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Ethical Issues in AI-Enabled Disease Surveillance: Perspectives from Global Health

Ann Borda [1,2,*], Andreea Molnar [3], Cristina Neesham [4] and Patty Kostkova [5]

[1] Centre for Digital Transformation of Health, University of Melbourne, Parkville, VIC 3010, Australia
[2] Department of Information Studies, University College London, London WC1E 6BT, UK
[3] Department of Computing Technologies, Swinburne University of Technology, Hawthorn, VIC 3122, Australia; amolnar@swin.edu.au
[4] Newcastle University Business School, Newcastle University, Newcastle upon Tyne NE1 7RU, UK; cristina.neesham@newcastle.ac.uk
[5] Institute for Risk and Disaster Reduction, University College London, London WC1E 6BT, UK; p.kostkova@ucl.ac.uk
* Correspondence: aborda@unimelb.edu.au or a.borda@ucl.ac.uk

Abstract: Infectious diseases, as COVID-19 is proving, pose a global health threat in an interconnected world. In the last 20 years, resistant infectious diseases such as severe acute respiratory syndrome (SARS), Middle East respiratory syndrome (MERS), H1N1 influenza (swine flu), Ebola virus, Zika virus, and now COVID-19 have been impacting global health defences, and aggressively flourishing with the rise of global travel, urbanization, climate change, and ecological degradation. In parallel, this extraordinary episode in global human health highlights the potential for artificial intelligence (AI)-enabled disease surveillance to collect and analyse vast amounts of unstructured and real-time data to inform epidemiological and public health emergency responses. The uses of AI in these dynamic environments are increasingly complex, challenging the potential for human autonomous decisions. In this context, our study of qualitative perspectives will consider a responsible AI framework to explore its potential application to disease surveillance in a global health context. Thus far, there is a gap in the literature in considering these multiple and interconnected levels of disease surveillance and emergency health management through the lens of a responsible AI framework.

Keywords: AI; disease surveillance; pandemics; global public health; ethics

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1. Introduction

Infectious diseases such as COVID-19 pose a global health threat in an interconnected world. In the last 20 years, resistant infectious diseases such as severe acute respiratory syndrome (SARS), Middle East respiratory syndrome (MERS), H1N1 influenza (swine flu), Ebola virus, Zika virus, and now COVID-19 are impacting global health defences, and aggressively flourishing due to the rise of global travel, urbanization, climate change, and ecological degradation.

In parallel, this episode in global human health highlights the potential for artificial intelligence (AI)-enabled disease surveillance to collect and analyse vast amounts of unstructured and real-time data to inform epidemiological responses. The exploration of the requirements of a global data-driven and epidemic intelligence surveillance system finds precedence in the literature [1], but the implementation has still a long way to go. A 2020 Lancet commentary provides insights into what might be possible in a collective approach to address the unpredictable and evolving COVID-19 transmission rates using AI [2]. However, this promise is also hampered by the challenges of AI, including the opaqueness of the outputs derived from informal sources, and the commensurate need for transparency at multi-stakeholder levels [3,4].

AI as a component of global health surveillance systems is relatively new and largely bounded by both specific applications and geographies [5,6]. Global health itself is built

on national public health actions and institutions, primarily concerning population-wide interventions. However, global health is ideally concerned with all strategies for health improvement, whether population-wide or individual-based health care actions. In other words, it goes across geographical administrative boundaries. There is no formalized definition for *global health*, but Koplan et al. [7] is widely cited for defining it as: "an area for study, research, and practice that places a priority on improving health and achieving health equity for all people worldwide". Taking on board the parameters of this approach, we are faced with both opportunities and ethical stumbling blocks of an AI-enabled disease surveillance for global health. For example, how might we take into account the interconnected levels of individual and population disease contexts and stakeholders, multiple data sources, and geographical boundaries, and the implementation of equitably applied interventions?

2. Disease Surveillance

Surveillance is already a core function of both public health and global health practice. It is defined by the World Health Organization (WHO) as the "continuing scrutiny of all aspects of the occurrence and spread of disease that are pertinent to effective control". It is characterised by "methods distinguished by their practicability, uniformity, and frequently by their rapidity, rather than complete accuracy" [8].

