and compile the report, and convert unstructured text information into structured data for storage. In recent years, Jian adopted NLP and knowledge reasoning to extract import information from cases reports and analysis [69]. Adi V. identified important patient-related features from free-text electronic medical records to assist in public health investigations with NLP-based methods [70]. However, the application of these technologies in the field of epidemic investigation also faces some challenges. One of these is how to closely integrate with the current business processes of disease control department and compatible with the current usage habits of frontline investigators, which requires us to polish the technology usage in working with frontline investigators. In addition, there is a lack of unified schema for the investigating methods and report contents of different infectious diseases in different regions, which also brings certain obstacles to the further promotion of technologies, and government departments need to formulate unified specifications.

Based on computable data after information extraction, the next step is the risk assessment of groups and public places so as to provide guidance to targeted prevention and control measures. Retrospective studies had shown that some characteristics of cases were related to the transmission of COVID-19. Luo found that the severity and expectoration of index cases would increase the secondary attack rate [71]. Li supposed that children and adolescents were more infectious than older individuals. Symptomatic cases were more infectious than the asymptomatic [72]. Bi mentioned that household contacts had higher risk of infection, as well as those travelling with cases [73]. Lee explained that the higher the viral load of the case, the more infectious it would be [74]. Meanwhile, many epidemiological field cases had shown that the public places that COVID-19 patients visited such as restaurants [75], conference [76], KTV [77], etc. were the trigger for the rapid spread of the epidemic. Research had revealed the environmental factors with public places associated with the occurrence of COVID-19 transmission. Lu found the virus spread in the restaurants by the airflow of air-conditioned which caused three family clusters infected with COVID-19 [75]. Kang provided the probable evidence of fecal aerosol transmission of SARS-CoV-2 in a high-rise building [78]. Yuan presented that a COVID-19 outbreak in a densely populated community might have been transmitted by sewage [79]. As a retrospective study, limitations exists in practice. First, the recall bias could not be avoided and quantitative measurement was not available for all variables. Second, there are limited samples with detailed data to study, and the result maybe not absolutely suitable to other countries and regions. In the future, risk assessment system should continually be upgraded as a covering more variables to improve the performance.

3.3 Interrupting transmission of epidemic

While an outbreak occurred, it needs to be interrupted early to avoid greater damage. In this case, the allocation of resources is particularly important. Interrupting the epidemic involves the allocation of nucleic acid testing resources, the allocation of ambulances and medical staff, the allocation of isolation areas, medicines, etc. An article from JACC [80] mentioned that the scheduling of medical resources in the prevention and control process was not the responsibility of clinicians. Scientific allocation of medical resources will provide additional efficiency for epidemic prevention and control. An article from the American Academy of Pediatrics [81] also stated that for the medical resources of scarce, it was necessary to reasonably allocate based on age spectrum.

In the process of interrupting the epidemic, the allocation of resources will also face some technical challenges. First of all, reasonably predicting the trend of the epidemic, so as to optimize the distribution and reserve of resources, is a necessary condition to make the epidemic under control. Since the outbreak of COVID-19, various types of traditional statistical methods and deep learning methods have emerged for epidemic prediction research [82-84]. If accurate predictions can be made on the scale of the epidemic, nucleic acid testing resources, the proportion of severe cases, and the distribution of ambulances and isolation areas can be preliminarily estimated to prevent a run on medical resources. However, there are many factors affecting the growth of the epidemic in the real world, such as the concentration of people in different areas and climatic reasons. Sudden events can cause the spread of the epidemic without warning as well. These factors are difficult to be accurately described and analyzed through models. So correspondingly, there are certain difficulties in the prediction of the epidemic situation and the allocation of resources. The excessive reserve of resources will cause a certain waste. At the same time, insufficient resource reserves will result in an excessive burden of prevention and control. Maximizing social benefits while ensuring economic benefits is a challenge which has to be faced in the current resource allocation process.

In addition to resource management, scientific intervention is also a prerequisite for ensuring the early interruption of the epidemic. Specifically, all countries have formulated various prevention and control interventions and adjusted them to varying degrees according to the changes in the epidemic situation, which also produced different prevention and control effects. The University of Oxford compiled the implementation of daily epidemic prevention and control policies in various countries and constructed the OxCGRT dataset [85]. These include control policies for work spaces, schools, gatherings of people, and mask wearings and so on. Different policies also control the epidemic from multiple perspectives. The study of relevant simulation models based on actual policies can assist decision makers in formulating policies and evaluating the effects [86]. An article published in Science [87] mentioned that the effects of all policies were estimated through a bayesian hierarchical model to obtain the impact on the final transmission effectiveness. There are also other related studies which simulate the impact on various non-pharmaceutical interventions based on more realistic parameters or agent-based models [88-89]. However, model estimations still has limitations. In the process of estimating policy effectiveness, it is necessary to take into account the non-independence of policies and other factors outside the policy, such as vaccines, strains, and the impact of personnel compliance. These are big challenges for simulation. In addition, the existing model research mostly learns features from data, but more practical epidemiological models or related knowledge are not introduced. These models cannot achieve the purpose of accurate optimization based on expert knowledge. Therefore, it is difficult to obtain customized applications in actual scenarios. In short, the purpose of the prevention and control policy is to interrupt the epidemic in a timely manner. However, how to carry out effective epidemic prevention and control with minimal economic cost through scientific scheduling is the current challenge for policy formulation, especially in the stage of regular epidemic prevention and control.

