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### Chapter

## Artificial Intelligence (AI) in Evidence-Based Approaches to Effectively Respond to Public Health Emergencies

Lap Yan Wong, Chun Kit Yip, Dao Shen Tan and Wai Lim Ling

#### **Abstract**

Artificial intelligence (AI) techniques have been commonly used to track, predict early warning, forecast trends, and model and measure public health responses. Statistics have traditionally been used to track public health crises. AI-enabled methods, such as machine learning and deep learning–based models, have exploded in popularity recently, complementing statistical approaches. A wide range of medical fields have used various well-developed deep learning algorithms. Surveillance of public health emergencies is one region that has gained greatly from AI advancements in recent years. One of the examples of effectively reacting to public health emergencies is the need for developing AI evidence-based approaches to public health strategies for the scientific community's response to the COVID-19 pandemic.

**Keywords:** Artificial Intelligence AI Public Health Emergencies

### 1. Introduction

In the first two decades of the twenty-first century, two big deadly epidemics posed a global public health challenge. Infectious disease known as serious acute respiratory syndrome (SARS) cases first appeared in 2002, and a novel coronavirus (SARS-CoV-2) was reported as the etiologic agent in coronavirus disease 2019 (COVID-19), with the start of a new outbreak at the end of 2019. SARS spread to five continents, prompting the World Health Organization (WHO) to declare the outbreak was caused by a novel pathogen, a member of the coronavirus family that had never been seen before in human history [1]. In 2019, a mysterious pneumonia outbreak occurred in Wuhan, China, which the WHO classified as a pandemic in March 2020 [2]. Globally, cases have been recorded in over 20 nations, regions, or territories across five continents [3].

The world is in the midst of a time of recurrent crises, and conventional crisis management models are struggling to cope with today's dynamic crises. The new crisis management system should be converted from a passive crisis response to a dominant crisis management system. It is essential to develop a modernization management system for effective crisis response, which should include the

immediate implementation of basic preventive measures against emergencies, as well as accurate and rapid diagnosis for containment and clinical management. Furthermore, new developments in disease-related applied research and technology would be needed to slow the COVID-19 pandemic's spread.

The fields of medicine, research and development, and public health are all being transformed by artificial intelligence (AI) [4]. AI has taken over some routine tasks in the last decade, and its effect on repetitive tasks has already begun. We have all witnessed the information revolution, which in just a few decades has totally transformed the way people operate. The AI era has also resulted in the creation of intelligent advanced solutions for different aspects of life: AI can be used to optimize quantitative activities on a wide scale; it can be used to measure and practice a planned action or project under various conditions; and it can be used to assist in job optimization processes in various industries.

AI has reached a crucial juncture in its growth and implementation. Artificial neural networks, machine learning, and deep learning are examples of AI systems that have made substantial progress. In several tasks, AI algorithms have been able to mimic or even outperform the human brain. Machine learning, as opposed to traditional statistical analysis methods that use a predetermined equation as a model, can account for all interactions among variations and integrate new data to update algorithms [5]. Due to their important information processing properties in terms of nonlinearity, high levels of parallelism, noise and fault tolerance, as well as learning, generalization, and adaptive capabilities, AI systems are advantageous [6]. AI is not only a tool for assisting humans with all types of technological and mental tasks, but also an extension of their senses and abilities.

There is an immediate need for safety assurance and cost efficiency in the management of public health crises as a result of the recent global epidemic. Public health surveillance has benefited greatly as a result of recent AI advancements. There is an increasing body of knowledge in the field of AI-enabled and AI-enhanced public health monitoring research [7]. AI is becoming increasingly important in evidence-based approaches to efficiently respond to public health emergencies.

### 2. Public health emergency

### 2.1 Definition of public health emergency

Public health emergencies are a subset of public emergencies that are related to health incidents and have an inclusion and exclusion arrangement with public emergencies. The Emergency of Public Health (Emergency of Public Health) is described as "mainly including infectious diseases, mass diseases of unknown origin, food safety and occupational hazards, animal epidemics, and other events that seriously affect public health and life safety" in the "China National Overall Emergency Plan for Public Emergencies" promulgated on January 8, 2006.

