An artificial intelligence—based decision support and resource management system for COVID-19 pandemic

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1. Introduction

The COVID-19 pandemic showed that the world was not ready. Effective use of information technologies is necessary to reduce the effects of any epidemic or pandemic. It is critical to model the epidemic and meet the quarantine conditions to control the spread of the COVID-19 pandemic or an epidemic that may occur in the following years. On the other hand, it is necessary to collect accurate and real-time information about infected people and their contacts in an epidemic. When this information is shared and analyzed quickly, effective and targeted interventions can be carried out to prevent or mitigate the outbreak. This need arose during the Ebola outbreak in West Africa in 2014—16, and 11 key components of an outbreak response were outlined by World Health Organization (WHO) [1]. Considering these components, the functions required in an epidemic management system (EMS) can be summarized as follows:

- Collecting data about the epidemic
- Model and predict the possible future spread of the epidemic
- Ensure the quarantine conditions; monitor the infected patient's movements
- Resource management
- Decision support

  The following should be satisfied respectively:

- All different kinds of available data resources should be integrated. Data resources should be verified and the collected data should be validated.

- Correct epidemic models should be used to reach the best accuracy.
- Privacy of the collected personal data and trust in the system should be ensured.
- Consistency and usability of the system should be ensured.
- Best visualization mechanisms should be used to help the users in decision making.

An EMS model is proposed in this chapter as a solution. Although EMSs should include decision support systems, several solutions in the literature do not contain decision support system tools to assist in making forward-looking decisions [2]. On the other hand, the decision support systems proposed for epidemics are stand-alone applications, and they are not integrated with the EMSs [3]. One of the most important contributions of the system we proposed is to enhance an EMS with a decision support system based on automatic machine learning and stochastic epidemic modeling. Epidemic modeling will be used to help in analyzing the related data to realize the current state of the epidemic and predict the possible future spread of the epidemic. In addition, since outbreaks may require urgent and correct decisions, the selection of the correct machine learning method, which will be effective in decision making, can be ensured by the automatic machine learning techniques. Consequently, the proposed decision support system will be used for effective resource management and for supporting EMS.

Moreover, this system will use mobile technology, blockchain as well as epidemic modeling, and artificial intelligence (AI) technologies. There is a need for sharing information between nations and organizations. The resources of the data should be verified and the collected data should also be validated by the parties involved.

The system is designed according to the Multi-Platform Interoperable Scalable Architecture (MPISA) model [4], which is the integration of multiple platforms and provides a solution to scalability and interoperability problems. A realistic model of the outbreak will be created using data from mobile applications, MiPasa, and other data sources.

Decentralized identity (DID) management systems can be used to ensure the privacy of the patient. These systems and zero-knowledge proof-based mechanisms are used to make the user in control of how his/her data are shared.

This chapter aims to summarize the current studies for epidemic management and propose a new EMS model. We start with a brief discussion of the needed functions in epidemic management, why current EMSs fail to serve these functions, and which technologies can be used as a solution. Fundamentals, mathematical epidemic models, decision-making in an epidemic, visual analysis, blockchain, data protection, and privacy issues are covered in section two. Related works about epidemic management are given in section three. The system model is given in section four. Possible data resources are given in section five. Methods are explained in section six. Finally, conclusion and future works are given.

2. Fundamentals

In this section, we present background information about the basic concepts that are essential for the proposed system. These include mathematical epidemic models, decision making in an epidemic, visual analysis, data protection and privacy, and blockchain, respectively.

2.1   Mathematical epidemic models

A mathematical epidemic model mathematically represents the spread of a disease in a population [5]. Epidemic models help to observe the development of an outbreak and evaluate its impact when epidemic or mitigation decisions are implemented. It also enables emergency response and risk analysis.

Although there are many mathematical epidemic models in the literature, two of the most known models are Susceptible-Infectious-Recovered (SIR) [6] and Susceptible-Exposed-Infectious-Recovered (SEIR) [7] models. The diagram of these two models is shown in Fig. 2.1. In the SIR model, S (Susceptible) refers to the number of individuals who can get the disease, I (Infectious) means the number of infected and infectious individuals, and R (Recovered) is the number of isolated, immune, or dead people. In the SEIR model, the number of infected but not contagious individuals (Exposed) is also included in the model. While the total population (N) is represented by $N = S + I + R$ for the SIR model, $N = S + E + I + R$ for the SEIR model. Both models predict how the population numbers in each state will change over time.

In both models, the progression from one state to another begins when a susceptible person (S state) is infected at the rate of infection (β), as a result, the individual moves to state I for the SIR model or state E for the SEIR model. In the SEIR model, the exposed individual becomes infectious after the incubation time (σ) and eventually moves the individual to an infectious state. Finally, the infected individual is recovered at the
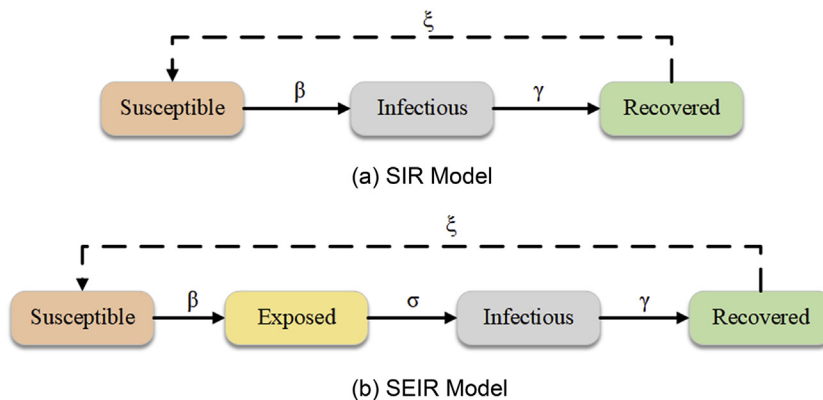
FIGURE 2.1 Susceptible-Infectious-Recovered and Susceptible-Exposed-Infectious-Recovered models. (A) Susceptible-Infectious-Recovered model. (B) Susceptible-Exposed-Infectious-Recovered model.

recovery rate (γ), as a result, the individual moves to the recovered (R) state. If individuals lose immunity, they can return to a susceptible person (S state) which is controlled by ξ rate. Mathematical models can expand to include interventions such as mitigation strategies or resource capacity to reduce the impact of disease spread.