Facing these challenges in the early interruption of the epidemic, it is necessary to combine medical resources, social resources and prevention and control policies to carry out joint and dynamic control. Mathematical models can simulate the effectiveness of different prevention and control policies, so as to estimate the consumption of corresponding resources based on model predictions. In the process of simulating the interventions, it is possible to find a balance between economic and public safety by adjusting the implementation of policies. Therefore, the model needs to learn more parameters to adapt to more scenarios. Wu and Jiao proposed a hybrid model that combined compartment model and tree model based on strains, vaccines and various policies [90], which could more accurately conduct policy regulation and simulation for various epidemic scenarios and ensure public safety. In addition, collective prevention and control mechanisms are also the key to epidemic prevention and control. An article from Environmental Research and Public Health [91] studied a survey of 533 villagers in Henan Province, China. A corresponding model was created to demonstrate that the exchange of information and public leadership can contribute positively to COVID-19 prevention and control. Another article introduced China's experience in the implementation of Cross-Regional Collective Response Mechanism and analyzed its huge role in epidemic prevention and control [92]. Therefore, scientific scheduling combined with joint prevention and control measures can ensure effective interruption in the early stage of the epidemic so as to prevent the spread of the epidemic.

3.4 Treatment of patients

For COVID-19 patients, timely treatment is required. When the number of infected people is increasing, medical resources need to be allocated reasonably to ensure the controllable condition of all patients. An article from Nigerian Postgraduate Medical Journal stated that COVID-19 had caused a great burden on the global medical system, and even affected service delivery of other diseases [93]. The core problem of medical resource mismatch caused by the pandemic of COVID-19 mainly focuses on the lack of ICU resources. In this case, big data and AI technologies can be applied to the process of resource scheduling, thereby indirectly reducing the severe and mortality rate of COVID-19. Specifically, an article from the international journal of epidemiology estimated the number of ICU beds by using the epidemic situation under different policy control to predict the demand for future medical resources [94]. A letter from Intensive Care Medicine introduced a patient simulation model to support planning decision of ICU capacity changes [95]. Although these methods can model and estimate the consumption of medical resources based on realistic factors such as prevention and control policies, total number of patients, etc., the allocation of specific resources still remain a challenge. The high contagiousness of COVID-19 leads to frequent outbreak in clusters. Therefore, the distribution of patients in a specific area is often uneven so that it is difficult to estimate patient distribution in advance. Therefore, the advance allocation of medical resources is also a challenge to ensure that all patients receive treatment as soon as possible.

Vaccines and antiviral drugs are important means to prevent and treat infectious diseases. The research and development of vaccines and new drugs are characterized by high technical difficulty, large investment, high research and development risk, high return rate and long research and development cycle. Big data and AI are empowering research in the field of life sciences and accelerating the process of new drug research and development. Involvement of big data and AI in the development of a pharmaceutical product from the bench to the bedside can be imagined given that it can aid rational drug design [96]. AI can recognize hit and lead compounds, and provide a quicker validation of the drug target and optimization of the drug structure design [97-98]. The process of discovering and developing a drug can take over a decade and cost US$2.8 billion on average. Even then, nine out of ten therapeutic molecules fail Phase II clinical trials and regulatory approval. Algorithms of AI are used for virtual screening based on synthesis feasibility and can also predict in vivo activity and toxicity [99-100]. It is vital to predict the structure of the target protein to design the drug molecule. AI can assist in structure-based drug discovery by predicting the 3D protein structure because the design is in accordance with the chemical environment of the target protein site, thus helping to predict the effect of a compound on the target along with safety considerations before their synthesis or production [101]. AI can assist in selecting only a specific diseased population for recruitment in Phase II and III of clinical trials by using patient-specific genome-exposome profile analysis, which can help in early prediction of the available drug targets in the patients selected [102].