### 2.2 Overview of AI application in public health

2.2.1 The stage of crisis recovery is important in the management of public health

The recovery phase in public health crisis management refers to the stage during which the crisis is gradually alleviated and eliminated. The flow of factors that trigger disasters has slowed, and public health emergencies have been effectively addressed. The government's goal at this time is to reduce the impact of public health crises, contribute to social and economic recovery, summarize crisis management flaws, and improve the experience of managing public health emergencies in crisis.

It is critical to use AI and other technologies to promote the resumption of work and development in order to ensure sustainable and stable economic growth. Intelligent network systems have been used in China [8] to carry out online workplace, online teaching, and other activities. Companies must "not close" during the epidemic, and schools must "suspend classes without suspension." During the nationwide "war epidemic," AI networks such as WeLink, DingTalk, and Tencent Conference were widely popularized in order to minimize the losses incurred by shutdowns and output shutdowns, which played a positive role in reducing crowd gathering and reducing the risk of cross-infection while going out [9]. On the other hand, using a big data platform to analyze the migration and traffic situation in each region, as well as AI technology to prevent the epidemic from resuming, and to genuinely achieve safe resumption of work and development. Manually processing these data makes it difficult to ensure the data's validity and timeliness. Experts use AI to assist them, collect crisis-related data, and determine the type of crisis [10]. Moreover, AI calculates the severity of the crisis' effects and analyzes the causes of the crisis. Furthermore, AI allows for early detection of a problem, allowing for more time to deal with it.

### 2.2.2 The use of AI to predict the results of public health emergencies

The period in which the crisis will break out in the crisis management of public health crises is referred to as the preparatory stage of crisis management for public health emergencies. Since the onset of public health emergencies is uncertain and unpredictable, it is important to track and alert them. For this stage, improving the ability to monitor and respond to public health emergencies is the main focus of the government's work. The preparatory stage of crisis management for public health emergencies consists of two parts: crisis early warning, crisis training and exercises [10].

Early notice of public health crises is a vital task in the planning stage of disaster prevention. When a crisis occurs, successful early warning will significantly speed up the organization's response time. To develop an infectious disease outbreak early warning system, governments of various countries currently depend primarily on conventional surveillance methods (collaboration of medical institutions at all levels, disease prevention and control centers, and influenza-like case monitoring sentinel hospitals, and medical institutions diagnose and record clinically diagnosed and confirmed cases of influenza). However, there are some disadvantages of this monitoring system: the data collected is from a single source, and there is no comparison or correction of data from other sources; the data acquisition process of daily sampling and weekly summary, the data results are comparatively lagging; the monitoring consumes a lot of manpower and material resources, and the monitoring covers the entire country; the monitoring consumes a lot of manpower and material resources, and the monitoring covers the entire country. The accuracy of the data would be affected by an error in any node in the network [10]. The use of AI to perform infectious disease forecasting and early warning work, as well as monitoring social media, online news posts, and government reports for signs of infectious disease outbreaks, can significantly assist relevant government agencies in keeping track of the epidemic, rationally allocating medical resources, and improving advances. The cost of national disease prediction and infection prevention and control is reduced by the success rate of prevention.

By scanning foreign language news stories, animal and plant disease reports, and various official statements, the AI system provided alerts to its customers, recognizing the first foreign alert of the epidemic at an early stage. Machine learning has been used to track, locate and report on infectious spread. It provides alerts to a wide range of clients, including health care, government, industry, and public health organizations. It also serves as an alert about the existence of a new coronavirus [11]. In several aspects of the global battle against the epidemic, AI has already played a valuable but fragmented role. Screening, contact tracing, contact alerts, diagnosis, automatic deliveries, and laboratory drug discovery are only a few of the applications. AI has already played a useful but fragmented role in many aspects of the global fight against the epidemic. It has been widely used in screening, contact tracing, contact alerts, diagnosis, automated deliveries, and laboratory drug discovery [11]. It also predicts whether or not a person is infectious in advance, as well as the seriousness of the infection. By doing some general data analysis, one can significantly reduce waiting time, determine whether or not one has come into contact with virus carriers, and prevent the virus from spreading. Systematic planning and drills are an important way to enhance emergency response in the event of a disaster. Knowledge map technology can be used in public health emergency training to combine and link all of the information in the knowledge base and create a bottom map that covers all knowledge and records the connections between knowledge and knowledge, significantly increasing the scope and depth of training. The use of AI technology to perform public health emergency simulation exercises, build public health emergency simulation scenarios, deduce public health emergency handling protocols, and summarize the effects of public health emergency crisis exercises. It will help the government assess the epidemic's condition, develop decision-making and deployment capabilities for epidemic prevention and control, and test a range of mature response plans in simulation, setting the groundwork for potential rapid response and precise policy implementation in actual combat in the future [18].