2.2   Decision-making in an epidemic

Deciding the best action among the alternatives to solve a particular problem is called decision-making [8]. Decisions in an epidemic are made based on the facts about the epidemic situation and the public health officials' own experience and assumptions. Situational awareness plays an important role to make the right decisions. Situational awareness is defined as the perception of the elements in the environment, comprehension of their meanings, and projection of their near future situations in terms of time and space [9]. The perception, comprehension, and projection mentioned here determine three levels of situational awareness, and each level is built based on the previous one. These levels can be summarized as follows:

1. Perception level: Important elements in the environment are identified at the perception level.
2. Comprehension level: Decision-makers should combine the knowledge obtained at the perception level with their own experiences at the comprehension level.
3. Estimation level: In this level, the ability to predict according to different possibilities should be gained by using the obtained understanding capacity.

Therefore, at the initial stage, public health professionals need to collect different types of data about the epidemic. These may include data such as the characteristics of the virus, the proportion of infected people, and their geographic location, demographic structure of the population, the number of hospital beds and ventilators. Public health experts evaluate these precautions to prevent the spread of the epidemic by using their own expertise and the collected data. Some of these interventions can be curfews, school closures, vaccinating some groups of people, increasing social distance, or increasing hospital resources. But it is necessary to predict what the decisions will lead to in the future. If detailed research is not done in this regard, these decisions may increase the pace of the epidemic or increase in mortality rates or lead to unnecessary economic losses. Therefore, public health experts need to raise their situational awareness levels to the third degree to make the right decisions. However, it is very difficult for public health experts to reach this level without an auxiliary tool as there is an incredibly fast and irregular flow of data, and often the process is uncertain. This causes decision-makers to drown in a lot of data and to remain in the possibilities of many estimation combinations. Thus, the right decision-making process becomes difficult. Decision support systems can filter and present appropriate decision options using these collected big data. Therefore, decision support systems can make a significant contribution to public health experts in reaching the projection level of situational awareness.

2.3   Visual analysis

Visual analysis has an important place in decision support systems. Visual analysis, called a multidisciplinary branch of science, aims to facilitate the processing of big data and to support the decision-making processes of users [10]. For this, interactive visualization methods are integrated with automated data analysis approaches. In this way, complex data can be perceived much better and the transition from data to knowledge can be provided faster. Also, new meaningful information can be discovered by interacting visually with meaningful attributes in the data. As a result, visual analytics prevents overloading of the data and helps users gain a faster comprehension and make appropriate decisions [10].

2.4   Blockchain

Blockchain is technology to keep a list of records in a decentralized way. The level of decentralization may vary but the aim is to establish trust without intermediaries. Transaction information is collected and stored in records called blocks in a time period. A new block is linked to the chain of blocks by using cryptographic techniques. This chain structure forms an immutable registry which is called a ledger. The ledgers are kept in distributed nodes. These nodes run consensus protocols to agree on transactions. The whole blockchain system is connected to each other by peer to peer protocols.

Blockchain technology can be used to make any process autonomous. This becomes possible by storing program code in the ledger. Applications can be programmed to use these codes by using the code's blockchain addresses. These codes can be triggered by any condition. These codes will increase efficiency and speed as the processes will not require any intermediaries then. This autonomous code concept was firstly used by the Ethereum framework and is named as the "smart contract." Hyperledger Fabric framework calls this type of code as "chain code" [11]. The applications which are developed in this way are called the decentralized applications (DAPP) [12]. Transparency can be satisfied if public ledgers are used. Private ledgers can also be used for enterprise solutions. Hybrid solutions are also possible where both features are needed.

Blockchain enables security services such as integrity, availability, and fault tolerance by design. The nodes, which enable the blockchain system, run the same software and act in the same consensus. The consensus protocols enable them to agree on the same decision. The integrity of the records is satisfied as they are synchronized and the records are the same. The number of nodes and their distribution in different networks will serve the availability service. The consensus and the availability enable the fault tolerance. Blockchain does not support privacy by default [11].

Private data, especially personal data should not be kept on the ledger. However, DID is an exception. Digital identities are used to keep identities. DID systems can be developed to keep this personal identity encrypted and store it decentralized. Smart contracts can use zero-knowledge proof-based methods to ensure the privacy of the personal data.

Blockchain technology is still evolving. Energy-efficient, more scalable solutions are being developed. Such solutions are covered in detail in a recent study [4]. AI can also be integrated with blockchain in two different ways; AI can be used for blockchain, blockchain can be used for AI. These are covered in detail in a recent study [12].

2.5   Data protection and privacy

The right to private life is a fundamental right protected by international conventions [13]. The legislation is not sufficient to protect privacy, so privacy protection technologies should be used [14]. Contact tracing applications are being used in many countries; data protection and privacy should be taken into account. Every country (Data Protection Act 2004—DPA for the United Kingdom) and European Union has data protection laws (EU General Data Protection Regulation 2016/679—GDPR) and developers are responsible for their developed systems [15]. That is in brief:

- Security of the collected data: The organizations are responsible if these data are not protected and are compromised or sold to other parties.
- The right to be forgotten: The user has the right to request the removal of his/her data. The organization should have the means to assure that.

Citizens must have the means to control how his/her personal data is shared and by whom. Cryptography techniques [15] and blockchain can be used for data security and privacy. ZKP methods can be used to ensure privacy. ZKP is a way of proving a statement without giving any extra information. Noninteractive zero-knowledge proof (NIZK) is a variant where this can be accomplished in decentralized solutions with autonomous codes [16].

3. Related works

In an epidemic, it is necessary to collect accurate and real-time information about infected people and their contacts. When this information is shared and analyzed quickly, effective and targeted interventions can be carried out to prevent or reduce the outbreak. This need arose during the Ebola outbreak in West Africa in 2014—16, and 11 key components of an outbreak response were outlined by the WHO [1]. When the literature is examined, there are 58 management system applications that target more than one of these components for the Ebola outbreak only [2]. However, only three of them are important because they contain many features. These systems are Surveillance and Outbreak Response Management and Analysis System (SORMAS) [17], CommCare Ebola Response [18], and Sense Ebola Application [19].

The SORMAS system is an open source system and is the most comprehensive. In this system, real-time analyzes can be made over the data collected from mobile devices. In addition to tools that can perform epidemic management, there are visualization and visual analysis tools in the system.