However, it also faces some challenges as an emerging field. First, the entire success of big data and AI depends on the availability of a substantial amount of data because these data are used for the subsequent training provided to the system. Access to data from various database providers can incur extra costs, and the data should also be reliable and high quality to ensure accurate result prediction. Second, the complexity brings great challenges to data acquisition and AI algorithm design for the combination and reaction process between compounds and human targets. Besides, it is difficult to define the role of drugs in biological systems with a limited set of parameters, and these neglected factors make AI face greater uncertainty in drug discovery and efficacy evaluation. Therefore, the research and application of big data and AI in the development of vaccine and antiviral drugs requires the deep integration of the basic science of traditional medical research and the core AI technology, as well as the joint efforts of technical experts, biologists, physicians, etc.

4. Discussion

Recently, the trend of epidemic in China has been further consolidated in a gradually improving situation, which accelerates a great advance in the resumption of work and production and the economic-social operation order in the whole country. Along with the epidemic, big data and AI are developing rapidly, and have become those of the important leading forces in industrial upgrading and evolution. Big data and AI are the inevitable requirements of the intelligent era to quickly, scientifically and effectively organize all parties to work together, which plays an important role in winning the battle of epidemic prevention and control.

On the other hand, it is still in its initial stage of the practice using big data and AI in epidemic prevention and control as a systematic project, and there are still shortcomings and problems in many aspects. To overcome these difficulties, the concerted efforts are required from technical support, legal guarantee, organization and coordination, international cooperation and so on, which involve the participation of medical, health, transportation, communication and other multi subjects.

First, the focus should be put on core technologies of big data and artificial intelligence, which have the characteristics of multidisciplinary synthesis and high complexity. We should take problems from public health as a guide, and comprehensively enhance the scientific and technological innovation ability of big data and artificial intelligence, to speed up the establishment of a new generation of key common technology system. On one hand, we need to strengthen medical data sharing. At present data silos is ubiquitous, because the unified schema of medical data is absent, and the quality of data is usually poor or incomplete, which hinders the development of medical artificial intelligence to a great extent. Therefore, we should speed up the construction of medical big data application sharing cloud platform, including formulating national medical big data schema, establishing a unified and standardized clinical medical terminology to ensure the safe and efficient sharing of medical data. On the other hand, for AI algorithm innovation, intellectual property protection and property incentives should be strengthened, and scientific researchers should be given the ownership or long-term use right of scientific and technological achievements.

Second, the guarantee of the rule of law should be improved. Bringing the development of big data and AI into the track of rule in law is an important guarantee to ensure the safety, reliability and controllability. At present, there is a lack of forward-looking, operable and guiding laws and regulations in the development, and issues such as personal information protection and data sharing urgently need to be clarified by legislation. In view of this, we should strengthen the theoretical research of AI law, and deeply analyze the particularity, innovation and risk of the technologies in the application of epidemic prevention and control, to clarify the ownership of intellectual property rights and the liability of infringement, to guide the standardized development of AI. Besides, industry specifications should be formulated by analyzing and summarizing the existing technological achievements to clarify the industry access threshold, and establish relevant industry standards, technical standards and product certification systems. In the epidemic, we should legislate to clarify the rules for the collection, use, processing and transmission of patients' personal information, and clarify the standards for information sharing among departments and organizations. In addition, new challenges are posed to network security. It is necessary to clarify the network security prevention and control responsibilities of relevant subjects, clarify legal responsibilities, and create a safe and reliable network security space.

Third, concerted efforts should be made by all participants. It plays an important role in winning the battle of epidemic prevention and control by using big data and AI to quickly, scientifically and effectively organize all parties to work together. To this end, an intelligent prevention and control system for major national epidemics should be established. An intelligent prevention and control system should coordinate the epidemic prevention and control systems of all parts of the country, departments and scenes, and form an intelligent prevention and control system for epidemics, including epidemic early warning, epidemic controlling, emergency treatment and so on.

Fourth, strength should be put on international exchanges and cooperation. To develop the technology of big data and AI, we must have a global vision to strengthen policy coordination and planning docking with other countries on the basis of mutual benefit and win-win results, and actively reach strategic cooperation with other countries and international organizations. We should speed up the formulation of AI related rules of international law, and give play to the role of international law by actively communicating and coordinating with other countries and international organizations. A global collaborative research and development system should be constructed for AI epidemic prevention and control technology to strengthen the sharing of scientific research achievements by encouraging exchanges and cooperation between domestic and foreign scientific research institutions.

Nowadays, the application of big data and artificial intelligence plays an important role to win the battle of epidemic prevention and control. What we need to do now is to take the epidemic seriously, abide by relevant policies and regulations, and provide support for the progress of epidemic prevention and control.

Conflicts of interest statement

The authors declare no competing interests.

Funding

This work was supported by the National Key R&D Program of China (Grant No. 2021ZD01144101).

Author contributions

Zengtao Jiao: Investigation, Resources, Writing - Original Draft; Hanran Ji: Investigation, Resources, Editing; Jun Yan: Writing – Review, Editing; Xiaopeng Qi: Writing – Review, Editing, Supervision, Project administration.