Is it a Cough or a Covid? COVID-19 Detection Using Artificial Intelligence from Cough Sounds.

Increased disease screening and early warning capabilities can help to dramatically delay the spread and effect of a disease. Recent progress in developing deep learning AI models to classify cough sounds as a COVID-19 prescreening tool has shown early promise. Cough-based diagnosis is a non-invasive, cost-effective, and scalable method of diagnosing COVID-19 that, if approved, could be a game-changer in the battle against the virus. Cough sounds have recently been tested as a preliminary diagnostic or a prescreening technique for Covid-19 identification in asymptomatic individuals by AI researchers [11]. This is advantageous because the virus can trigger subtle changes in the body that can be identified by complex algorithms combining audio signal processing and machine learning, even though no symptoms are present. This technology may also be more efficient than the standard strategy of prescreening for COVID-19 based on temperature, especially in asymptomatic patients.

### 2.2.3 AI accelerating healthcare outcomes

AI expands data access. AI's predictive ability is based on the volume and variety of data available; optimizing emerging tools requires extensive data access across the healthcare ecosystem. To prevent gaming of findings and prejudice, data scientists must commit to robust research over several parameters. AI allows for more concentrated collaboration. Thousands of inputs must be incorporated by scientists and technologists in collaboration with clinical specialist physicians,

including lab results, vital signs, drug administration, prescription doses and durations, length of stay in hospital, and patient and hospital demographics, to name a few. Clinicians can participate in the validation process and feature engineering for each organ- or condition-specific version of an AI surveillance system so that the solution can produce customized, actionable risk scores that clinicians will use. Moreover, transparency in clinical surveillance is aided by AI. These surveillance solutions can enable clinicians to apply their own clinical judgment to the performance by offering a visual representation of how and why AI made the predictions. Any AI-enabled tool should do the same thing to promote clinician buy-in and the requisite change management for widespread adoption.

### 2.3 AI aids decision-making by simulating a real-life epidemic

The government's approaches or policies to combat the outbreak are unquestionably important in effectively controlling the virus's spread. AI can be used to help them make the best decision possible.

Key parameters that define the characteristics of the spread, such as the transmission rate, incubation time, population density in the region, and so on, can be used to create a simulated model that mimics the actual environment of pandemics.

Following the development of the environment simulator, Reinforcement Learning can be used to determine the best strategy for achieving our aim of preventing virus spread while minimizing economic costs.

#### 2.3.1 The SIR models

A simple compartmental model in epidemiology, known as the SIR model, is commonly used to simulate the spread of disease [12]. *S* represents the number Susceptible/Healthy individuals, *I* represents the number of Infectious individuals and *R* represents the number of Recovered individuals. It can be modeled by the below set of ordinary differential equations:

$$\frac{dS}{dt} = -\frac{\beta IS}{N}$$

$$\frac{dI}{dt} = \frac{\beta IS}{N} - \gamma I$$

$$\frac{dR}{dt} = \gamma I,$$
(1)

where N is the total population,  $\beta$  is the probability of disease transmission in a contact between a susceptible and an infectious subject.  $\gamma$  is the probability of an infectious individual being recovered in dt.

### 2.3.1.1 The agent-based model

The SIR model is a fundamental model for studying individual flow between compartments, assuming that all individuals within a compartment are homogeneous. An Agent-Based Model is developed to simulate the behavior of heterogeneous individuals, taking into account their characteristics [13, 14].

We may, for example, identify various types of agents, such as individuals, families, businesses, and governments, and then enable them to communicate with one another. Each type of agent may have different attributes, such as age, location of the person, location of the house/business, and wealth of the agents. Different activities, such as going to work, going home, or making business connections, can be simulated at different times.