With CommCare, data of users are collected from mobile devices and analyzed data can be distributed back to mobile devices. The data collected in the cloud system are analyzed on CommCare Headquarters.

Sense Ebola is a mobile application developed for the Ebola epidemic that occurred in Africa in 2014. The purpose of the application is to guide healthcare professionals in a person registration and tracking process.

All these mobile application solutions produced in the Ebola epidemic left the contact tracing and patient tracing system data entries to the users in the central authority. In addition, decision support systems within these systems can make estimates to a limited extent.

A decision support system that can be developed for outbreaks needs to model the tackling epidemic correctly and be supported with AI techniques [20]. When the literature is examined, there are many epidemic modeling studies developed to predict outbreaks. While many of these studies model the previous epidemics, other studies have used mathematical models to predict ongoing outbreaks. Christakos et al. [21] published a book on this subject by making a detailed modeling study on the black death epidemic that caused a massive crime in Europe in 1347−1351. There are many epidemic modeling studies in the literature especially for the Ebola outbreak, and some of these studies are [22−26]. Local modeling studies are also available for the COVID-19 outbreak. Khrapov and Loginova [27] tried to develop a mathematical model of the outbreak in China. While Traini et al. [28] made a modeling proposal for the outbreak in Italy, Moghadami et al. [29] has done modeling work on the outbreak in Iran. All these models proposed for COVID-19 epidemic are theoretical studies and could not be integrated into a real-life application.

Although many of these studies are theoretical, there are some important applications that use mathematical epidemic models within decision support systems. GLEAMviz [30] is the most important one where different stochastic mathematical models and mitigation strategies can be defined and submitted directly to the system. Using real population and mobility data, it can simulate the spread of a disease around the world. Another decision support system is PandemCap [3] which is built based on an EU project. It is designed to be a common visualization and resource modeling tool that can be used during the outbreak period. It can basically perform simulations using mathematical models and mitigation strategies and resources such as hospital beds, vaccines, and ventilators. PanViz [31] is another epidemic modeling and visualization tool designed for public health officials. The tool, which was originally designed for the influenza pandemic, can display the spatio-temporal estimations on the US map, and simulations can be performed according to the factors affecting the spread.

The summary of these outbreak management or decision support systems are listed in Table 2.1 with their capabilities. Table 2.1 also compares our proposed system capabilities with the aforementioned systems.

Table 2.1 Comparison of outbreak management or decision support systems.

Capability	SORMAS	CommCare ebola	Sense ebola	GLEAMviz	PandemCap	PanViz	The proposed System
Surveillance	Yes	Yes	Yes	No	No	No	Yes
Contact tracing	Yes	Yes	Yes	No	No	No	Yes
Hospital data	Yes	Yes	Yes	No	Yes	Yes	Yes
Epidemic model	No	No	No	Flexible	Susceptible-Exposed-Infectious-Recovered	Modified Susceptible-Infectious-Recovered	SEIR + EM
Machine learning	No	No	Restricted	No	No	No	Yes
Management system	Yes	Yes	Yes	No	No	No	Yes
Decision support system	No	No	No	Yes	Yes	Yes	Yes
Open source	Yes	No	No	No	No	No	Yes
Data privacy	Encrypted	Encrypted	Encrypted	No	Unknown	Unknown	Blockchain
Privacy of personal data	No	No	No	No personal data	No personal data	No personal data	Yes

On the other hand, the use of AI in the fight against the COVID-19 pandemic has been an important topic of discussion recently and many applications have been introduced to the market [32]. Some of these applications are:

- Chatbots which assist patients,
- Applications that catch the early symptoms of the disease in healthcare workers who are at high risk of getting the virus,
- AI applications on diagnosis and also researches on coronavirus gene,
- Applications that predict how long patients can get worse and applications that tracks the hospital beds and materials or risky patient groups.

When mathematical epidemic models and machine learning techniques are used together, the course of outbreaks can be determined prospectively, and spatio-temporal risk regions can be determined. Thus, medical, sociological, and economic precautions can be taken in advance. In the light of this idea, the proposed system provides tools based on mathematical modeling and AI techniques to minimize the negative effects of the ongoing epidemic while maintaining the privacy of the citizens.

4. System model

The EMS is shown in Fig. 2.2 which is composed of the following subsystems:

1. **Mobile platform:** Mobile application will be developed for the clients. It should be user friendly, energy-efficient, Global positioning system (GPS) based, and supporting all possible communication protocols. Smart contracts will be used to access decentralized platforms.
2. **Decentralized identity platform:** The personal data will be kept in this platform and privacy-based implementation will be based on blockchain technology.
3. **Open data resources:** All available public and private resources.
4. **MiPasa blockchain:** It will be used for sharing quarantine-based data between countries and organizations.
5. **EMS DB and management panel:** Database platform and web management panel should be designed for the best performance and usability.
6. **Decision support system:** The decision support system will analyze all data resources and give estimation reports to the outbreak management system. IoHT sensors may be added to the system, and a digital twin like system can also be formed in the future.
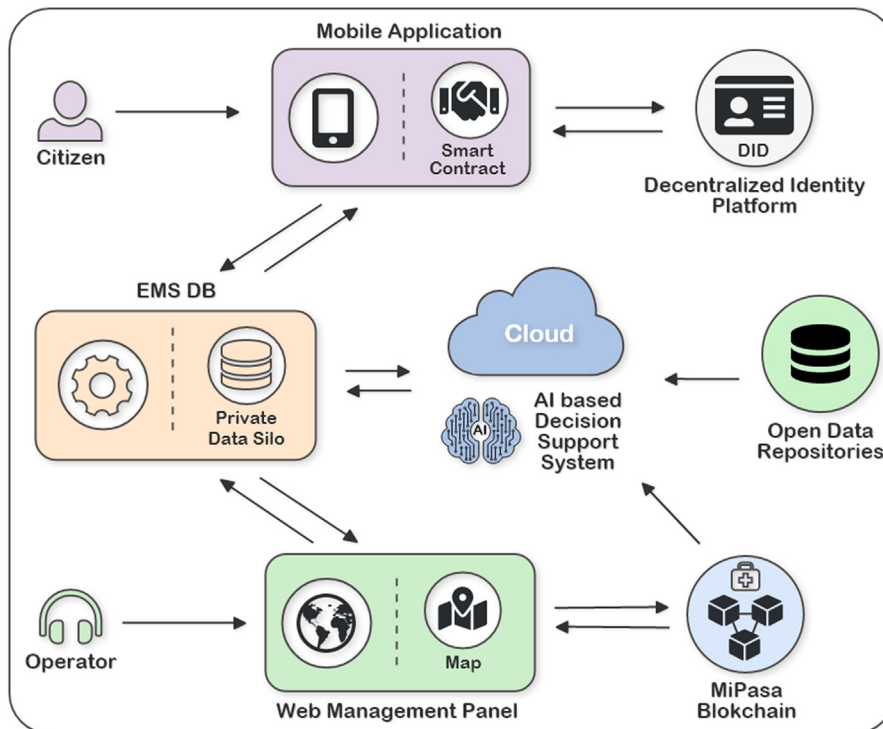

FIGURE 2.2 Epidemic management system.