The enabling components of surveillance systems may include laboratory diagnostics to detect or confirm health conditions; information technologies to support the surveillance processes of data collection, analysis, and dissemination; clinician consultation and reporting; public health education and training; and legislation, regulations, and policies that support the conduct of surveillance and response. Communicable disease surveillance can operate at international, national, state, and local levels. The primary responsibility for public health action often lies with state and national health departments or public health agencies (e.g., Public Health England in the UK). For the purposes of this paper, WHO [9] has defined a disease epidemic as "the occurrence of cases of disease in excess of what would normally be expected in a defined community, geographical area, or season". In practice, infectious disease data collection and analysis is complicated and encompasses a multi-stage process with several stakeholders across various organizational boundaries [10]. The main objective of infectious disease surveillance is to identify changes in incidence, either in the form of an acute outbreak (e.g., COVID-19) or a change in long-term trends [11].

Disease surveillance intelligence includes activities related to the prompt identification of potential health hazards and their verification, assessment, and investigation to enable public health control recommendations [12]. The 2005 International Health Regulations (IHR) are designed to ensure the timely recognition of outbreaks of infectious disease with the potential to spread widely [13]. The IHR 2005 also serves as a foundation for the Global Health Security (GHS) agenda [14]. The GHS agenda is "an effort by nations, international organizations, and civil society to accelerate progress toward a world safe and secure from infectious disease threats; to promote global health security as an international priority; and to spur progress toward full implementation of the IHR". They require WHO member nations to report outbreaks of international concern to the WHO within 24 h of discovery [15].

For case-based surveillance, member states can report using the WHO outbreak toolkit [16] to develop an initial case report. For example, consistent with the IHR, during the initial months of the H1N1 pandemic in 2009, the WHO requested that countries report the initial cases and, thereafter, the number of confirmed cases and deaths throughout the H1N1 pandemic. The resulting database represented one of the most comprehensive and timely outbreak reporting databases available to the public on the Internet at the time [13]. By contrast, the overwhelming human resource demands to effectively undertake COVID-19 data collection and analysis over the initial months of the pandemic swiftly required a shift from case-based reporting to aggregate and accelerated forms of reporting [17].

A critical component of disease surveillance which is growing in importance due to the availability of big data is 'epidemic intelligence' [18,19]. Epidemic intelligence incorporates two components: an indicator-based component and an event-based component [9,12,20,21]. The goal of indicator-based surveillance is to find increased numbers or clusters at a specific time, period, and/or geolocation that may indicate a threat [22]. The indicator-based component refers to structured or formal data collected through routine surveillance systems, such as the number or rates of cases based on standard case definitions, and the computation of indicators upon which abnormal disease patterns to investigate are detected [12]. Traditional indicator-based surveillance systems are based on the obligatory reporting of certain diagnosed diseases to a central health agency.

Event-based disease surveillance systems use information on events impacting human health from Internet-based sources, including news aggregators and social media channels [21–23]. Event-based surveillance complements traditional approaches to public health surveillance and can provide early warning of emerging events, whereas there may be a lag in other forms of data aggregation due to delays in sample collection, laboratory confirmation, and country reporting, for example [24,25]. The Medi + Board is an example of a dashboard framework which integrates public health surveillance data streams with zoonotic surveillance data [26], illustrating multiple geo-referenced and time series data.

There are several established and active disease surveillance systems utilized to monitor disease trends, mainly using online news sources, across the globe. Among these are: the Global Public Health Intelligence Network (GPHIN), HealthMap, and ProMED [20,21,25,27,28]. A short description of these systems is outlined in Table 1.

Table 1. Disease Surveillance Systems.