Different social, epidemiological, and economic parameters, such as individual mobility, incubation, transmission, recovery time, income, and GDP, must be specifically defined by domain experts, using empirical evidence, or designed by the author to simulate the attributes and actions of agents. During simulation, the economic impact and pandemic statistics, such as individual wealth and the number of active cases, can be generated for evaluation.

### 2.3.1.2 Reinforcement learning

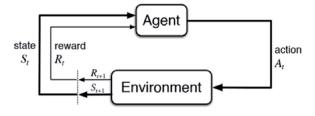
Reinforcement Learning (RL) is an area of machine learning that focuses on learning strategies or sequential decisions in order to optimize long-term reward in the defined environment.

A basic reinforcement learning model is shown in **Figure 1** [15]. It involves an Agent who interacts with the environment in each time steps by taking different actions. At time t, the agent will receive the current State  $S_t$  of the environment and the current Reward  $R_t$ . The agent will perform Action  $A_t$  based on the *policy* and  $S_t$ . Then, the environment will move from current State  $S_t$  to the next State  $S_{t+1}$  and the associated "reward"  $S_t$  will be output. The state  $S_t$  and reward  $S_t$  will be fed back to the agent. The process iterates until the terminal state is reached. The goal of the model is to learn the *policy* which optimizes the cumulative reward.

To train the RL model and learn the optimal policy, one way is to use Monte Carlo Tree Search, which is a searching algorithm to determine the best moves. It repeated the process of "Selecting → Expanding → Simulating → Updating" to update the nodes in a tree (Figure 2) [16]. Each node in the tree represents the action we can take, with a node value which can be the probability of winning or the expected reward. At "Selecting" stage, we select the path by the value of the node until we reach the leaf node at the end of the branch. At the leaf node, we "Expand" by randomly choosing the action from the action space. Then, we "Simulate" the complete rollout, until the terminal state and obtain the final cumulative reward. The reward will then be backpropagated to update the values in each node along the path.

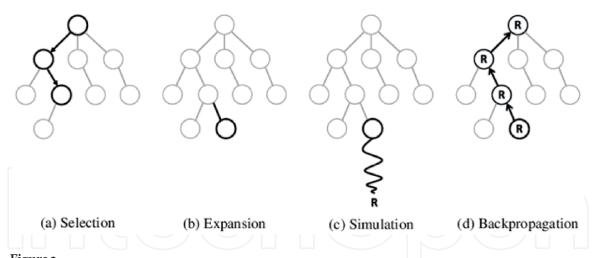
RL, in combination with the Agent-Based Model and the SIR model, will help the government make the best decision possible to combat the pandemic [17]. The state and the environment in RL can be simulated by the Agent-Based Model and SIR Model.

The reward function can be designed based on the pandemic statistics and economic statistics generated from the Agent-Based Model. The trained RL model will



**Figure 1.**Basic reinforcement learning model.

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**Figure 2.**Phases of the Monte Carlo tree search algorithm. A search tree, rooted at the current state, is grown through repeated application of the above four phases.

be able to advise the government on the best course of action to take at various stages of the pandemic and scenarios in order to contain the pandemic with the least amount of economic effect. The agent is to be trained with empirical demographic data, pandemic data and economic data in pandemic time to simulate the impacts of policies conditioned with the predicted pandemic data. An Action space can be defined. Social distancing, lockdown, company and school closures, wearing a face mask, doing nothing, public hygiene promotion and so on. The impact of policies can be highly dimensioned vectors and subject to execution error. However, all these attributes can be inputs of the simulations and the prediction error can be reduced by more data input.

With the numerous simulations, government can have a full profile of impacts of policies to be taken in different scenarios by making assumption on the parameters of the effectiveness of policy, say the shut-down of schools reduce the younger age group infection by {38.2%, 50%, 61.8%}, and the impact of this reduction can be propagated to other age groups through a trained Boltzmann Machine which depict the dynamics of infection rate between the age groups. The fidelity of the simulations is correlated with the complexity of model and number of data used to train the model.

The reward functions can deviate across regions; however the reward function can be designed based on the pandemic statistics and economic statistics generated from the Agent-Based model. The trained RL model would allow the government to select the optimal policy and evaluate the drawbacks before the policy is implemented.