Thus, a decision support system will be developed to assist in making decisions, providing medical needs and developing a kanban system. This decision support system should be designed to adapt all its operations according to different scenarios. In this way, the behavior of the epidemic can be modeled in any quarantine condition. Some data and estimations provided by the decision support system can be as follows:

- Virus spread rate estimates
- Virus spread region estimates
- Virus propagation centers and the rate of change in virus propagation over time
- Distribution of deaths through virus spreading centers
- Changes in mortality rates and outbreak estimates
- Analysis of the consumption of medical supplies
- Analysis of future needs of medical supplies
- Estimation of medical center occupancy rates
- Analysis of medical center needs of available beds
- Region-based quarantine measures recommendations by classifying regions

Details of such a system will be presented and discussed in the chapter.

5. Data resources

The integration of all different kinds of available data resources is needed. The system we have proposed can take different data and transform them into meaningful information for public health professionals. These data sources are as follows:

Mobility data: These data are spatiotemporal mobility data of infected patients obtained from the mobile epidemic-tracking application. These data provide important information about where the disease can spread and to whom. Privacy measures should be assured as it is described in the following sections.

Infectious disease data: Different stages of an infectious disease are shown in Fig. 2.3. Although these stages are known for diseases transmitted from person to person, the
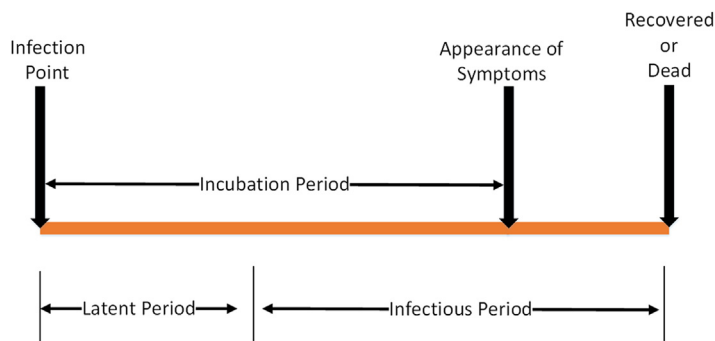
FIGURE 2.3 Different stages of an infectious disease on a person (Christakos et al., [21]).

time elapsed for each stage varies according to the type of disease and the epidemic region. Data on infectious diseases are used to create a mathematical epidemic model, and most of these data are probabilistic. Generally, they can be obtained directly from the literature. For instance, an instance of predictive parameters of COVID-19 is available in the MIDAS research network (https://github.com/midas-network/COVID-19).

Population and transportation data: Location-dependent population data and transportation lines can be entered into the system by the system users. On the other hand, demographic data for each country is open to everyone and can be obtained from https://www.populationpyramid.net/ directly. Since the spread of each infection varies with population density and age groups, population data plays an important role in decision making.

Meteorological data: The spread of an infectious disease usually varies depending on the weather conditions. Therefore, the system considers the meteorological data which are usually obtained from the central authority. For instance, the meteorological data for Turkey is presented by the general directorate of meteorology.

Hospital locations and resources data: Hospital location and hospital capacities (existing beds, ventilators, and necessary medical supplies) data can be entered into the system by the system users. These data are important for meeting the medical needs with a kanban system as well as significantly affecting the estimations of the mortality and transmission rates.

Scientific data: Scientific findings on the epidemic may be a source that can be used with decision making. Organizations such as the WHO, European Center for Disease Prevention and Control (ECDC), and the Centers for Disease Control and Prevention (CDC) have datasets in which some of them are publicly available. Several scientific publishers also made COVID-19 related publications freely available to the public. A global research dataset is available at WHO (https://www.who.int/).

International clinical trials are also being experimented in multiple countries for the treatment. These clinical trials can be downloaded from the WHO International Clinical Trials Registry Platform (ICTRP) (https://www.who.int/ictrp/en/) (Fig. 2.4).

The clinical trials dataset had 5343 rows (at the time of the writing), 40 fields; not all fields are entered for each record, and some fields have text data which includes detailed information. This dataset needs data cleaning as it also includes formatting text content like "
." An example record of inclusion criteria field is as follows:

Inclusion criteria: (1) Hospitalized patients with novel coronavirus pneumonia confirmed by pathogenic detection and (2) Meet any one of the criteria for severe type:

 (1) Respiratory distress: RP $\geq$ 30/min;

 (2) At rest, the oxygen saturation $\leq$ 93%;

Arterial partial pressure of oxygen (PaO$_2$)/Fraction of inspiration (FiO$_2$) (Oxygenation index, P/F) $\leq$ 300 mmHg.

 3. Aged 18—75 years;

 4. Signed informed consent.

FIGURE 2.4 World Health Organization international clinical trials registry platform.

Research-development company data: Research-development areas and related companies should also be known. Such a list will also help in seeing the status of the national and international companies, finding contact points for collaboration, finding alternative companies to produce resources like ventilators.

Supplier data: Company list for critical resources like test kits, masks, ventilators, their availability, estimated time for the shipment, and related data should be collected and be available. Such a list for Turkey was generated in social media during COVID-19.

Global data: As the epidemic becomes pandemic, we need global data that is shared between nations, NGOs, and related parties. The geographic distribution of COVID-19 cases worldwide can be downloaded from many resources such as ECDC; however, these data give limited information showing the current incident numbers with geographic distribution (Fig. 2.5). There are scripts to download this file into "R" software on their page [33]. The fancy graphics and maps (Fig. 2.6) are generated by similar datasets and lack details.