Reference

[1] Wiersinga WJ, Rhodes A, Cheng AC, et al. Pathophysiology, Transmission, Diagnosis, and Treatment of Coronavirus Disease 2019 (COVID-19): A Review. JAMA 2020;324(8):782-793. doi:10.1001/jama.2020.12839.
[2] Araf Y, Akter F, Tang YD, et al. Omicron variant of SARS-CoV-2: Genomics, transmissibility, and responses to current COVID-19 vaccines. J Med Virol 2022;94(5):1825-1832. doi:10.1002/jmv.27588.
[3] Jain N, Hung IC, Kimura H, et al. The global response: How cities and provinces around the globe tackled Covid-19 outbreaks in 2021. Lancet Reg Health Southeast Asia 2022;4:100031. doi:10.1016/j.lansea.2022.100031.
[4] Li BH, Hou BC, Yu WT, et al. Applications of artificial intelligence in intelligent manufacturing: a review. Frontiers Inf Technol Electronic Eng 2017;18(1):86-96. doi:10.1631/fitee.1601885.
[5] Benzeghiba M, De Mori R, Deroo O, et al. Automatic speech recognition and speech variability: A review. Speech Commun 2007;49(10-11):763-786. doi:10.1016/j.specom.2007.02.006.
[6] Rajpurkar P, Chen E, Banerjee O, et al. AI in health and medicine. Nat Med 2022;28(1):31-38. doi:10.1038/s41591-021-01614-0.
[7] Pacis DMM, Subido EDC, Bugtai NT.Trends in telemedicine utilizing artificial intelligence. AIP conference proceedings.2018. doi:10.1063/1.5023979.
[8] Liu Q, Huang Z. Research on intelligent prevention and control of COVID-19 in China's urban rail transit based on artificial intelligence and big data. J Intell Fuzzy Syst 2020;39(6):9085-9090. doi:10.3233/jifs-189307.
[9] Abd-Alrazaq A, Alajlani M, Alhuwail D, et al. Artificial Intelligence in the Fight Against COVID-19: Scoping Review. J Med Internet Res 2020;22(12):e20756. doi:10.2196/20756.
[10] Ara Shaikh A, Kumar A, Jani K, et al. The Role of Machine Learning and Artificial Intelligence for making a Digital Classroom and its sustainable Impact on Education during Covid-19. Materials Today: Proceedings. 2022;56:3211-3215. doi:10.1016/j.matpr.2021.09.368.
[11] Ye J. The Role of Health Technology and Informatics in a Global Public Health Emergency: Practices and Implications From the COVID-19 Pandemic. JMIR Med Inform 2020;8(7):e19866. doi:10.2196/19866.
[12] El-Sherif DM, Abouzid M, Elzarif MT, et al. Telehealth and Artificial Intelligence Insights into Healthcare during the COVID-19 Pandemic. Healthcare (Basel) 2022;10(2):385. doi:10.3390/healthcare10020385.
[13] Bharti U, Bajaj D, Batra H, et al. Proceedings of 5th International Conference on Communication and Electronics Systems (ICCES). 2020. doi:10.1109/icces48766.2020.9137944.
[14] Carroll C, Bhattacharjee S, Chen Y, et al. Time dynamics of COVID-19. Sci Rep 2020;10(1):21040. doi:10.1038/s41598-020-77709-4.
[15] Kim S, Kim M, Lee S, et al. Discovering spatiotemporal patterns of COVID-19 pandemic in South Korea. Sci Rep 2021;11(1):24470. doi:10.1038/s41598-021-03487-2.
[16] Kretzschmar ME, Rozhnova G, Bootsma MCJ, et al. Impact of delays on effectiveness of contact tracing strategies for COVID-19: a modelling study. Lancet Public Health 2020;5(8):e452-e459. doi:10.1016/S2468-2667(20)30157-2.
[17] Gibney E. Whose coronavirus strategy worked best? Scientists hunt most effective policies. Nature 2020;581(7806):15-16. doi:10.1038/d41586-020-01248-1.
[18] Khan M, Mehran MT, Haq ZU, et al. Applications of artificial intelligence in COVID-19 pandemic: A comprehensive review. Expert Syst Appl 2021;185:115695. doi:10.1016/j.eswa.2021.115695.
[19] Garba SM, Lubuma JM, Tsanou B. Modeling the transmission dynamics of the COVID-19 Pandemic in South Africa. Math Biosci 2020;328:108441. doi:10.1016/j.mbs.2020.108441.
[20] Cuadros DF, Xiao Y, Mukandavire Z, et al. Spatiotemporal transmission dynamics of the COVID-19 pandemic and its impact on critical healthcare capacity. Health Place 2020;64:102404. doi:10.1016/j.healthplace.2020.102404.
[21] Yang Z, Zeng Z, Wang K, et al. Modified SEIR and AI prediction of the epidemics trend of COVID-19 in China under public health interventions. J Thorac Dis 2020;12(3):165-174. doi:10.21037/jtd.2020.02.64.
[22] Rath S, Tripathy A, Tripathy AR. Prediction of new active cases of coronavirus disease (COVID-19) pandemic using multiple linear regression model. Diabetes Metab Syndr 2020;14(5):1467-1474. doi:10.1016/j.dsx.2020.07.045.
[23] Jayatilaka G, Hassan J, Marikkar U, et al. Use of Artificial Intelligence on spatio-temporal data to generate insights during COVID-19 pandemic: A Review. 2021.MedRxiv: 2020.2011. 2022.20232959.
[24] Yahya BM, Yahya FS, Thannoun RG. COVID-19 prediction analysis using artificial intelligence procedures and GIS spatial analyst: a case study for Iraq. Appl Geomat 2021;13(3):481-491. doi:10.1007/s12518-021-00365-4.

