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How Artificial Intelligence can Help Pandemic Preparedness and Management: A Review

Qinghan Jia[1] *

[1]West High School, Torrance, CA, USA
*Corresponding Author: qjia4132020@gmail.com

Advisor: Nikki Chambers, Chambers.Nikki@tusd.org

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Abstract

Pandemics are a pressing global phenomenon and improving methods to curb their effects is extremely important. As the field of Artificial Intelligence (AI) broadens, its potential benefits to healthcare are greater than ever before. AI can streamline current pandemic management methods, such as contact tracing and disease modeling, and also unveil promising advancements in healthcare such as telecare and autonomous delivery of medicine. This review aims to provide an overview of AI's developments within the healthcare industry and support its continued development as a promising tool in pandemic preparedness. Sources were accessed from the PubMed databases with an emphasis on AI's role in pandemic preparedness. This review briefly summarizes historically significant pandemics and outlines methods which can be taken for their mitigation. Though not without its flaws,the current state of AI has immense potential for the healthcare industry. AI has reshaped modern pandemic preparedness for the better, and will continue to benefit the medical world in the future.

Keywords: Artificial Intelligence (AI), Pandemics, Health guidelines

1. Introduction

Pandemics are a pressing issue that cause social and economic upheaval on a massive scale. Unlike endemic viruses, pandemics cause substantial spikes from baseline mortality rates (Doran et al., 2024). Unlike epidemics, which usually are contained to a single geographical area, pandemics are characterized by their global area of effect. Pandemics are both dangerous and costly, with measures taken to combat the COVID-19 pandemic in the United States costing $13 trillion in the first 20 weeks (Vardavas et al., 2023). The Covid-19 pandemic led to approximately 18.2 million deaths worldwide in a span of roughly two years (Doran et al., 2024), even with firm health regulations and procedures in place. Traditionally, travel restrictions and quarantine, early detection systems, contact tracing, and other non pharmaceutical interventions have been used effectively against pandemics (Hatami et al. 2022). Recent advances in Artificial Intelligence (AI) have provided unprecedented benefits to both pharmaceutical and non pharmaceutical pandemic interventions. During this time of rapid AI progress, a review is necessary to contextualize AI's advances through a medical lens. By utilizing the strengths of AI, healthcare providers can respond to pandemics more efficiently and safely. The objective of this literature review is to provide a comprehensive snapshot of the current state of AI within pandemic preparedness, and support its future development as an indispensable tool in the field of healthcare. Let's begin by discussing some famous examples of pandemics throughout human history, and notice how AI can be used to assist in a pandemic response.

1.1 Antonine Plague

One of the first large-scale pandemics was the Antonine Plague, which devastated the Roman Empire and its

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surrounding regions from 165 CE to 180 CE. The Greek physician Galen recorded unusual symptoms such as blackish diarrhea (suggesting gastrointestinal bleeding) and exanthem, which leads scientists today to speculate that smallpox could have been the disease behind the Antonine Plague (Horgan, 2019). Recording symptoms remains an important aspect of pandemic preparedness, and is pivotal in detecting early cases of an outbreak. AI's ability to comb through large databases and to identify patterns is crucial to modern pandemic response, and quickly identify if new, unique symptoms of a virus have begun to spread across a large area. Roman conquest in the East as well as travelers coming westward along the Silk Road spread the virus quickly throughout Rome. According to Roman historian Dio Cassius, (155-235 CE) the daily death rate was approximately two thousand, and decimated the Roman population. The staggering death rate caused an immense shortage in Roman manpower, emboldening other tribes to encroach on Roman territory (Horgan, 2019). The Antonine Plague also halted the agricultural economy, causing a spike in the ever dwindling food supply of the empire.