Google cloud hosts several COVID-19 public datasets [34] and allows query mechanisms for free during the pandemic. Data world Coronavirus (COVID-19) Data Resource Hub [35], Worldometer [36], and Kaggle also provide access to COVID-19 related data. One of the richest data repositories is from the Center for Systems Science and Engineering at Johns Hopkins University [37] which is a collection of several public datasets worldwide. As it is written in their Github page [37], there is no verification and validation mechanisms of these resources. Many of the other datasets on the web also lack of validated records.

dateRep	day	month	year	cases	deaths	countriesAn	geoId	count	popData20	continent	Cumulative_nu
8/27/2020	27	8	2020	55	4	Afghanistan	AF	AFG	38041757	Asia	2.05300717
8/26/2020	26	8	2020	1	0	Afghanistan	AF	AFG	38041757	Asia	2.10820967
8/25/2020	25	8	2020	71	10	Afghanistan	AF	AFG	38041757	Asia	2.67074941
8/24/2020	24	8	2020	0	0	Afghanistan	AF	AFG	38041757	Asia	2.48411239
8/23/2020	23	8	2020	105	2	Afghanistan	AF	AFG	38041757	Asia	2.48411239
8/22/2020	22	8	2020	38	0	Afghanistan	AF	AFG	38041757	Asia	2.31061883
8/21/2020	21	8	2020	97	2	Afghanistan	AF	AFG	38041757	Asia	2.41576644
8/20/2020	20	8	2020	160	8	Afghanistan	AF	AFG	38041757	Asia	2.26855978
8/19/2020	19	8	2020	0	0	Afghanistan	AF	AFG	38041757	Asia	2.02409158
8/18/2020	18	8	2020	3	0	Afghanistan	AF	AFG	38041757	Asia	2.23964419
8/17/2020	17	8	2020	45	5	Afghanistan	AF	AFG	38041757	Asia	2.32901966
8/16/2020	16	8	2020	120	7	Afghanistan	AF	AFG	38041757	Asia	2.21072859
8/15/2020	15	8	2020	7	0	Afghanistan	AF	AFG	38041757	Asia	1.89528575
8/14/2020	14	8	2020	79	9	Afghanistan	AF	AFG	38041757	Asia	2.3185049
8/13/2020	13	8	2020	76	10	Afghanistan	AF	AFG	38041757	Asia	2.29747538
8/12/2020	12	8	2020	215	32	Afghanistan	AF	AFG	38041757	Asia	2.09769491
8/11/2020	11	8	2020	0	0	Afghanistan	AF	AFG	38041757	Asia	1.80328159
8/10/2020	10	8	2020	0	0	Afghanistan	AF	AFG	38041757	Asia	2.07929408

FIGURE 2.5 Geographic distribution data.
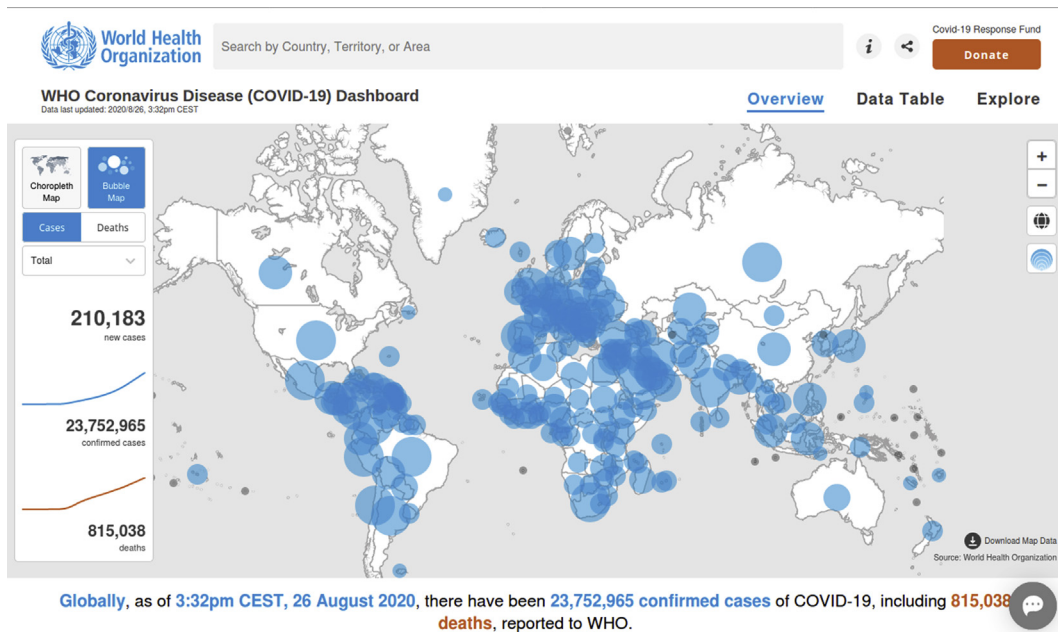
FIGURE 2.6 World Health Organization COVID-19 map. *From: https://covid19.who.int/*.

MiPasa blockchain [38] which is being developed with the support of the WHO can be used to serve as a reliable resource of information flow between nations and organizations. This or alike attempts have the potential to serve trusted resources of the information.

All these data should be transferred to the cloud and used by the decision support system and the management system. Big data management systems should be used.

6. Methods

The methods we will cover in this section is as follows:

- Mobile application−based tracking
- Decision support system
- Blockchain

6.1   Mobile application−based tracking

It is important to identify potential carriers and employ mechanisms that can be used to prevent the spread of the disease. The most common method is to learn from the infected person and try to understand who they were in contact with. However, the infected person may not know all the people who he/she met in the market or another place.

As most of the citizens have mobile devices, mobile applications can be used to track the possible infected citizens. Main aims will be:

1. Trace contacts of the infected citizen
2. Map spread of the virus and risky locations

A possible usage scenario is given in a recent study [39] and shown in Fig. 2.7.

However, such tracking applications are far from being perfect. The limits and privacy concerns are covered in detail in American Civil Liberties Union (ACLU's) report [40]. The data are collected through the following technologies [40]:

1. Location from cellular communication infrastructure
2. GPS Coordinates
3. Location from Wi-Fi, Bluetooth, or other radio
4. Quick response Codes

Infection is said to be possible with close contact with an infected person. CDC defines it as being within approximately 2 m and for a long period of time. None of the aforementioned technologies are accurate enough to detect with that precision [40]. However they may be useful to a point so many countries have started to build their own (https://en.wikipedia.org/wiki/COVID-19_apps).