[25] The Lancet. COVID-19: protecting health-care workers. Lancet 2020;395(10228):922. doi:10.1016/S0140-6736(20)30644-9.
[26] da Silva CC, de Lima CL, da Silva ACG, et al. Covid-19 Dynamic Monitoring and Real-Time Spatio-Temporal Forecasting. Front Public Health 2021;9:641253. doi:10.3389/fpubh.2021.641253.
[27] Sun S, Xie Z, Yu K, et al.COVID-19 and healthcare system in China: challenges and progression for a sustainable future. Global Health 2021;17(1):14. doi:10.1186/s12992-021-00665-9.
[28] Abdelmageed MI, Abdelmoneim AH, Mustafa MI, et al. Design of a Multiepitope-Based Peptide Vaccine against the E Protein of Human COVID-19: An Immunoinformatics Approach. Biomed Res Int 2020;2020:2683286. doi:10.1155/2020/2683286.
[29] Ong E, Wong MU, Huffman A, et al.COVID-19 coronavirus vaccine design using reverse vaccinology and machine learning. Preprint. bioRxiv 2020;2020.03.20.000141. doi:10.1101/2020.03.20.000141.
[30] Ge Y, Tian T, Huang S, et al.A data-driven drug repositioning framework discovered a potential therapeutic agent targeting COVID-19. 2020. bioRxiv: 2020.2003.2011.986836.doi:10.1101/2020.03.11.986836.
[31] Hofmarcher M, Mayr A, Rumetshofer E, et al. Large-Scale Ligand-Based Virtual Screening for SARS-CoV-2 Inhibitors Using Deep Neural Networks. SSRN 2020. doi:10.2139/ssrn.3561442..
[32] Beck BR, Shin B, Choi Y, et al. Predicting commercially available antiviral drugs that may act on the novel coronavirus (SARS-CoV-2) through a drug-target interaction deep learning model. Comput Struct Biotechnol J 2020;18:784-790. doi:10.1016/j.csbj.2020.03.025.
[33] Hu F, Jiang J, Yin P. Prediction of potential commercially inhibitors against SARS-CoV-2 by multi-task deep model. 2020. arXiv preprint arXiv:200300728.
[34] Khurana D, Koli A, Khatter K, et al. Natural language processing: state of the art, current trends and challenges. Multimed Tools Appl 2022:1-32. doi:10.1007/s11042-022-13428-4.
[35] Komal K, Sharma A. Natural Language Processing: an approach to aid emergency services in COVID-19 pandemic. IJIRCST 2020;8(3):213-217. doi:10.21276/ijircst.2020.8.3.32.
[36] Hassan A, Shahin I, Alsabek MB. Proceedings of International conference of Communication, Computing, Cybersecurity, and Informatics, UAE, 2020.
[37] Silverman GM, Sahoo HS, Ingraham NE, et al. NLP methods for extraction of symptoms from unstructured data for use in prognostic covid-19 analytic models. J Artif Intell Res 2021;72: 429-474.doi:10.1613/jair.1.12631.
[38] Zhou K, Constantinides M, Joglekar S, et al. Predicting Meeting Success With Nuanced Emotions. IEEE Pervasive Comput 2022;21(2):51-59. doi:10.1109/mprv.2022.3145047.
[39] Dong D, Tang Z, Wang S, et al.The Role of Imaging in the Detection and Management of COVID-19: A Review. IEEE Rev Biomed Eng 2021;14:16-29. doi:10.1109/RBME.2020.2990959.
[40] Wang XV, Wang L. A literature survey of the robotic technologies during the COVID-19 pandemic. J Manuf Syst 2021;60:823-836. doi:10.1016/j.jmsy.2021.02.005.
[41] Hariri W. Efficient masked face recognition method during the COVID-19 pandemic. Signal Image Video Process 2021;16(3):605-612.doi:10.1007/s11760-021-02050-w.
[42] Tan W, Liu J. Proceedings of 19th IEEE International Conference on Machine Learning and Applications (ICMLA). 2020:1112-1116.doi:10.1109/ICMLA51294.2020.00179.
[43] Chu L, Liu Y, Wu Z, et al. Proceedings of IEEE/CVF Winter Conference on Applications of Computer Vision Workshops, WACVW 2022.doi:10.1109/WACVW54805.2022.00026.
[44] Kagan D, Alpert GF, Fire M. Zooming into video conferencing privacy and security threats. 2020. arXiv:200701059.
[45] Ghani T, Jahan N, Khan MM, et al. Development and Analysis of a Machine Learning Based Software for Assisting Online Classes during COVID-19. J softw eng appl 2021;14(03):83-94. doi:10.4236/jsea.2021.143006.
[46] Wu S, Wu D, Ye R, et al. Pilot Study of Robot-Assisted Teleultrasound Based on 5G Network: A New Feasible Strategy for Early Imaging Assessment During COVID-19 Pandemic. IEEE Trans Ultrason Ferroelectr Freq Control 2020;67(11):2241-2248. doi:10.1109/TUFFC.2020.3020721.
[47] Khan ZH, Siddique A, Lee CW. Robotics Utilization for Healthcare Digitization in Global COVID-19 Management. Int J Environ Res Public Health 2020;17(11):3819. doi:10.3390/ijerph17113819.
[48] Podpora M, Gardecki A, Beniak R, et al. Human Interaction Smart Subsystem-Extending Speech-Based Human-Robot Interaction Systems with an Implementation of External Smart Sensors. Sensors (Basel) 2020;20(8):2376. doi:10.3390/s20082376.
[49] Ramalingam B, Yin J, Rajesh Elara M, et al. A Human Support Robot for the Cleaning and Maintenance of Door Handles Using a Deep-Learning Framework. Sensors (Basel) 2020;20(12):3543. doi:10.3390/s20123543.
[50] Ahir S, Telavane D, Thomas R. Proceedings - International Conference on Smart Electronics and Communication, ICOSEC 2020. doi:10.1109/ICOSEC49089.2020.9215294.