1.2 The Black Death

The Black Death, also known as the bubonic plague, was one of the deadliest pandemics of history, claiming 25 million lives in Europe during its reign during the fourteenth century. The Black Death was caused by *Yersinia pestis*, which spread via fleas on rats (Glatter and Finkelman, 2020). Victims would often be proclaimed dead within a week of contracting the disease, and common symptoms were high fevers and swellings on the body. Early strains of the Yersinia pestis bacterium most likely originated in Central Eurasia (Spyrou et al., 2022), and made their way to Europe by way of trade ships. The Black Death also led to the emergence of the miasma theory, popularized by the physicians Hippocrates and Galen (Glatter and Finkelman, 2020). The theory presumed that the Black Death was transmitted through "poisoned air", which led to the popularized image of a "plague doctor" sporting long capes and the iconic beak-like mask in an attempt to protect themselves from the plague. The emphasis on isolation in combating pandemics is still apparent today, and can be made easier due AI's ability to autonomously deliver medical supplies and aid without direct human contact (Ashique et al., 2024). The bubonic plague's frequency and level of concern have drastically decreased into the twentieth century due to the success of antibiotics, but isolated outbreaks still occur across the world (Glatter and Finkelman, 2020).

1.3 Smallpox

Smallpox is a now-eradicated infectious disease that led to the formation of distinctive large rashes on the body. Smallpox was caused by the variola virus, which scientists speculate to have begun roughly 3000 years ago in Egypt based on rashes on mummies from that era that were possibly caused by the disease (CDC, 2024). Roughly 3 out of 10 cases of smallpox were fatal, and survivors were often left with terrible scars (CDC, 2024). The last case of naturally occurring smallpox was in 1977, thanks to worldwide efforts of mass vaccination and case surveillance. Before the advent of vaccines, people practiced variolation (inoculation), which meant exposing a healthy individual with a sample of the smallpox virus in the hopes of achieving immunity (Riedel, 2005). This practice was thought of as a safer alternative than achieving natural immunity from the virus, as the mortality rate from variolation was "10 times lower" (Riedel, 2005) than a natural smallpox infection. In 1796, English doctor Edward Jenner applied the idea of variolation to a more advanced form of inoculation: vaccination. Jenner exposed 8 year old James Phipps to a sample of cowpox (a much milder disease), which subsequently protected Phipps from a sample of smallpox (CDC, 2024). Thanks to the work of Jenner, vaccination gradually replaced variolation due to its safer nature. New advances in AI streamline vaccine production, allowing for vaccines to be produced much more efficiently and keep up with the constantly dynamic nature of viruses.

1.4 Spanish Flu

The Spanish Flu is considered one of the worst pandemics in modern history due to its estimated global death toll of 50-100 million (Martini et al., 2019). The first of three waves of the pandemic began in March of 1918, with

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subsequent waves in August and December. An H1N1 influenza virus caused the Spanish Flu (Aassve et al., 2021), and mostly targeted young adults. It is hypothesized that persons above the age of 43 during 1918 already had previous exposure to substrains of influenza A (Shanks and Brundage, 2012), and although persons below the age of 17 during 1918 were susceptible to the virus, they had below-average mortality rates. Transmission was most likely exacerbated by WW1 soldiers returning home as well as the displacement of refugees across Europe (Martini et al., 2019). Since no vaccine was available at the time, the next best course of action was quarantine and isolation as well as surveillance of new cases. The disinfection of public spaces such as streets and theaters was widely believed to curb the spread of the Spanish Flu, but those methods proved ineffective (Martini et al., 2019).

1.5 Covid-19

The Covid-19 pandemic began in Wuhan, China in late 2019 and was declared a pandemic on March 11, 2020 by the World Health Organization (Lv et al., 2020). Many initial cases began after contact with the Huanan Seafood Market in Wuhan, where infected individuals were exposed to live animals such as bats, frogs, and snakes. It was originally hypothesized that the virus was transmitted only from infected animals to humans, but human to human transmission through aerosols soon increased in frequency (Shereen et al., 2020). Much like severe acute respiratory syndromes (SARS), Covid-19 spread through droplets created by an infected individual and symptoms included fever and muscle aches. Even though the mortality rate of Covid-19 is 2-3%, its rate of transmission was far faster than SARS. By March 15, 2020, Covid-19 had spread to 144 countries across 5 continents (Shi et al., 2020). The two most common pathways for the spread of Covid-19 were by respiratory droplets or by aerosol droplets (Shi et al., 2020). The urgency of the Covid-19 pandemic led to the creation of the Covid-19 in a record-breaking one year. New technology coupled with previous research on the coronaviruses MERS and SARS allowed for the remarkably swift development of the Covid-19 vaccine (Chakraborty et al., 2023).