As an example, China's search engine Baidu showed confirmed and suspected cases on a map layer on its map application (Fig. 2.8) in real-time so that people would stay away from those locations. This also included travel recommendations and epidemic control locations [41]. China was the first to make usage of a mobile application obligatory for its citizens. The public health risk can be calculated by several parameters, and the citizen is given color codes. These color codes can allow them to access shops (green) or oblige them to be in a quarantine (red) [42].
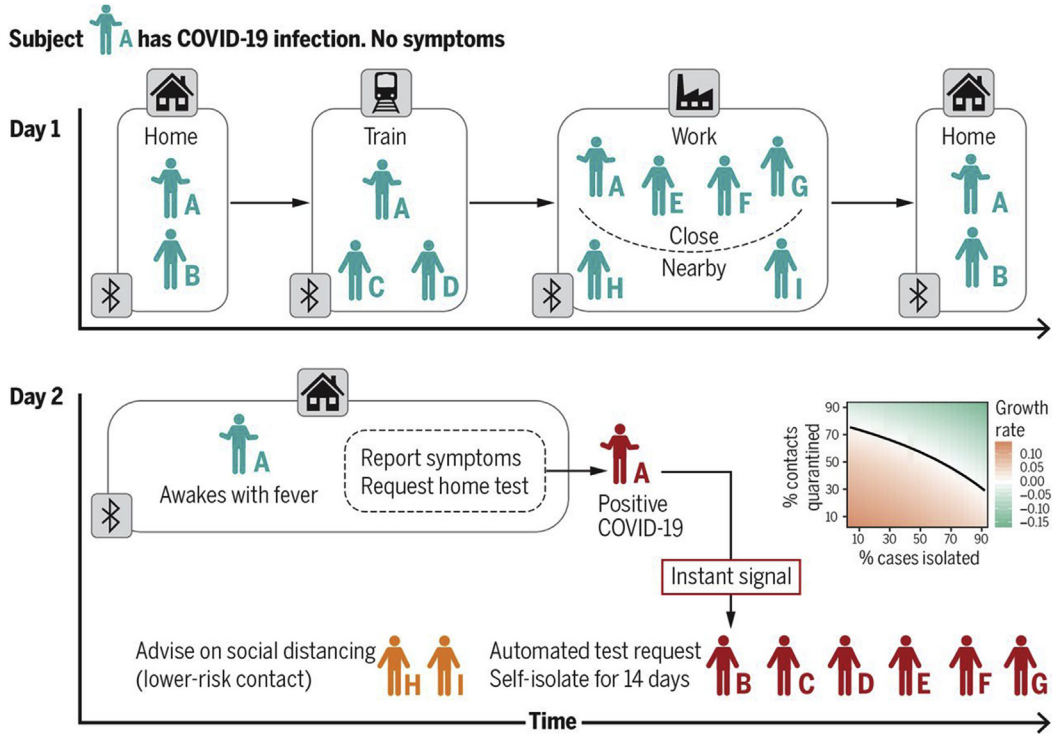
FIGURE 2.7 Possible usage scenario [39].

FIGURE 2.8 Baidu epidemic map [41]. courtesy of Baidu.

There are variations of such applications where mobile carriers are also involved to track people. Covid Takip (Hayat Eve Sığar) mobile application is used in Turkey. The reported incidents in Turkey show that the citizens' locations are tracked and old citizens are warned when they want to leave their locations. However, there is no obligation to install the Covid Takip software, but it is pledged that this application will warn you of possible risks around you and your loved ones. There is also a questionnaire to understand if you have possible COVID-19. You voluntarily serve information to the overall system after you install the software. The application has evolved as more citizens installed it and more data were feed to it. The application screenshot is given in Fig. 2.9 which shows the risky places in Muğla (Turkey) on August 27, 2020. The least risky places are colored with blue (gray in printed version) and the most risky places are colored with red (dark gray in printed version). However, there are some uncertain details about what percentage of the current situation can be given by this system and what happens when the infected people disable GPS, WiFi, and bluetooth on their mobile devices.

The cell phone manufacturers can also include such mechanisms in their operating systems. The recent news says that Android and Apple are preparing application interfaces which can be used for the health authorities' applications [43]. According to the recent white papers [44,45], short-range bluetooth communication is used and privacy is taken into consideration during design by using privacy-preserving cryptography. Data of proximity devices will be collected and kept on the phones. If the user installs official applications of the public health authorities, these applications will use
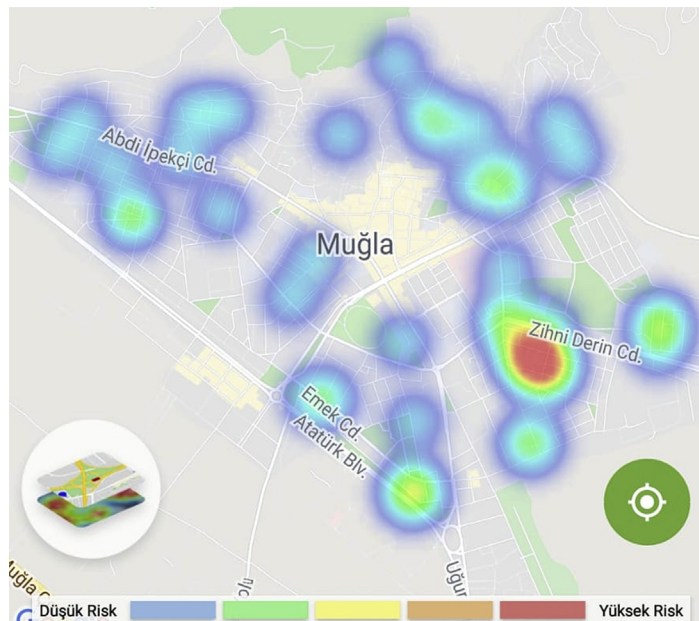

FIGURE 2.9 TR—life fills in home [hayat eve sığar] application risk map.

these collected data to understand if the user was in proximity to an infected citizen. The user should give consent to share his/her data and location. It is also said that these two firms will continue their work on integrating this functionality into their operating systems [43].

6.2   Decision support system

One of the most important components of the proposed EMS is the decision support system that uses several data resources. The proposed decision support system aims to make forward predictions and perform classification procedures to assist in resource and outbreak management. It includes two components to tackle these tasks. The first of these components is stochastic epidemic modeling, and the other is machine learning techniques. In the following subsections, epidemic modeling and machine learning techniques designed for the proposed decision support system are explained in detail.