Global Public Health Intelligence Network (GPHIN)
• GPHIN was established by the Public Health Agency of Canada in the late 1990s. • GPHIN is an automated surveillance tool, which collects non-structured, event-based, digital data from news feed aggregators and then reports to national and international health agencies, such as the WHO Global Outbreak Alert and Response System (GOARN). • In 2004, GPHIN detected severe acute respiratory syndrome (SARS) more than two months before the first publications by the WHO [29]. • URL: https://gphin.canada.ca/cepr/aboutgphin-rmispenbref.jsp?language=en_CA (accessed on 1 November 2021)
HealthMap
• HealthMap was established in 2006. • HealthMap uses online informal sources, such as ProMed and official-validated outbreak RSS feeds, for disease outbreak monitoring and real-time surveillance of emerging public health threats. • HealthMap also brings together disparate data sources, including online news aggregators, eyewitness reports, expert-curated discussions, and validated official reports. • The freely available website 'healthmap.org' and mobile app 'Outbreaks Near Me' deliver real-time intelligence on a broad range of emerging infectious diseases. • URL: https://healthmap.org/en/ (accessed on 1 November 2021)
Program for Monitoring Emerging Diseases (ProMED)
• ProMED is a program of the International Society for Infectious Diseases (ISID). • ProMED was launched in 1994 as an internet service to identify unusual health events related to emerging and re-emerging infectious diseases and toxins affecting humans, animals, and plants. • ProMED is one of the largest publicly accessible surveillance systems conducting global reporting of infectious disease outbreaks. • URL: https://promedmail.org/ (accessed on 1 November 2021)

The IHR has emphasized the importance of both indicator-based and event-based components of epidemic intelligence for the early detection of events [30]. Informal information sources are important in this context, with the WHO reporting that more than 60% of initial disease epidemic reports come from unofficial sources and this percentage continues to increase with the availability of internet-based and social media sources [25]. During the COVID-19 crisis, the frequently changing government platforms used to publicly disseminate data included Facebook and Twitter, as well as government-authorized websites [31].

Common informal sources found on the internet include search queries, news feeds (e.g., Google and Baidu news), blogs, and social media channels [25,32]. Social media platforms, such as Twitter, are perceived as an increasingly useful form of real-time data with a geolocation resolution that can be systematically mined, aggregated, and analysed by algorithmic applications to inform public health agencies [30,33,34]. The increasing number of smartphones worldwide and lower policy barriers in many lower-middle income countries (LMICs) also provide an opportunity for the usage of AI-enabled mobile applications in event-based surveillance [18,35,36].

There are also emergent forms of epidemic intelligence [12] which are arising from newly identified microbes through advances in DNA sequencing technology. This primarily relates to genomic epidemiology in which lab-based molecular diagnostics and genotyping methods are being enhanced or replaced by rapid genomics- and AI-based methods to aid epidemiologic investigations of communicable and outbreak diseases [37]. From DNA to environmental exposures, climate change is similarly modifying the public and global health environment such that disease spread can take on new patterns, and subsequently new types of surveillance data are required, e.g., meteorological data [38].

3. AI and Public Health Disease Surveillance

Rapid epidemic detection and real-time monitoring are critical objectives of event-based surveillance to minimize the morbidity and mortality caused by infectious diseases and to enable the preparation of rapid response public health services and personnel. Automated event-based surveillance systems have the potential capacity to aggregate and sort vast amounts of heterogeneous data for patterns and abnormalities using forms of AI [39].

AI machine learning classifiers play an important role in real-time analysis and trend predictions [40]. AI applications used with social media sources can be effective in providing trends for climatic and socio-economic contexts [38,41]. Social networks can further provide an efficient method for risk communication to prevent disease outbreaks and serve as real-time dissemination channels for declaration of pandemic events [42].

Machine learning models analysing internet and open health data sources have precedence across a number of disease surveillance projects to improve infectious disease surveillance and prediction, e.g., malaria [43], dengue fever [44], and cholera [45]. In the example of influenza, algorithmic and machine learning models have been applied to influenza tracking for nearly two decades. Bernardo et al. [32] indicate that the use of internet-based sources for disease surveillance is traceable to 2006, with early work focusing on influenza. Influenza can be highly contagious and easily spreads as people move about and travel, for instance, making tracking and forecasting flu activity a challenge. To address these challenges, researchers have proposed methods utilizing internet-based sources, mobile phones, and other event-based surveillance methods. Research in the use of internet data has demonstrated a positive predictive value of the incidence of infectious diseases, e.g., seasonal influenza [46], but it has shown in some cases to have a low predictive value [47].

To monitor the volume of influenza cases, there is an increasing use of "flu tracker" apps, whereby flu symptoms are reported using crowdsourced platforms to improve the global surveillance of influenza [35,48]. The U.S. Centres for Disease Control and Prevention (CDC) developed the FluView app, which draws on the U.S. influenza-like illness surveillance network (ILINet) that records the percentage of patients reporting to outpatient

clinics with symptoms of influenza-like illness (ILI), such as fever, a sore throat, or cough, over the total number of patient visits, for example. The data are integrated in the weekly joint WHO and European Centre for Disease Prevention and Control (ECDC) COVID-19 and influenza (www.flunewseurope.org (accessed on 15 January 2022)) bulletins [49].