2. Health Guidelines

2.1 Social Distancing and Isolation

Social distance was a major effort seen during the Covid-19 pandemic, and attempts to reduce transmission of diseases in public settings. According to the World Health Organization, social distancing can occur at both a personal (maintaining distance from others) and community level (the shutting down of public spaces). A study from January to May 2020 across 41 countries demonstrated that when public gatherings were limited to 10 people, the rate of transmission of disease reduced by 36% (Sun et al. 2023). Furthermore, the study estimated that the closure of non-essential businesses would reduce the rate of transmission by 29%. A lockdown can be defined as social distancing on a national level, which also proved an effective curbing mechanism for Covid-19. During the lockdown, the average number of new infectants according to a survey in Shanghai decreased from 18.8 to 2.3 (Sun et al. 2023).

2.2 Mask Wearing

Face masks are a common public measure to reduce the rate of transmission of infectious diseases. The concept of mask wearing to block unwanted pathogens from the mouth and nose is straightforward, and is most effective with a high degree of compliance from the public. In a scenario where both an infected and a susceptible individual wears a mask, the probability of transmission decreases by 54%, a much greater reduction than 7%, the reduced probability of transmission if only one or the other wore a mask (Kollepara et al., 2019). Furthermore, different types of masks provide different levels of protection. A standard surgical mask provided minimal protection against aerosol droplets, but an N95 mask provided adequate protection for aerosol droplets (Kollepara et al., 2019). A study conducted by Gurbaxani et al., (2022) discovered that in a model which assumed a 50% mask-wearing rate for persons below the age of 65 against SARS-CoV-2, case reduction over a 6 month period was as follows: “57% (N95), 32% (medical procedure), 28% (cloth), 28% (gaiter), and 20% (bandana)”.

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2.3 Hand Washing

According to the CDC, hand hygiene is the most important method in reducing transmissions of pathogens between individuals. This is due to the fact that transient microorganisms gather on superficial skin layers after contact with objects, people, among other unsterilized items (Tammy et al., 2023). Hand washing should take roughly 20-30 seconds if using an alcohol based hand rub but take 40-60 seconds if washing with soap and running water (Chen et al., 2023). To effectively rid the hand of most contaminants, studies suggested a six step hand washing process including rubbing of the palm, dorsum, thumb, fingers, and fingertips of each hand (Shi et al., 2023).

2.4 Food Cleanliness

Many foodborne illnesses are due to improper consumer handling of food items before consumption (Redmond and Griffith, 2023) and can cause severe diseases such as Salmonella and E. coli. Foodborne illnesses account for 420,000 deaths each year (Negassa et al., 2023) but can be combated by maintaining food cleanliness. In addition, aerosol droplets from sneezes, coughs, and breath can contaminate food (Shiferaw et al., 2017), making social gatherings such as parties and weddings prime hubs for disease transmission. The USDA recommends sanitizing hands and surfaces that will become in contact with food thoroughly and frequently, as well as avoiding cross-contamination between raw and cooked foods.

2.5 Vector Control

Insects such as mosquitos are responsible for spreading a plethora of diseases including malaria, dengue, and yellow fever. Additionally, fleas served as the main vector for the spread of the Black Death. Historically, the main form of insect control lay in insecticides (Dusfour and Chaney, 2022) such as neonicotinoids, organophosphates, and carbamates (Araújo et al., 2023). However, the production of insecticides was extremely costly and insecticides also harmed helpful insects such as bees as well as the environment (Onen et al., 2023). Recently, green biotechnology has been a promising alternative to traditional insecticides due to its nontoxicity and biodegradability (Onen et al., 2023).

Wildlife also carries many diseases that can be transmitted to humans, such as classical swine fever and tuberculosis, so controlling diseases found in wildlife is of utmost importance. A key way to detect diseases in animals is through monitoring systems, which are followed by assessments for the impact of found diseases (Gortazar et al., 2015). A comprehensive approach (including mass surveillance and animal vaccination, awareness, and governmental support) was also highly successful at controlling zoonotic diseases, and was used by Ethiopia in 2015 to control canine rabies across the country (Shiferaw et al., 2017).