6.2.1   Epidemic model

Different epidemic models are implemented in different studies. A recent research [46] implemented real-time visualization on the collected data and served country-based graphs on the "Covid19 Takip" website (https://covid19takip.com/). Autoregressive Integrated Moving Average (ARIMA) and SIR models are implemented for the prediction of the pandemic. Blue (gray in printed version) color for recovering, orange (light gray in printed version) color for the infected, green (mild gray in printed version) color for susceptible, red (dark gray in printed version) color is used for the observed values. The reliability of the used models is questioned in this study, and it is stated that the long-term nature of the epidemic and not including birth/death rates affects the accuracy of the model. The model will enhance the results in time with more data [46] (Fig. 2.10).
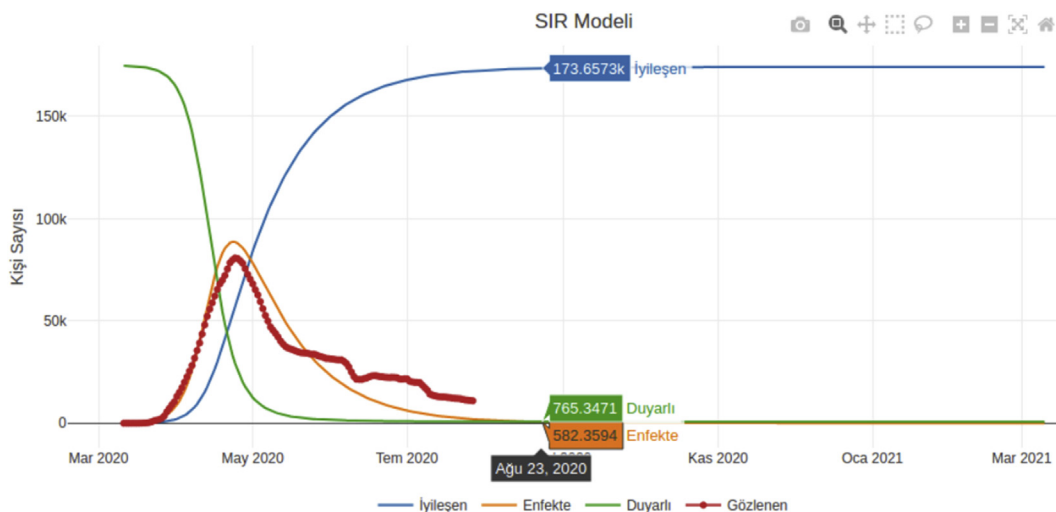

FIGURE 2.10 Susceptible-Infectious-Recovered model implementation (Covi19takip).

Although many of the epidemic models are deterministic, it is more appropriate to use stochastic models in the simulation of the epidemic distribution over space and time. This is because many parameters are uncertain in outbreaks as it is in many natural events, and data can only be made meaningful and transformed into useable information with the stochastic approaches [21]. For this reason, the expanded version of a stochastic SEIR model can be used in combination with the maximum entropy [47] approach. Moreover, the metapopulation model [48], in which different groups were created according to age ranges, can be preferred to enhance the proposed SEIR model. The metapopulation model contributes to the accurate estimation of hospital resources by simulating these processes over time. The following should be studied for each age group:

1. Spread and effect of infection: The spread effect of the epidemic in each population can be modeled according to each type of the infection.
2. Infection type: Each infection type (such as mild, severe, asymptomatic) should undergo a different treatment process.

To increase the accuracy of the SEIR model that we had proposed, several spatio-temporal data can also be included. These data are from various resources such as the data from MiPasa, the mobility data from the tracking application, demographic data, transportation data, hospital resource data (vaccines, number of beds, and ventilators), and the effects of preventive/mitigation precautions (curfew, social distance, isolation, etc.) implemented by the government agencies. Consequently, the proposed mathematical model provides important information to the public health professionals in estimating several cases such as estimating the virus spread rates and regions, mortality rates, number of beds, and ventilators needed in the medical centers.

6.2.2   Machine learning

In an epidemic, public health officials need to reach the third situational awareness level to identify the best decisions that can be implemented. However, in epidemics, data grows rapidly, and also many data contain uncertainties. In this case, decision support systems can be used as a solution. While one of the most important components of decision support systems is the outbreak mathematical model, the other one is the machine learning techniques.

Machine learning techniques have made significant improvements especially in the last 20 years and started to be used in many fields. However, the performance of many machine learning techniques significantly depends on making the right design decisions. In essence, for a machine learning service to be successful in a particular dataset, it is necessary to determine the effective machine learning technique, the appropriate pre-processing stages, and how to set the hyper parameters of all selected algorithms. Otherwise, it is not possible to get sufficient performance from the system. Solving this problem requires expertise in machine learning. On the other hand, even experts are often forced to use trial and error sections to determine the correct methods for a particular dataset. This task is time-consuming and costly.

Automated machine learning (AutoML) [49] can be used to create the most appropriate model in an automated and data-driven manner. With AutoML, only the data are evaluated and the best performing approach for the application is determined automatically within the candidate algorithms. Thus, even if every scientist is not familiar with the technologies behind them, he can use machine learning techniques with AutoML. Moreover, many automatic models produced by AutoML perform better than models created by the machine learning experts. Therefore, with AutoML, public health officials can quickly create the appropriate machine learning model against different large data sets and scenarios and make decisions right and fast.

The system we recommend uses the Auto-sklearn tool [50], which is based on scikit-learn [51], a machine learning library written in python. Auto-sklearn is designed to select the appropriate choices among 110 hyperparameters using 15 classifiers, 14 feature preprocessing methods, and 4 data preprocessing methods for a data set. In addition, estimation outputs of the epidemic model can be given as input to AutoML, and thus, the system can classify the predicted situations. The decision support system can perform the following classification and analysis tasks using AutoML:

1. Risk scoring can be done in the regions. Accordingly, each region can be classified as risk-free, low risk or high risk. It can be observed how this situation will change in the future.
2. Spread points of the infectious disease and contagious main transportation lines can be determined.
3. The condition of pandemic hospitals can be analyzed. Accordingly, hospitals can be classified by analyzing the condition of beds, ventilators, and other medical materials in pandemic hospitals. Thus, new cases in need of medical care can be directed to appropriate hospitals. On the other hand, the number of patients in the hospital intensive care units and mortality rates can be evaluated and the service quality of the hospitals can be scored. Thus, necessary steps can be taken to improve low-quality hospitals. Since the machine learning methods evaluate the estimation results in the epidemic model, the status of each hospital can be classified prospectively by evaluating the number of beds, ventilators, and medical equipment that may be required in the future. Thus, a suitable kanban system can be realized for each hospital.
4. The effectiveness of preventive or mitigation precautions taken by public health professionals or central authority can be classified. Thus, the precautions for an epidemic are learned with experience. Effective preventive precautions can be taken in the early stages of an outbreak that will arise in the future.