### 2.4 Public health emergencies accelerate the implementation of AI

Many AI technologies, such as robots assisting in hospital transportation, have accelerated as a result of the epidemic's social isolation. One of the most contentious examples is contact tracing. Many countries around the world have successfully developed contact tracing systems, allowing them to efficiently monitor the epidemic's spread. This strategy, however, is seen as an infringement of privacy in the United States, Europe, and other countries. Although it has a bright future, there are challenges in the areas of privacy, data processing, ethics, and social issues. When it comes to medical information, these questions must be seriously addressed in the light of public health or personal health. During a public health crisis, the government must strike a balance between citizens' rights and the need for effective prevention and control measures to efficiently control disease transmission until the outbreak is over, and then return to normal.

No one wants to replicate the epidemic's mistakes. AI will be used in the future to prevent epidemics from arising and spreading. Hospitals will make effective use of sensors and wearable devices to collect outbreak data and report possible hazards in a timely manner, allowing them to properly respond to the crisis and avoid losing control again. Inevitably, privacy concerns would arise in the former. There are some notable inconsistencies between privacy rights and the requirements of machine learning. Although privacy security necessitates as little data sharing as possible, machine learning necessitates as much data as possible. Many countries are concerned that misuse of contact tracing could compromise privacy, so they have developed and implemented a variety of privacy security technologies. AI techniques, processes, and technology are being used to develop health care and programs. The good news is that they can coexist, and AI is a double-edged sword that can help to foster global governance and cultural change.

### 2.4.1 AI enables and promotes medical reform and public health emergencies by speeding up their incorporation into the medical system

Deep learning has the ability to process multidimensional data at high speeds while also facilitating the recognition of unique features, making it one of AI's most far-reaching applications. Deep learning and deep neural networks have already been widely used in a variety of medical applications, including medical image recognition, drug design, decision support, and predictive analytics, to deliver accurate and rapid algorithmic interpretation [18]. A straightforward blueprint for how AI will be infused into health care as a result of the pandemic. The most accurate insights into health and disease can come from all of the world's results. AI will assist us in being adequately prepared for the next pandemic, efficiently responding to public health monitoring and emergencies, and advancing global healthcare systems.

### 2.4.2 AI-enhanced data analysis for outbreak detection, early warning and flow adjustment

In order to enhance the timeliness and accuracy of outbreak detection and early warning approaches, public health researchers continuously analyze and explore sensor data and indicators to and from the physical world, including health, environmental, social, financial, and economic aspects, among others. Deep learning has been used to identify multiple infectious disease outbreaks. A dynamic neural network model was created to predict the probability of infectious disease outbreaks in the United States, such as Zika virus (ZIKV). Decisionmakings can easily modify the risk of an indicator, the risk classification system, and the forecast window for prediction based on their own unique needs [19]. Support vector machine (SVM), gradient boosting machine, and random forest (RF) were applied to simulate the global distribution of infectious diseases. To train the models, multidimensional and multidisciplinary datasets were qualified and quantified, such as social variables, incident medical records, high-risk areas, and cyberspace data. The suitability of the temperature has been stated to have the best discriminatory power among variables, and random forest (RF) is known to obtain the highest area under curve (AUC) value [20]. Each bootstrap sample was fitted with an unpruned decision tree. The risk maps were accurate in over 80% of the observed risk ranks falling within the 80% prediction interval, according to random bootstrap samples drawn from the results [21]. The use of data from

the cyberspace, such as keyword google searches, Key Opinion Leaders' blogs, and social media networking messages, has taken significant effort. Machine learning has been used for sentiment analysis and text classification from social media data for surveillance purposes. In India, a social media-based early warning system for mosquito-borne disease has been proposed [18].

2.4.3 What are the latest effects of intelligent early detection of infectious diseases, and what does this mean for the global battle against the epidemic in the future?

There are a number of major effects: For instance, there was no intelligent big data research in the past. The network accounts of various hospitals could not be compared after a single patient was diagnosed with an infectious disease. Now, using AI's dynamic perception, the device may display an outbreak or cluster of infectious disease under uncommon conditions in real time via case reports. Second, the use of AI technology to evaluate the infectious case's time, space, and meteorological factors may have an effect on the local agricultural product market and economic conditions. Third, disease patterns can be forecast and early alerts for key ties can be issued using infectious disease data and local environmental monitoring. While AI's dynamic models of infectious diseases are consistent, the neural network model of experts must be introduced because infectious diseases have different epidemics in different regions.