2.6 Surveillance

Detection systems for new diseases are one of the most important factors in managing pandemics because they both serve to curb the initial phase of a disease as much as possible as well as notify the public. In a model of Covid-19 early detection systems in Wuhan, China, it was found that hospital monitoring discovered Covid-19 about 1121 cases earlier than without monitoring (Liu et al., 2023). A study conducted by Ricoca Peixoto et al. (2020) found that if action in Wuhan was taken 1 week earlier, cases could have been reduced by 66% in China. A comprehensive routine surveillance is perhaps the most helpful type of early action since it combs through all suspected cases of the disease. However, it is often not feasible for low-income countries to conduct or act upon such a large pool of cases. Another approach has been reporting, where active cases were reported to the WHO. This method often fails to detect cases early on, which can lead to greater disease transmission (as compared to comprehensive routine surveillance).

Contact tracing can be seen as an extension of a surveillance system where persons in proximity with a newly infected individual are notified in order to reduce the transmission of the disease. These close contacts are often asked to quarantine and monitored to check if they test positive for the disease. Manual contact tracing (asking an infected individual to recall their close contacts and then notifying them) was effective yet time-intensive, and new digital apps have greatly increased efficiency (Pozo-Martin et al., 2023). Secondary contact tracing is another useful tracing

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method where close contacts of each primary contact are also notified. Models show that if 90% of close contacts are traced and notified in 0.5 days, the reproduction number would reduce from 2.2 to 0.57, greatly halting the spread of a pandemic (Juneau et al., 2023). Due to vigilant contact tracing in Hong Kong, only 1084 cases of Covid-19 were recorded in Hong Kong after around 4.5 months even though the dense population made Hong Kong more vulnerable to Covid-19 (Lam et al., 2020).

2.7 Disease Modeling

Disease modeling has many different uses, and can assist in creating predicting transmission trends, the effectiveness of proposed regulations, and epidemiological features of the disease. Usually, models that estimate transmission trends of a disease aim to bring down the parameter to a threshold level, where a disease can be thought of as "contained" (Marion et al., 2022). Models relied on the collection of large amounts of data, and observable data include cases for infected individuals and their demographic data as well as environmental and societal factors surrounding the disease (Rui et al., 2024). Furthermore, models needed to be prompt and transparent to the public (Marion et al., 2022). If predictions or assumptions are present in the model, the modeler should fully disclose them to the public and emphasize full transparency in their data. Additionally, peer-reviewing models that influence public health policy have been extremely important (Sutherland and Lythgoe, 2020).

2.8 Vaccines

Vaccines are a life changing technology that have saved countless lives since its inception and led to cornerstone medical achievements such as the eradication of smallpox. The contemporary vaccine traced its roots to Louis Pasteur, who developed a vaccine for chicken cholera (Iwasaki and Omer, 2020). Vaccines work by exposing the immune system to harmless traces of the target pathogen, which primes the immune system towards future pathogens of that kind and bolsters immune response towards future invasions (Policy (OIDP), 2024). The development of the Covid-19 vaccine was completed in a record breaking 10 months, but implemented decades of prior research. The Covid-19 vaccine relied on the mRNA platform, which sent a mRNA molecule into the body which prompted the creation of a harmless piece of the virus and the subsequent creation of antibodies to trigger an immune response (Cohen). However, vaccines have so far been ineffective at treating diseases where prior infection has not led to future immunity, such as malaria and HIV-1 (Iwasaki and Omer, 2020).

2.9 Patient Treatment

Once a disease is contracted by a patient, there are a plethora of treatment procedures that they may undergo in order to combat the virus. One of the most common treatments for viruses were antivirals, which were medicines used to treat viral infections (Kausar et al., 2021). Immunomodulators are also commonly used as a treatment for cancer and infections and modulate the activity of the immune system. In cases where the respiratory system has been damaged (such as Covid-19 or the flu), invasive ventilation methods via an endotracheal tube or noninvasive ventilation methods such as High Flow Oxygen Therapy have helped the patient maintain adequate oxygen levels. (Popat and Jones, 2012).