[51] Ding F, Fu J, Jiang D, et al. Mapping the spatial distribution of Aedes aegypti and Aedes albopictus. Acta Trop 2018;178:155-162. doi:10.1016/j.actatropica.2017.11.020.
[52] Ong J, Liu X, Rajarethinam J, et al. Mapping dengue risk in Singapore using Random Forest. PLoS Negl Trop Dis 2018;12(6):e0006587. doi:10.1371/journal.pntd.0006587.
[53] Akhtar M, Kraemer MUG, Gardner LM. A dynamic neural network model for predicting risk of Zika in real time. BMC Med 2019;17(1):171. doi:10.1186/s12916-019-1389-3.
[54] Shah Z, Dunn AG. Event detection on Twitter by mapping unexpected changes in streaming data into a spatiotemporal lattice. IEEE Trans Big Data 2019:1-1. doi:10.1109/tbdata.2019.2948594.
[55] Chen F, Neill DB. Proceedings of the 20th ACM SIGKDD conference on knowledge discovery and data mining. 2014. doi:10.1145/2623330.2623619.
[56] Dai X, Bikdash M, Meyer B. Proceedings of IEEE SoutheastCon. 2017. doi:10.1109/secon.2017.7925400.
[57] Wagner MM, Tsui FC, Espino J, et al. National Retail Data Monitor for public health surveillance. MMWR Suppl 2004;53:40-42.
[58] Ginsberg J, Mohebbi MH, Patel RS, et al. Detecting influenza epidemics using search engine query data. Nature 2009;457(7232):1012-1014. doi:10.1038/nature07634.
[59] Li Z, Luo X, Wang B, et al. A study on graph-structured recurrent neural networks and sparsification with application to epidemic forecasting. Advances in Intelligent Systems and Computing 2019:730-739. doi:10.1007/978-3-030-21803-4_73.
[60] Wang LJ, Chen JZ, Marathe M. Proceedings of the AAAI Conference on Artificial Intelligence 2019;33(01):9607–12.doi:10.1609/aaai.v33i01.33019607.
[61] Soliman M, Lyubchich V, Gel YR. Complementing the power of deep learning with statistical model fusion: Probabilistic forecasting of influenza in Dallas County, Texas, USA. Epidemics 2019;28:100345. doi:10.1016/j.epidem.2019.05.004.
[62] Su K, Xu L, Li G, et al. Forecasting influenza activity using self-adaptive AI model and multi-source data in Chongqing, China. EBioMedicine 2019;47:284-292. doi:10.1016/j.ebiom.2019.08.024.
[63] Miller AC, Polgreen LA, Cavanaugh JE, et al. Missed Opportunities to Diagnose Tuberculosis Are Common Among Hospitalized Patients and Patients Seen in Emergency Departments. Open Forum Infect Dis 2015;2(4):ofv171. doi:10.1093/ofid/ofv171.
[64] Lee EWJ, Yee AZH. Toward Data Sense-Making in Digital Health Communication Research: Why Theory Matters in the Age of Big Data. Front Commun 2020;5. doi:10.3389/fcomm.2020.00011.
[65] Lee EWJ, Viswanath K. Big Data in Context: Addressing the Twin Perils of Data Absenteeism and Chauvinism in the Context of Health Disparities Research. J Med Internet Res 2020;22(1):e16377. doi:10.2196/16377.
[66] Beaglehole R, Bonita R, Kjellstrom T. Basic epidemiology. Geneva: World Health Organization. 1993.
[67] Gregg MB. Conducting a field investigation. Field epidemiology. 3rd ed. New York: Oxford University Press; 2008:81–96.doi:10.1093/acprof:oso/9780195313802.003.0005.
[68] Li Y, Gao Y, Li G. The Construction and Application of the Field Epidemiological Investigation System for COVID-19. Chinese Journal of Health Informatics and Management 2020;17(05):627-631.doi:10.3969/j.issn.1672-5166.2020.05.15.
[69] Wang J, Wang K, Li J, et al. Accelerating Epidemiological Investigation Analysis by Using NLP and Knowledge Reasoning: A Case Study on COVID-19. AMIA Annu Symp Proc 2021;2020:1258-1267.
[70] Gundlapalli, Adi V, et al. Using NLP on VA Electronic Medical Records to Facilitate Epidemiologic Case Investigations. Advances in Disease Surveillance 5 (2008): 34.
[71] Luo L, Liu D, Liao X, et al. Contact Settings and Risk for Transmission in 3410 Close Contacts of Patients With COVID-19 in Guangzhou, China: A Prospective Cohort Study. Ann Intern Med 2020;173(11):879-87. doi:10.7326/M20-2671.
[72] Li F, Li YY, Liu MJ, et al. Household transmission of SARS-CoV-2 and risk factors for susceptibility and infectivity in Wuhan: a retrospective observational study. Lancet Infect Dis 2021;21(5):617-28.doi: 10.1016/S1473-3099(20)30981-6.
[73] Bi Q, Wu Y, Mei S, et al. Epidemiology and transmission of COVID-19 in 391 cases and 1286 of their close contacts in Shenzhen, China: a retrospective cohort study. Lancet Infect Dis 2020;20(8):911-9.doi: 10.1016/S1473-3099(20)30287-5.
[74] Lee LYW, Rozmanowski S, Pang M, et al. SARS-CoV-2 infectivity by viral load, S gene variants and demographic factors and the utility of lateral flow devices to prevent transmission. Clin Infect Dis 2022;74(3):407-415. doi:10.1093/cid/ciab421.
[75] Lu J, Yang Z. COVID-19 Outbreak Associated with Air Conditioning in Restaurant, Guangzhou, China, 2020. Emerg Infect Dis 2020;26(11):2791-2793. doi:10.3201/eid2611.203774.