These symptom measurements are an established indicator of historical ILI activity, but an important drawback is that they require several days to collect from individual healthcare providers, causing a delay and reducing the opportunity for real-time situational awareness and data analysis. In an evaluation of surveillance systems, it was found that the systems issued alerts for human cases between 1.9 and 6.1 days, on average, before WHO reports [30].

As monitoring is improved over time, the heuristics improve as their outputs are confirmed against a set threshold for the epidemiological attributes of extracted health events [22]. Prior to returning the extracted information, the surveillance system aggregates the extracted events into outbreaks, across several documents and sources based on this 'learning'.

The Computational Health Informatics Program (CHIP) at Boston Children's Hospital is among numerous research groups developing forecasting techniques combined with machine learning to provide more predictive indicators and estimates of local flu activity. An application called ARGONet (autoregression with general online information) leverages information from electronic health records, flu-related Google searches, and historical flu activity in a given location. In a research study, ARGO was shown to outperform Google Flu Trends (GFT) [50], a flu forecasting system developed by Google that operated from 2008 to 2015, but notably failed to accurately predict peaks in the flu season [25,48], as described by Daughton et al. 2020. To improve its accuracy, ARGONet also draws on the spatial-temporal patterns of flu spread in neighbouring areas. "It exploits the fact that the presence of flu in nearby locations may increase the risk of experiencing a disease outbreak at a given location" [50].

In disease outbreaks before COVID-19, the application of AI was limited because of a shortage of the data needed to provide rapid updates. The millions of feeds about coronavirus on social media and news sites are allowing algorithms to generate near-real-time information for the public health services tracking its spread. For instance, the disease surveillance system HealthMap based at Boston Children's Hospital uses natural language processing and machine leaning to analyse data from government reports, social media, news sites in 15 languages, and other informal sources to constantly track the spread of outbreaks [51]. The future developments at the time of this study include building a symptom-checker to assess the symptoms of coronavirus that distinguish it from seasonal flu.

In the emergence of COVID-19, risk analysis companies using AI-enabled tools were able to provide early detection of the coronavirus, before the WHO was informed. An AI epidemiologist in the Canadian-based company BlueDot (https://bluedot.global/ (accessed on 1 November 2021)) is widely reported as the first source to reveal news of the COVID-19 outbreak in late December 2019 [2]. BlueDot analysed data from news reports, airline ticketing, and animal disease outbreaks to predict areas that would be prone to the outbreak, expanding from regions in China [51]. Data sources and AI played an important role in various countries' responses to the pandemic [18].

Another company using AI capabilities is Metabiota (https://www.metabiota.com/ (accessed on 1 November 2021)) based in San Francisco, which offers an epidemic tracker and a near-term forecasting model of disease spread. Metabiota, which also used analytics to track flight data accurately, anticipated that countries such as Japan, Thailand, Taiwan, and South Korea would be at risk of a coronavirus outbreak days before any case was reported in any of those countries [51,52].

Interest in syndromic surveillance based on social media data has greatly increased in recent years, leading to what might be termed "nowcasting" [50,53,54], that is providing predictions of disease levels which incorporate data from current social media activity but can include rolling data sources such as ever-hospitalized cases and persons tested [53]. The early detection and analysis of epidemics based on mining Twitter messages is a common

approach in nowcasting [53,54]. The VAC Medi + Board dashboard provides visualizations of vaccination threads extracted from Twitter, for example, illustrating the diffusion of information, the most influential users, and impact groups [55,56].

Over the course of the swine flu (H1N1) pandemic in 2009, novel big data streams from social media channels, in correlation with traditional surveillance reporting, demonstrated a potential for early-warning systems for infection disease outbreaks detecting a peak in an outbreak of swine flu up to two weeks before the official public health authorities [57]. Broniatowski et al. [34] reports that including Twitter data on influenza or influenza symptoms can improve nowcasting performance to a greater degree than was possible with search surveillance using Google Trends. During the 2012–2013 influenza season, a Twitter-based AI surveillance application also consistently predicted and mirrored CDC data with 85% accuracy [34].