3. Methodology

This paper focuses on the role of AI in pandemic management and response, and synthesizes information from recent studies conducted on this topic. A review of relevant literature was conducted using literature from the PubMed database published between Jan 2023 and Dec 2024. Sources were selected using the keywords "Artificial Intelligence", "AI", "pandemics", and combinations of those words. Sources were chosen based on relevance with AI's role in pandemic management. Literature not pertaining to AI, non-english literature, and non-human literature was excluded from the review. Out of 296 articles reviewed, 31 were chosen that pertained to the role of AI with pandemics from the 2023-2024 period.

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4. Where AI Can Help

The continually emerging field of Artificial Intelligence could greatly benefit the prevention and management of future pandemics. Though not without flaws, AI has the potential to greatly enhance current strategies in the field of pandemic response.

4.1 Automation

One of the greatest strengths of AI is automation. Robotic process automation (RPA), one of the simplest forms of AI, simply followed a script of rules (Davenport and Kalakota, 2019), and took over mundane tasks such as billing, clinical documentation, and more. Since a United States nurse spent about a quarter of work time solely on “regulatory and administrative activities” (Davenport and Kalakota, 2019), RPA systems can take on those tasks to allow for nurses and other healthcare providers to focus on patient care. Additionally, AI systems that help autocomplete annotations in a patient’s electronic health record have been shown to reduce keystroke burden by 67% (Chenais et al., 2023). Through AI systems, many menial and routine task completion times can be cut down drastically, allowing for more emphasis on high quality healthcare.

4.2 Autonomous Healthcare Options

AI chatbots and virtual healthcare providers are becoming an increasingly popular option to meet the demands for the limited healthcare resources around the world. At-home care could help combat the shortage of human resources in hospitals and other healthcare centers (Yang et al., 2022). These chatbots have simulated organic conversations and could interpret symptoms, give medical suggestions, and monitor vital signs (Alowais et al., 2023). AI has helped develop personalized treatment plans based on the patient's unique lifestyle and environment, providing the patient with a course of medical action. Coupled with AI technology that streamlined the patient experience, healthcare providers have educated patients on any concerns they may have and guided patients to online and in-person resources to aid their condition (Siwicki, 2024). AI has been extremely helpful for personalized treatment plans because it can analyze a patient’s genetic and environmental information to determine the best course of action (Iqbal et al., 2023). AI improved the homecare system, reducing the susceptibility of disease transfer between a patient and the healthcare provider (Mahalakshmi et al. 2023). Furthermore, wearable sensors and cameras could remotely monitor a patient’s health status (Khosravi et al., 2024). Additionally, chatbots have been used to educate patients on factual information about vaccines and in some cases encourage patients to take vaccines (Passanante et al., 2023). One of the most prominent sectors that chatbots work in has been mental health. Sweeney et al. (2021) discovered that 77% of healthcare professionals believed that chatbots were somewhat or very important, demonstrating the perceived usefulness of chatbots. For example, the mental health chatbot Woebot was shown to reduce symptoms of depression within two weeks of use (Sweeney et al., 2021), and the Watson AI conversation assistant addressed queries related to COVID-19 for 6.8 million users within 5 months (Hirani et al., 2024).

Since isolation and quarantine are extremely important factors in curbing the spread of a pandemic, human contact during drug/medicine delivery to patients is detrimental to the health of both the healthcare provider and patient. Autonomous drones serve as a promising alternative to resource delivery during pandemics. For example, drones in Geelong, Australia have been equipped to distribute self-test kits to residents across the city (Ashique et al., 2024). These drones optimized travel times via Modified Artificial Bee Colony (MABC) algorithms that gave the drone the fastest route to each household (Ashique et al., 2024). Furthermore, drones navigated through mountainous and remote regions to ensure quality healthcare for rural areas. Due to the advancement of drone technology, the "Medicine from the Sky" program aimed to distribute medicine to remote areas such as Telangana, India (Sharma and Sharma, 2024). Programs such as the MABC and “Medicine from the Sky” effectively allow for healthcare to be distributed to a wider range of individuals who may not otherwise have access to healthcare. The removal of the human-human interaction of delivering healthcare effectively mitigates the risk of a healthcare worker transmitting a disease to the patient, or vice versa.