### 2.5 Suggestions for accelerating AI-enabled public health emergency crisis response

### 2.5.1 Strengthen scientific research

The AI industry should concentrate on core technology research and development in order to address technological challenges. Overall, the application of AI technology for disease prevention and control is still in its early stages of growth. Furthermore, AI also has an inexplicability that prevents it from being fully incorporated into the epidemiological system. The use of AI technology in disease prevention has been hampered by the lack of timely data collection and integration capabilities. As a result, play a bigger role in command. Epidemic modeling can be used to perform theoretical research on interpretability and improve the processing of large multi-dimensional data to this end.

### 2.5.2 Expand AI application scenarios

AI has been commonly used in the medical field as a result of continuous optimization of medical data and algorithm models. AI has achieved a great improvement in work efficiency in a subversive way, particularly during this special time of the new crown epidemic, and has spawned new demands. The use of AI has demonstrated quick landings, a wide range of effects, and major effects. However, AI in disease prevention and control is still in its early stages of research, and there are still flaws and issues in many areas. The use of AI in disease prevention and control should be thoroughly investigated, and a set of creative and reliable AI approaches should be used to aid in the detection and treatment of epidemics, as well as to minimize the risk of staff cross-infection. Improve disease management and control effectiveness, and provide strong scientific and technical support for winning the fight against epidemic prevention and control.

### 3. Using AI to solve the issue of public health emergencies

AI models have been applied to detect outbreaks of infectious diseases. Researchers have a long history of successfully developing a global outbreak surveillance approach using Internet-based approaches. Internet-based disease tracking approaches have provided a real-time alternative to conventional indicator-based public health disease surveillance [22, 23]. Internet-based monitoring systems use a range of open-source Internet data, including online news and social media, as well as other Internet-based data sources, to detect early warning signals of threats to public health. AI techniques have played a significant role in a series of data processing and analysis activities. AI techniques have recently become popular for completing tasks in highly dynamic, complex, and data-rich environments. In the modern age of public health approaches, it is critical and important. Machine learning and deep learning as AI core technologies are among the most important, methodologically, for fundamental and increasing interests, intense research activities in the interdisciplinary field of AI. Despite the impressive list of achievements already achieved, AI technologies in the sense of public health and public health monitoring are still in their early stages of growth, with a lot of potentials yet to be realized. Outbreak identification, early warning, trend prediction, and public health evidence-based approaches effectively response modeling and assessment are among the core tasks of public health surveillance and response, particularly in light of the current COVID-19 pandemic.

### 3.1 Using AI to deal with public health emergencies

By pinpointing specific demographics or geographies where population health issues exist, AI and machine learning can help to target and precisely implement education and treatment programs and reduce spending waste. AI enables computers to mimic the cognitive function of human minds, and machine learning gives computers the ability to learn without being explicitly programmed. By using AI and machine learning to review vast sets of real-time data, health experts can identify at-risk populations for any number of diseases, from diabetes to heart disease. Throughout the coronavirus pandemic, the industry has witnessed the power of clinical surveillance. With a broad array of discrete tests that can identify a COVID-19 infection, health systems and public health authorities have needed a way to interpret and track the patients with infections.

### 3.1.1 Connecting the data with surveillance

Data is at the heart of clinical surveillance. When data is combined with evidence-based clinical decision support, a single source of reality can be created that connects the disease's related symptoms, allowing for the discovery of how quickly a disease is progressing and what lab tests reveal. Keeping up with the latest advances in medical terminology and the related diagnosis and procedure codes is critical for recognizing clinical patterns as well as securing support, funding and reimbursement. Many health systems have transitioned to finding out the patterns in COVID-19 and better predicting respiratory and organ failures associated with the virus, despite being reluctant to implement technology in the past.