[76] Rothe C, Schunk M, Sothmann P, et al. Transmission of 2019-nCoV Infection from an Asymptomatic Contact in Germany. N Engl J Med 2020;382(10):970-1. doi:10.1056/NEJMc2001468.
[77] Gu Y, Lu J, Su W, et al. Transmission of SARS-CoV-2 in the Karaoke Room: An Outbreak of COVID-19 in Guangzhou, China, 2020. J Epidemiol Glob Health 2021;11(1):6-9. doi: 10.2991/jegh.k.201007.001.
[78] Kang M, Wei J, Yuan J, et al. Probable Evidence of Fecal Aerosol Transmission of SARSCoV-2 in a High-Rise Building. Ann Intern Med 2020;173(12):974-80. doi: 10.7326/M20-0928.
[79] Yuan J, Chen Z, Gong C, et al. Sewage as a Possible Transmission Vehicle During a Coronavirus Disease 2019 Outbreak in a Densely Populated Community: Guangzhou, China, April 2020. Clin Infect Dis 2021;73(7):e1487-e8. doi: 10.1093/cid/ciaa1494.
[80] Kirkpatrick JN, Hull SC, Fedson S, et al. Scarce-Resource Allocation and Patient Triage During the COVID-19 Pandemic: JACC Review Topic of the Week. J Am Coll Cardiol 2020;76(1):85-92. doi:10.1016/j.jacc.2020.05.006.
[81] Laventhal N, Basak R, Dell ML, et al. The Ethics of Creating a Resource Allocation Strategy During the COVID-19 Pandemic. Pediatrics 2020;146(1):e20201243. doi:10.1542/peds.2020-1243.
[82] Fayyoumi E, Idwan S, AboShindi H. Machine Learning and Statistical Modelling for Prediction of Novel COVID-19 Patients Case Study: Jordan. Int J Adv Comput Sci Appl 2020;11(5):122-126. doi:10.14569/ijacsa.2020.0110518.
[83] Ghany KKA, Zawbaa HM, Sabri HM. COVID-19 prediction using LSTM algorithm: GCC case study. Inform Med Unlocked 2021;23:100566. doi:10.1016/j.imu.2021.100566.
[84] Luo J.When will COVID-19 end? Data-driven prediction. Singapore: Singapore University of Technology & Design.2020.
[85] Hale T, Webster S, Petherick A, et al. Oxford COVID-19 government response tracker (OxCGRT). 2020.
[86] Thompson RN. Epidemiological models are important tools for guiding COVID-19 interventions. BMC Med 2020;18(1):152. doi:10.1186/s12916-020-01628-4.
[87] Brauner JM, Mindermann S, Sharma M, et al. Inferring the effectiveness of government interventions against COVID-19. Science 2021;371(6531):eabd9338. doi:10.1126/science.abd9338.
[88] Kerr CC, Stuart RM, Mistry D, et al. Covasim: An agent-based model of COVID-19 dynamics and interventions. PLoS Comput Biol 2021;17(7):e1009149. doi:10.1371/journal.pcbi.1009149.
[89] Khajanchi S, Sarkar K, Mondal J, et al. Mathematical modeling of the COVID-19 pandemic with intervention strategies. Results Phys 2021;25:104285. doi:10.1016/j.rinp.2021.104285.