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4.3 Surveillance and Contact Tracing

AI can reliably discover trends quickly, making AI systems invaluable in surveillance. A form of AI known as machine learning is characterized by finding patterns within a large set of training data to react and interpret future data without human intervention. For example, systems such as the Arogya Setu in India and the Bluedot in Canada were widely used during the Covid-19 pandemic and helped users self-diagnose and provided contact tracing capabilities (Anjaria et al., 2023). Additionally, Bluedot sent notices to cities where infected individuals arrived (Farhat et al., 2023). By utilizing past regional data and environmental factors, AI can predict the timing and scope of a pandemic to a fine degree (MacIntyre et al., 2023). A proposed use of AI in contact tracing is by combining its functionalities with Bluetooth Low Energy (BLE) technology. In this approach, a hospital required patients, personnel, and visitors to wear BLE tags. AI could interpret signals from these tags to accurately determine interpersonal distance between potential contacts (Tang et al., 2021). AI models could also predict hospitalization times of patients, further helping medical professionals allocate resources between patients (Lv et al., 2024). AI controlled surveillance systems would better help in contact tracing by providing more reliable information.

4.4 Disease Modeling and Diagnosis

Machine learning has great potential for the collection and analysis of data, and disease modeling can be benefited by AI to provide greater and more efficient predictions. An application of machine learning is known as deep learning (DL), which is a process for combing through large amounts of data (Ghaffar Nia et al., 2023). DL has been used to diagnose Covid-19 with 98.91% accuracy (Saha et al., 2020) by analyzing x-ray images of patients. Similarly, a DL system was used in the UK to diagnose breast cancer after being fed a mammogram dataset, which decreased the rate of false positives by 5.7% and false negatives by 9.4% (Alowais et al., 2023). The CAD4COVID-CT has been used to detect Covid-19 from CT scans, which enabled more streamlined patient diagnosis (Ankolekar et al., 2024). DL systems have also been useful in diagnosis in microscopy, radiographs, and CT scans (Wong et al., 2023). Data augmentation and data generation are two processes to enhance the quality and quantity of an AI's turning dataset (Fang et al., 2024). In all cases, the AI program relied on quality data in order to help with disease diagnosis by reducing human error and streamlining the diagnosis process.When used this way, DL systems can analyze and detect abnormalities in patient x-rays, mammograms, etc. at a faster and more accurate degree than human medical workers. AI can also effectively be used to predict a community's rate of infection from a pandemic. Alakus created an AI learning model that predicted Covid-19 infections with an accuracy of 86.66% after analyzing "600 patients and 18 laboratory findings from the Hospital Israelita Albert Einstein at Sao Paulo Brazil" (Alakus and Turkoglu, 2020). Diagnosis was most accurate when data quality and quantity was high, and cross-validation was used to deter overfitting (El Morr et al., 2024).

4.5 Vaccine Production

Vaccines usually take about 10-15 years to produce, and are extremely labor and cost intensive. AI could help reduce the time for vaccines through an AI application known as Reverse Technology (RT) (Kaushik et al., 2023), which focused on a genome-based approach and eliminated the need for developing bacterial cultures. AI could accurately determine specific antigens amongst thousands that provide immunity to the vaccine's targeted disease (Kaushik et al., 2023). The Covid-19 vaccine was created in a record-breaking time of one year, and much is attributed to expanding technologies that help fight against pandemics. Another important factor to consider for a vaccine is its longevity, which relies on identifying antigens or parts of antigens that are relatively stable and will not mutate (Sharma et al., 2022). AI can help determine potential antigens and assist researchers in the step of finding a successful antigen for the vaccine. Since a major limiting factor in vaccine production is time, the use of AI to speed up the vaccine production process has allowed for vaccines to be developed faster and more cost efficiently than before (Sekaran et al., 2023).