When the pandemic struck, healthcare providers immediately shifted their focus to include COVID-19 updates in their clinical surveillance activities. Hospitals and healthcare systems have been able to proactively monitor patient status for earlier interventions and broaden data flow in significant ways with a centralized, global

view of COVID-19 cases coupled with real-time alerting. Age, where the disease was possibly contracted, if the patient was examined, and how long the patient was in the ICU are only a few of the important patient measurements that have been monitored. Patients' pre-existing conditions were taken into account during surveillance. This data trail assists providers in developing a constantly evolving coronavirus profile and provides key data points for reporting to state and local governments and public health agencies. Clinical monitoring now brings together information from various areas of the hospital and clinics into a centralized view of COVID care, such as lab results, patient data, co-morbidities, mortality, and drugs, since there are no other ways to put together seemingly fragmented information.

### 3.1.2 COVID-19 accelerated AI advancements

COVID-19 puts people at risk of sepsis, so they wanted to identify those who were most at risk. Many AI-powered fast-tracking techniques were put to the test. This health epidemic shows what can be done to anticipate and avoid a variety of chronic health concerns. This technology can then be used to save lives and money in cases where prevention has proven to be ineffective. To achieve those savings, it is necessary to refine the use of AI for clinical surveillance; 2) extend access to everything from electronic health records (EHR) to knowledge that exists outside of direct clinical settings, ranging from the omics to social determinants of health; and 3) differentiate AI hype from solutions that offer proven, actionable insights for specific clinical concerns.

### 3.1.3 The future of AI's prospects in clinical emergencies

Though COVID-19 appeared to be a test ground for machine learning and AI, the industry had been focusing on harnessing technology's power for healthcareassociated infections (HAI) for some time. According to publicly available reports, HAIs cost the US healthcare system up to \$45 billion a year [24]. On any given day, about one out of every 31 patients will be infected with at least one HAI [25]. One example is *C. difficile* infections (C. diff). C. diff raises the risk of inpatient death and duration of stay, putting hospitals at risk of financial penalties. Machine learning, on the other hand, will predict which patients are at risk for C. diff infection, allowing physicians to treat patients more effectively and avoid the spread of the infection in hospitals. Hundreds of thousands of variables that may lead to C. diff, as well as how those factors interact, are analyzed using machine learning. It is always learning and incorporating new data and information. Machine learning, when used in a clinical surveillance system, may identify at-risk patients before their infection progresses, adding variables that physicians frequently find difficult to detect when handling several patients, as well as conditions that are outside of their normal scope of practice.

Rules-based systems are less effective for these "edge" scenarios, as researchers know, since each new data feature necessitates a new rule. AI at warp speed will help hospitals and communities respond to complex cases like COVID-19, C. diff, and even sepsis until clusters, outbreaks, or critical medical emergencies worsen. Clinical surveillance based on AI can monitor when relevant factors arise in a specific way and understand how timing plays a role in interactions. Time is difficult to incorporate, but recognizing when the white blood cell count has increased or decreased, for example, is crucial to make reliable C. diff predictions.

These types of forecasts can make a huge difference in clinical emergencies like brain injury, heart arrest, and respiratory failure in healthcare organizations all over the world - cases where minutes can mean the difference between life and

death. Clinical surveillance with AI has the ability to provide next-generation decision-support resources that incorporate powerful technology, public health's preventive emphasis, and clinicians' diagnosis and treatment expertise. As a result, surveillance has the potential to play a key role in achieving the quality and cost goals that our industry has long pursued.

### 4. Conclusion

Overall, the use of AI technology for disease prevention and control is still in its early stages of investigation; there is an inexplicability about AI that prevents it from being effectively incorporated into the epidemiological system, and data collection and integration capacity building is still lacking. Due to lag and other problems, AI technology has been largely restricted from playing a larger role in epidemics prevention and control. To that end, disease modeling should be used for theoretical interpretability analysis, and large multi-dimensional data processing capacities should be enhanced to compensate for the corresponding technological flaws. However, it is important to understand and acknowledge the weaknesses and potentially major prejudices associated with public health big data, and there is still space for improvement. To comply with social ethics and norms, intellectual properties in algorithm methodologies and interpretability, as well as privacy security, should be given serious consideration. AI-enabled and -enhanced evidence-based public health monitoring and response, as seen in various AI applications in the medical sector, has real potential, but there are major challenges ahead.

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### **Conflict of interest**

The authors declare no conflict of interest.

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