[90] Wu JW, Jiao XK, Du XH, et al. Assessment of the Benefits of Targeted Interventions for Pandemic Control in China Based on Machine Learning Method and Web Service for COVID-19 Policy Simulation. Biomed Environ Sci 2022;35(5):412-418. doi:10.3967/bes2022.057.
[91] Yang L, Ren Y. Moral Obligation, Public Leadership, and Collective Action for Epidemic Prevention and Control: Evidence from the Corona Virus Disease 2019 (COVID-19) Emergency. Int J Environ Res Public Health 2020;17(8):2731. doi:10.3390/ijerph17082731.
[92] Ouyang P, Liu XY, Zhong YC, et al.Cross-Regional Collective ResponseMechanism for Major Epidemic Control and Treatment. China City Planning Review 2020,29(03):26-33.
[93] Akande OW, Akande TM. COVID-19 pandemic: A global health burden. Niger Postgrad Med J 2020;27(3):147-155. doi:10.4103/npmj.npmj_157_20.
[94] McCabe R, Kont MD, Schmit N, et al. Modelling intensive care unit capacity under different epidemiological scenarios of the COVID-19 pandemic in three Western European countries. Int J Epidemiol 2021;50(3):753-767. doi:10.1093/ije/dyab034.
[95] Alban A, Chick SE, Dongelmans DA, et al. ICU capacity management during the COVID-19 pandemic using a process simulation. Intensive Care Med 2020;46(8):1624-1626. doi:10.1007/s00134-020-06066-7.
[96] Duch W, Swaminathan K, Meller J. Artificial intelligence approaches for rational drug design and discovery. Curr Pharm Des 2007;13(14):1497-1508. doi:10.2174/138161207780765954.
[97] Mak KK, Pichika MR. Artificial intelligence in drug development: present status and future prospects. Drug Discov Today 2019;24(3):773-780. doi:10.1016/j.drudis.2018.11.014.
[98] Sellwood MA, Ahmed M, Segler MH, et al. Artificial intelligence in drug discovery. Future Med Chem 2018;10(17):2025-2028. doi:10.4155/fmc-2018-0212.
[99] Álvarez-Machancoses Ó, Fernández-Martínez JL. Using artificial intelligence methods to speed up drug discovery. Expert Opin Drug Discov 2019;14(8):769-777. doi:10.1080/17460441.2019.1621284.
[100] Fleming N. How artificial intelligence is changing drug discovery. Nature 2018;557(7707):S55-S57. doi:10.1038/d41586-018-05267-x.
[101] Wan F, Zeng J. Deep learning with feature embedding for compound–protein interaction prediction. bioRxiv.2016;2016.
[102] Harrer S, Shah P, Antony B, et al. Artificial Intelligence for Clinical Trial Design. Trends Pharmacol Sci 2019;40(8):577-591. doi:10.1016/j.tips.2019.05.005.