COVID-19 big data applications are drawing on increasing aggregations of both formal and informal sources, including Twitter and major published open data platforms, e.g., Johns Hopkins University's COVID-19 global map dashboard. Pilot initiatives for COVID-19 forecasting, modelling, and machine learning rose exponentially in 2020, demonstrating the capability of AI for disease surveillance applications [58]. The Global Partnership on Artificial Intelligence (GPAI) identified 84 initiatives supporting some form of AI tool, application, and/or platform, from across the global north and south, related to the pandemic [59].

4. Ethical Considerations

There is a noted asymmetry in the literature on the ethics of AI in healthcare, with less attention granted to global health, particularly disease surveillance [4,19,60,61]. Much of the AI-driven intervention research in global health has limited descriptions of the ethical, regulatory, or practical considerations specifically required for cases of widespread use or deployment at scale [59,62]. Not least, there is the interconnectedness of individual and population levels of disease surveillance, diverse data types, and sources which are required for reporting and decision-support [17–19].

Making AI systems transparent, fair, secure, and inclusive is essential in this context, but how these systems are interpreted and operationalized can vary [6]. The OECD has recognized that AI systems deployed in specific contexts require different approaches to policy-making and governance, and have produced an evaluation toolkit to address variations using scenario-based examples [63]. The OECD toolkit shares principles with increasingly pervasive responsible AI frameworks [59,61,64,65], although this still remains a relatively unexplored area when applied to disease surveillance systems.

The recent literature focusing on the COVID pandemic has only just touched on the potentially important application of responsible AI [59,64,65]. The Future Society in collaboration with the GPAI launched a responsible AI assessment framework aimed at applying a number of normative criteria to AI-related initiatives arising in the COVID-19 pandemic. This assessment is based on human rights, inclusion, diversity, innovation, and economic growth [59].

In an earlier and wider-ranging study, a meta-analysis of ethical AI frameworks by Floridi et al. [66] resulted in the development of the AI4People framework for a "good AI society". The five principles underlying the AI4People framework are [66]:

- Beneficence: promoting well-being, preserving dignity, and sustaining the planet
- Non-maleficence: privacy, security and "capability caution"
- Autonomy: the power to decide (whether to decide)
- Justice: promoting prosperity and preserving solidarity
- Explicability: enabling the other principles through intelligibility and accountability.

Of particular relevance to this study is the grounding of the AI4People framework in bioethics principles, which more closely aligns it with an ecosystem of agents, patients, systems, and environments [60–62,66]. In applying the AI4People principles in the context of global public health disease surveillance, we reflect on how such principles could inform

both ethical and practical considerations for future disease surveillance system practices and applications.

4.1. Beneficence: Promoting Well-Being, Preserving Dignity, and Sustaining the Planet

This principle establishes the requirements for doing good, in the sense of pursuing the good pro-actively, as a constructive outcome, adding value to existing benefits. In this context, the role of a public health disease surveillance system in itself depends on a wider global health network, through which we can promote collaborative actions for the protection of people and the environment [38,63]. Those systems of IHR member states already have some form of embedded transparency in protecting and promoting the value of human dignity in the time of pandemics and in the process of disease surveillance. However, the implementation of public health responses, particularly as post-surveillance events, as well as whole-of government approaches to public health disease outbreaks, need to also support and ensure a continuity of beneficence [4,61,63,66].

4.2. Non-Maleficence: Privacy, Security and "Capability Caution"

This principle promotes the idea of avoiding harm, in particular to people, human society, and the natural environment. In the context of this paper, key aspects of this "do no harm" norm are data sharing, data tracking, data quality, and algorithm benchmarking.

4.2.1. Data Sharing

The quality and completeness of the data on which the WHO relies depends on the capacity of its member states for surveillance and their willingness to share surveillance data. As the COVID-19 pandemic progressed, member states were asked by the WHO to submit detailed case data via line lists on more than 80 variables, the vast majority of which were incompletely reported [17]. This recent pandemic, in particular, has highlighted significant challenges in sharing, storing, and linking data from public, private, and quasi-public sectors, as well as between, across, and outside jurisdictions. Depending on the nature of the data, there may also be restrictions on linking or sharing outside of the geographical source of that data [19]. In the context of new technology and innovation, it is becoming increasingly important for people to share their data, so that disease prevention advances can be more impactful. For example, the sharing of SARS-CoV-2 genetic sequences has allowed scientists to track bio evolution and variants [37,67].