6.3   Blockchain

Blockchain can be used to provide the integrity, security, and privacy of the records. Autonomous codes called smart contracts/chain codes can be developed for the privacy issues of the personal/medical data.

The most efficient way to develop a blockchain-based system for a quarantine management system is to use an enterprise blockchain framework such as Quorum or Hyperledger Fabric. These solutions are recommended as they can provide blockchain solutions with the following characteristics:

1. Open-source environment and rich/active community support
2. No dependence or expense of any cryptocurrency
3. Easy development of smart contracts and a rich number of examples
4. Enabling confidential transaction records and ensuring privacy
5. Low-energy consumption

The nodes will be trusted and known, so energy-efficient consensus protocols can be used. The nodes can easily be set up with the blockchain as a service cloud services. The developer will then write autonomous codes that can run on the blockchain system.

DID systems can be developed to store the user credentials decentralized. The DAPPs can use autonomous codes (smart contract, chain code) to check the user identity with DID. Zero-knowledge proof-based mechanisms can be deployed to ensure the privacy of the personal data. The aim is to make the user be in control of how his/her data are shared with the others. These systems can be used autonomously to check the identity without revealing any private data [4].

Blockchain can be used to provide trustworthy data where different parties can write data. MiPasa [38] which runs on Hyperledger fabric is an attempt to integrate the verified data sources on a global scale. Data from the WHO, the United States CDC, Johns Hopkins University, and the Israeli Ministry of Health is being collected on this system. The protocol validates the original data and prevents the inconsistencies. Users of the system can also validate the data by reporting errors. IBM Watson is to be integrated for data analytics. Integrating ZKP for privacy is also planned [52].

MPISA model which is proposed in Ref. [4] involves integrating multiple platforms and is an attempt to solve the scalability and the interoperability issues. We recommend using the MPISA to share the common data in the blockchain and leave the private data in data silos. Blockchain infrastructure can be used to satisfy the security services; in this scenario, it will be used to share common data such as digital identities or global statistics about the pandemic.

The citizens will be in control of their personal identities by using DID systems. They will trust the system and use it. They will not try to abuse the system or find methods not to use the system. This will all increase the system's overall efficiency in fighting the epidemic. Keeping global statistics and global data in a blockchain structure will serve a trustful data source. MiPasa [38] is an attempt to serve such a purpose.

Keeping data in blockchain will also be useable as a central database where different parties can write at the same time. This will be useful in recording such data in various data silos and preventing inconsistencies between several copies. Such a design is a complex task without blockchain. Synchronized data will be available to all users of the

system and the maintenance costs of these data across systems can be reduced. We recommend using the blockchain to keep only links to actual data. The actual data can be kept in cloud or distributed storage [4,53].

7. Conclusion

Human impact on wildlife seems to be the cause of this disease. As US biologist Thomas Lovejoy says "we need more respect for the natural world" [54]. However, this disease is not the first and probably will not be the last one. We have to devise proper ways to handle this and the next diseases.

Humanity's response to the COVID-19 pandemic showed that we were not ready. There are many reasons for that. First of all, we can say that the world we live in is only interested in profit, and technology solutions for such diseases were not in the interest of the technology companies. We can summarize the technical issues as follows:

- Software development issues: The developed solutions mostly do not meet the demands of the fieldworkers. People from the field should be involved from the design phase to the test phases in the software development life cycle.
- Visual design issues: The generated systems are not always user friendly and can lack proper visualization.
- Runtime latency: The latency occurred during operations may result in unused systems.
- Technology issues: The technology used for AI (machine learning) is not perfect and mostly needs to be supervised which has a cost.
- Data science: Usage of improper machine learning models and improper parameters which gives wrong results.
- Data collection: Collected data mostly does not include detailed data (health issues of the patient, population density, age groups, gender etc.), lack of which will affect the accuracy of the machine learning models.
- Data coverage: Not enough international and cross-organizational data sharing.
- Being specific and limited: The systems usually have specific and limited usage.
- Trust and privacy: Users do not trust and do not use the system because of the privacy issues.

Real-world examples are given in this chapter. Data should be collected from different verified resources, and inconsistencies should be solved. Data should be aggregated; analytics and decision support systems should be developed. System developers should be aware of laws and their data protection responsibilities [15]. Epidemic times can be considered as exceptional, but this must be temporary. The privacy concerns of the citizens should be answered; these type of data collection should only be done in pandemic times. The life cycle of the collected data should be explained briefly to the citizens.

We proposed a model and gave the state-of-the-art technology that can be used in an EMS. This model uses mobile technologies, blockchain, modeling, and AI technologies. The system is designed according to the MPISA model. Such a system has several modules to be developed and research questions to be studied. Considering the spread rate of epidemic diseases, it is necessary to propose machine learning methods that can respond to the needs as fast as possible. One of the most important contributions of our study is proposing a decision support system based on automatic machine learning and stochastic epidemic modeling. We have proposed an extension of the stochastic SEIR model combined with the maximum entropy and enhanced with a metapopulation model. The use of AutoML techniques has been proposed for the first time for decision support systems developed for epidemics as well. Beyond them, proposing a decision support system that improves the outbreak management system is an important contribution in medical informatics.

The proposed system includes decentralized technologies that can be used for trusted systems. DID management systems can be devised to ensure the privacy of the citizens. However, these systems and zero-knowledge proof mechanisms are not mature yet. Decentralized structures like MiPasa can be used for verification of the resources and validation of the records.

AI can be used for blockchain; blockchain can be used for AI. The applicability of these two models on epidemic management should also be researched. Digital twin-based medical systems can also be developed. We believe that these questions are worth studying. Our joint team will be studying these topics in the future studies.

We will be facing the post COVID-19 world and we hope humanity will take enough lessons from now on.

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