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4.6 Pandemic Awareness and Education

AI-powered robots can be extremely helpful in spreading pandemic awareness as well as educating the population about public hygiene and risk factors for pandemics. Robots served as public health agents by reminding crowds in public spaces to practice social distancing (Aymerich-Franch, 2020). Additionally, LLMs such as ChatGPT effectively communicated essential health updates to the public during the Covid-19 pandemic (Younis et al., 2024). Robots can significantly reduce the risk of human to human disease transmission, and during the Covid-19 pandemic, provided patients with key information about the virus (Ashique et al., 2024). Because these social robots act as agents in human-human interactions, they reduce the risk of a medical worker spreading a disease by being on the front line, and essentially act as an immune proxy to aid the public and spread awareness about pandemic preventative measures such as mask-wearing.

5. Weaknesses

5.1 Bias and Misinformation

Though AI can aid in the fields of diagnosis and analysis of information, it is unfortunately influenced by societal and cultural biases within human-curated datasets (Khan et al., 2023). In this way, AI perpetuates current societal norms and exacerbates current inequalities. Furthermore, AI systems often experience "hallucinations", which refer to cases where the information they generate is inaccurate (Monteith et al., 2023). The availability of generative AI applications such as large language models (LLM) lowers the cost of spreading misinformation online (Monteith et al., 2023), making it easier for individuals to post inaccurate yet compelling messages. Because AI systems can be trained on faulty and biased data, they can overfit towards the training set and have low accuracy during actual use (Aslani and Jacob, 2023). Additionally, the time constraint with developing a detection system for a pandemic such as Covid-19 meant that many datasets weren't verified for authenticity, and were prone to lowered accuracy (Sailunaz et al., 2023). In a study of 192 datasets from MEDLINE and Google Dataset Search, "48% of datasets documented individuals' country of origin, 43% reported age, and under 25% included sex, gender, race, or ethnicity" (Alderman et al., 2024), highlighting the inherent bias and potential inaccuracies from training AI on incomplete databases.

5.2 Privacy

A large issue in the use of AI in healthcare is trust and privacy. To put it simply, people do not yet trust AI with sensitive info. As therapy chatbots and telecare continue to rise in popularity, the public perception of these tools is still one of uneasiness: in a study, "almost 60% of participants were apprehensive that AI threatened data privacy" (Hasan et al., 2024). Since health information is very confidential and relates directly to the well-being of a patient, many are wary of trusting such sensitive information to a machine. Hasan's study also notes that 58% of participants are worried about issues of cybersecurity and hacking, further cementing the distrust of AI by the populace.

5.3 Inaccessibility

Though AI has many robust applications for medicine, a large portion of its usability is restricted by inaccessibility. For example, in 2018, the US Census Bureau found that 58.1%-87.7% of households in the Navajo Nation did not access the internet (Ehrenpreis and Ehrenpreis, 2022), and high-speed internet is essential to AI programs (Sharma et al., 2023). Such inaccessibility to technology leads to AI and its applications having a much lesser impact on poorer communities who often need healthcare technology the most. Additionally, data barriers such as data quality and access can further deter from the effective use of AI (Ahmed et al. 2023). For example, there was a shortage of Covid-19 image datasets during the onset of the virus, leading to a weaker database for AI systems (Paul et al., 2023). The lack of transparency and understandability as to how AI systems come to conclusions also isolates professionals and generates skepticism towards the use of AI in healthcare (Olawade et al., 2023). Prioritizing transparency and accessibility is a way to provide accountability towards AI models (Tornero-Costa et al., 2023).

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6. Conclusion

Humanity has developed many methods of combating pandemics through history such as quarantine, personal protection devices, surveillance, contact tracing, and vaccines. In light of the recent Covid-19 pandemic, pandemic preparedness is as important as ever before. AI enhances many methods of combating pandemics, allowing healthcare professionals to work more efficiently and widen their impact of care. AI makes healthcare more accessible and effective, allowing more rural and isolated regions to receive the same quality of healthcare as urban areas. Modeling and contact tracing systems are vastly improved with AI's ability to quickly recognize patterns, allowing for a more coordinated response to pandemics. Though AI technology contains flaws such as bias, misinformation, privacy concerns, and inaccessibility, further research and refinement of AI using responsible methods would open up new possibilities in medicine. The continued careful and ethical use of AI would allow it to assist the field of medicine greatly as an indispensable tool for healthcare workers.

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