4.2.2. Data Tracking

Here, there are concerns related to the privacy of the people whose data is being used, especially when the data is linked from different sources such as self-reporting mobile apps or trackers, or CCTV video, making it easier to identify the people involved. Many countries relied on an extrapolation of infection-control and public-health measures to contain the COVID-19 pandemic. These have ranged from extreme quarantine measures in China to detailed contact tracing in South Korea to enforced stay-at-home policies and travel restrictions [51,68]. Such measures have been variously implemented as COVID-19 contact tracing has revealed ethical trade-offs between public health and privacy. For instance, in South Korea, there were human rights concerns that the excessive disclosure of private information could cause people with symptoms to avoid testing [68].

Bluetooth privacy-presenting, anonymous, voluntary opt-in apps have been championed by human rights and data protection groups and supported by the WHO [69]. The decentralized privacy-preserving proximity tracing (DP-3T) protocol developed by several European academic institutions was among those developed in response to the COVID-19 pandemic to safely facilitate digital contact tracing of infected individuals at the population level [70]. These were intended to offer a comprehensive set of technical and legal safeguards against the potential misuse of personal data. However, a majority of individuals have not downloaded national digital contact tracing apps [70]. According to the Future Society report [59], public hesitancy querying the purpose of COVID-19 contact

tracing apps has also emerged, caused by mistrust in public authorities and by fears around the establishment of continuing forms of government surveillance. Additional means of tracking and screening such as thermal image scanning are among the potential privacy breaches and creep of mass surveillance [71].

What should the ethically acceptable trade-offs be between stopping the spread of disease (a public good) and protecting a person's privacy from potential breaches (a private good)? This is a sensitive issue.

4.2.3. Data Quality

Real-world disease data tends to be noisy and incomplete. Although reporting of most notifiable diseases through various public health agencies is required by law, for the most part hospitals, laboratories, and clinicians participate voluntarily. This reinforces the need for careful evaluation of data sources and collection procedures. Moreover, event-based surveillance systems can generate a sizable amount of information on any given outbreak topic, sometimes overwhelming the systems themselves [21]. For example, the Argus system generated approximately 22,000 reports on the pandemic (H1N1) 2009 from April 2009 to March 2010 [20]. In stark contrast, the COVD-19 case reports captured early in the pandemic tallied 49,659 daily cases and 2739 deaths for 27 March 2020 only [17]. Given the serious consequences of using poor quality data to manage global health related decisions, improving data quality becomes a crucial ethical concern [63].

4.2.4. Algorithm Benchmarking

Each syndromic surveillance system also implements a unique set of outbreak detection algorithms. This requires a better understanding of the strengths and limitations of various detection techniques and their applicability, which may require capability caution in the process [71]. For instance, algorithms can perform differently in the field than in the lab, and this may create a major challenge in ensuring high performance, accurate benchmarking against any current standard care, and continuously assessing performance after deployment [63,72]. Given the wide and powerful impacts of the decisions informed by such benchmarking, again, considerations of technical accuracy become ethical issues.

4.3. Autonomy: The Power to Decide (Whether to Decide)

The use of AI-based technology for global health surveillance also raises ethical questions around who should have the power to decide on these matters, and who should decide whether (and when) to decide at all. Concerns have been expressed about significant shifts of the locus of control on such decisions from humans to machines. In the context of global health surveillance, we note specificity, misinformation, consent, and data governance as the main aspects that would require further ethical analysis (and, possibly, regulation).

4.3.1. Specificity

In event-based surveillance, reports may be generated by automated machine-based processes, e.g., HealthMap, or by human analysts or subject matter experts, e.g., GPHIN, ProMED [25,27,28]. For the automated systems, manual report examination for relevancy typically occurs post-dissemination. ProMed utilizes local observers on the ground for some of its outbreak reporting; otherwise event-based biosurveillance systems often disseminate reports that are not observer or laboratory verified [27,37]. Thus, although the reports provide near real-time alerts to users, the data they provide may not be specific enough. One consequence of this on human autonomy may be that individual human agents end up being constrained by limited one-size-fits-all (general) data and may not be able to see where (and how) they can act in different circumstances [63].

4.3.2. Misinformation

Syndromic surveillance systems often generate false detections because it is sometimes difficult to distinguish natural data variations resulting from outlier and dynamic system

changes, e.g., with time or space variables, from real outbreaks [73]. Human reviews and follow-up investigations are necessary for verification, which can be costly in time and labour. The prompt identification of novel microbes is often not matched with equally prompt epidemiological assessments [37]. The scarcity of such data, and the lack of transparency in algorithms could compound challenges of misinformation or false alarms that could potentially occur with AI-enabled platforms, especially if they rely on social media or non-authoritative data sources, for example. False detections can erode public trust in these surveillance systems, and such misinformation could weaken an agency's or individual's power to effectively make decisions [74–76]. The role of social media in trending public attitudes can also be put to effective use to disseminate risk communication in real time [26,42], but could be a double-edged sword increasingly prone to misinformation and the spread of fake news [74–76].

4.3.3. Consent

In an article by Blasimme and Vayena [60], the authors raised ethical questions around consent when employing AI-driven social media analysis for digital epidemiology. For example, ubiquitous surveillance for use by AI systems through personal devices, such as mobile phones, introduces the concern that granular data can be re-identified, and personal health information can be hacked [35,71]. The main concern here is that this personalized data can be used by third parties without the subject's knowledge or approval. In the case of contact tracing apps, for example, there are ethical considerations to gather and act on information without consent [69]. Such digital surveillance on individual-level data can lead to unique complications [74], and relates to the trade-offs between the public good and individual rights [75].

4.3.4. Data Governance

The COVID–19 pandemic has exposed long-standing data governance issues such as intellectual property rights, data sharing, reuse, and ownership [59,63,76,77]. Globally, persistent data gaps and fragmented approaches to governing disease surveillance data need to be addressed through global cooperation and clear, unified direction. The Global Pandemic Data Alliance (https://gpdahub.org/, (accessed on 1 November 2021)) is a collaboration of data-focused organizations across the G7 countries meeting the challenge of establishing health data as a global public good. This need for globally integrated data governance for the public good is highlighted in the Future Society report [59], the OECD Framework [63], and in the WHO Health Data Governance Summit [78].

4.4. Justice: Promoting Prosperity and Preserving Solidarity

It is increasingly accepted that principles of justice should apply when AI is used to support event-based surveillance efforts in global health policy. Justice is not just a lofty ethical ideal, and an end in itself. It is also a means to distribute prosperity widely within society and to foster social cohesion and solidarity across different social groups. Geographic scope, human rights, and equity in predictive decisions are the three main aspects of ethical concern to be discussed here.

4.4.1. Geographic Scope

The geographic scope of an event-based disease surveillance system may vary [21,27]. It could cover a region, a country, a continent, or the entire globe. The following jurisdictions have established, hosted, and maintained such systems: United States, European Union, Canada, Japan, Australia, Brazil, Singapore, Mexico, and Thailand [11,15]. While there is immense potential opportunity for AI to support event-based surveillance of aggressive disease outbreaks such as COVID-19, the issue of missing data is especially present in low- and middle- income countries (LIC and LMIC), which may also lack the infrastructure and human capital required to maintain these systems [17,36,74,75,79]. Geographic inequalities in event-based system maintenance may constitute significant barriers to achieving justice

in global health outcomes, hence improvements in geographic coverage should become a priority.

4.4.2. Human Rights

The protection of human rights is paramount and, as stated in the UN Declaration of 1948, should be universally guaranteed. However, individuals from vulnerable groups and stateless communities may discover that current disease surveillance practices are still a long way from safeguarding them from discrimination and oppression [79]. The IHR [15] has introduced important safeguards to protect the rights of travellers and other persons in relation to the treatment of personal data, informed consent, and non-discrimination in the application of health measures under the regulations. The effectiveness of these measures on the ground remains to be determined.

4.4.3. Predictive Decisions

With respect to ensuring equity in predictive decisions, there is some debate as to whether responsible AI frameworks can address the explicit and implicit biases embedded within these systems [62]. To verify that an AI system is not using data in ways that result in bias or discriminatory outcomes, some level of transparency is necessary to explicitly addresses diversity and inclusion [59,60].

4.5. Explicability: Enabling the Other Principles through Intelligibility and Accountability

It is now recognized that the 'black-box' nature of first-generation AI systems can be a source of injustice, dominance, and harm [4,72]. The need for explainability (or explicability), in the sense of having algorithmic processes and outcomes explained in clear terms to the human intellect, has become evident. None of these processes and outcomes can be submitted to human judgment and scrutiny without certain explainability requirements being met [72]. The main aspects we discuss here are: data noise; meeting regulatory standards or policy requirements; assessing risks, robustness, and vulnerability; and understanding and verifying the outputs from a system.

4.5.1. Data Noise

Noisy data are a result of data corruption which can carry a large amount of additional or meaningless information. High noise data are a weakness of real-time data streams analysis which can introduce small errors that in turn can have an outsized effect on large-scale predictive models [80]. Some systems, such as HealthMap, relieve noise by integrating data from an assortment of online sources that have been moderated already [73].

4.5.2. Meeting Regulatory Standards or Policy Requirements

Transparency is essential to legal compliance. Without it, enforcing individuals' legal rights in relation to the uses and applications of a technological system, establishing that a service meets regulatory standards, and determining liability may prove impossible [41,63,75]. While most nations have in place the procedures needed to foster compliance with existing data protection and privacy regulations, many such procedures are time consuming and create significant barriers to explicability [17,41,74].

4.5.3. Assessing Risk, Robustness and Vulnerability

Understanding how a system works can be important in assessing risk [41]. This can be particularly important if a system is deployed in a new environment, where the user cannot be sure of its effectiveness [63,80]. Interpretability can also help developers understand how a system might be vulnerable to so-called adversarial attacks, in which actors seeking to disrupt a system identify a small number of carefully chosen data points that they could alter in order to prompt an inaccurate output from the system [72,81,82].

4.5.4. Understanding and Verifying the Outputs from a System

Interpretability can be useful in verifying the outputs from a system, by tracing how modelling choices, combined with the data used, affect the results. In some applications, this can help developers understand cause-and-effect relationships in their analysis. Furthermore, people are more likely to trust an algorithm when they can easily understand its implications and can modify it [72,81,82].

5. Key Issues of Normative Ethics

We preface this discussion by noting that our conceptual approach inevitably presents limitations in the application of responsible AI principles in general. Challenges that may not be covered by such principles, for example, point to finer grained considerations relating to the complexity of disease surveillance systems, from a system alert to reporting to different levels of health authority with varying governance capabilities and a reliance on automated data generation and analysis in a global health emergency scenario.

What is summarily highlighted in the process is that AI is both a technical problem and a human problem. AI models are increasingly used in decision-making contexts in global health disease surveillance. At the same time, they "are more complex and less interpretable than ever" [83]. Scientific and practical work on the application of AI in supporting disease surveillance must consider that it is ultimately humans who need to understand the technological parameters. From a normative-ethical perspective, we see two issues bearing on AI-based decision-making in disease surveillance systems: (1) it is 'ethically blind' unless curated for value alignment (i.e., values shared by the human community are embedded in the algorithm); and (2) it complicates the issue of who is responsible for the consequences/outcomes of this decision-making process and their impact on various stakeholders.

The application of responsible AI has considerable potential for supporting transparency which, in itself, promotes respect for the human dignity of stakeholders in the decision-making process. It also makes value alignment and judicious responsibility attribution possible in the first place. Without responsible AI principles, meeting the two conditions systematically would be impossible.

6. Conclusions

Introducing *responsible AI* applications could support a more ethical and equitable approach [66] to combatting pandemics and maintaining global public health [59]. However, the layered complexity and scale of global disease surveillance systems raise challenges for the integration of *responsible AI* at different levels. These go beyond data, algorithm, prediction, and privacy concerns. The long-term goal relies on responsible health actors limiting the power of private corporate interests, ensuring transparency and protection of individual rights, and not least fostering trusted networks of partnerships and shared commitment through responsible global governance [63,66,84]. Further research should be engaged in developing effective approaches for value alignment in AI-assisted global health surveillance systems, as well as in normative-ethical analyses of responsibility attributions in the context of global health decision-making—the latter particularly in reference to the management of volatile pandemics, such as COVID-19.

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