World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Review Article)

Check for updates

AI Health Cloud for Real-Time Infectious Disease Surveillance: Predicting and Preventing Future Outbreaks

Oluwasanya Luke Ogunsakin [1,*] and Kehinde Sulaimon [2]

[1] *Bournemouth University.*
[2] *Lincoln University.*

World Journal of Advanced Research and Reviews, 2026, 29(01), 214-224

Publication history: Received on 15 September 2025; revised on 01 November 2025; accepted on 04 November 2025

Article DOI: https://doi.org/10.30574/wjarr.2026.29.1.3618

Abstract

The threat of infectious disease persists into the twenty first century, leaving stark vulnerabilities in worldwide systems of tracking of population health, which are still largely in the reactive, segmented and overly slow-moving phase in responding to outbreaks. This research critically analyzes the way artificial intelligence (AI) and cloud computing technology will help transform disease surveillance methods and introduce a novel paradigm: preventing outbreaks rather than detecting them at the early stages of attack. The research establishes that predictive analytics that use AI-based models pretrained on a wide range of data types including electronic health records (EHRs), wearable sensor information, mobility data, and even environmental data can foresee outbreaks even before an established system becomes aware of them. Cloud and edge computing also increase scalability and responsiveness enabling decentralized, synchronized monitoring both on the ground and across boundaries. With geospatial intelligence, the optimal way to allocate resources is to recommend adaptable policies through reinforcement learning (RL) whereas spatial visualization of the process of disease spread allows such distribution. Applications and case analyses in outbreaks of COVID-19, Ebola, and Zika demonstrates how AI could enhance surveillance accuracy and response time. Nevertheless, the research also notes that there are major challenges, such as privacy, and data-quality variations, algorithm-bias, inadequate interoperability, limited infrastructure, or insufficient infrastructure, as predominantly faced by the low- and middle-income economies. This paper contends that technological innovation will not provide the proper means of preventing diseases effectively without fair data management, effective cybersecurity, and inclusive system development. Overall, integrating AI-based predictive value and responsible governance will decide whether AI health clouds can turn into powerful solutions to prevent future outbreaks or reinforce existing disparities related to global health monitoring. The paper concludes with the recommendation to institutionalize representative datasets and open governance structures to help build trust, deploy ethically, and make the world healthier.

Keywords: Artificial Intelligence; Health Cloud; Infectious Disease Surveillance; Predictive Analytics

1. Introduction

The vulnerability of the public health systems in the twenty first century still manifests through the threat of infectious diseases. Despite the development of epidemiology and data systems, the surveillance systems are still viewed as a reactive element that is fragmented and slow to react with regard to rapidly spreading outbreaks (Choi et al., 2016). The COVID-19 outbreak has revealed these gaps in a quite inhuman fashion, with most governments failing to coordinate and mobilize response on a timely basis (Sharma et al., 2022). The impact of unpreparedness was because of its reliance on manual reporting and making sure the data is verified sometime later on, hence it will show that real-time, predictive and integrated surveillance systems shall be necessary and tertiary in the future (Alwakeel, 2025).

* Corresponding author: Oluwasanya Luke Ogunsakin

Artificial intelligence (AI) has been created in order to recreate these inadequacies into a solution. AI can analyze extensive and heterogeneous datasets, such as clinical histories, behavioral trends, gait patterns, and more, at incomparable timespans compared to the traditional models, with the aid of machine learning, deep learning, and natural language processing (Tripathi and Rathore 2025). The models fueled by AI can change surveillance systems into proactive government with their capacity to not only recognize the abnormal behavior but also only tell the future or provide early warning (Ali, 2024). Moreso, the efficient acquisition of various types of data is a significant advantage of these approaches, as well as speed, and this reduces the ignorance that existed before in the area of epidemic management (Islam, 2025). This is because, one must take a closer look at this account of technological confidence.

Although the deployment of AI applications can be a very predictive factor in bureaucratically planned settings, the technology often does not work with disaster (Sharma et al., 2022). More so, the quality of data remains a constraining bottleneck and underreporting, mistakes, and omission of datasets can cause prediction of inaccuracies in data (Folasole, 2023). In addition to this, quality of algorithmic output may be doubted because it relies on the quality of the data that the system has been trained on as data, and, therefore, in the situation where the system is of low-resource and its reporting structure is of low quality, the application of surveillance systems comes into the question concerning equity (Leite et al., 2021). The existence of such disabilities indicates that development of technology may not substitute structural strength.

Besides that, the surveillance based on AI opens severe ethical and social issues that the regulative system faces. For instance, threats to the integrity of its data, over-monitoring and discrimination in algorithms put the loss of trust in the health authorities of the citizens at risk (Tripathi and Rathore, 2025). The same tools, intended to protect groups, prove to cause the threat of re-textualization in favor of a new form of exclusion should the forms of protection not be evaluated in the medium of their creation and in conveying them (Ali, 2024). The contrast between innovation and responsibility is often overlooked in the accounts of AI perceived power, nevertheless, it might simply determine whether a rise in technological application will render people healthily sincere or dishonest (Sharma et al., 2022).

The next generation such as federated learning or edge computing can also be viewed as Pareto examples of AI-informed surveillance representing the both the opportunity and irony. It, on the one hand, would provide the protection of privacy and enhancing of pandemic resilience through decentralized data-processing (Choudhury et al., 2025). On the other hand, they are infrastructurally intense, resource-intensive and permanent which the vast majority of current public health systems do not possess (Badidi, 2023). Similarly, cloud-enabled AI-based systems introduce greater scalability to jurisdictions though they present difficult challenges in the spheres of cybersecurity, data sovereignty, and laws regulation across borders (Islam, 2025; Narla et al., 2020). Hence, technological development is not divisible of larger conflicts of power, equity and regulation with the world.

Despite such constraints, there is an extremely high rate of AI application in the field of disease surveillance. Predictive modelling is now capable of modeling the dynamics of outbreaks with more precision and can help us respond with faster feedback that could mitigate the outbreak of diseases and death of individuals (Folasole, 2023). Urban centers dispose of dense populations that makes them vulnerable to scalability of threats which transmit the disease through mobility and other environmental elements concurrently; therefore, they require edge AI appliances to assist them track it in real-time (Alwakeel, 2025). Furthermore, the Nnatural language processing research also has more potentials considering that since digital platforms can be mined, identifying outbreaks at the beginning even before any formal channel publishes news about it (Tripathi and Rathore, 2025). Combined, these types of innovation are another shape of a new paradigm where systems of surveillance are not reactive at all, but strategic pre-emptives.

However, the possible revolution of AI must be addressed. Where there is no such thing like leadership and similar means of accountability and creditable change, there is the risk of AI-based systems only repeating the same mistakes they are meant to avert (Chakilam, 2022). Very soon, the transition to the progressive, real-time and predictive monitoring, across the fragmented and late surveillance, is not only a matter of technical work, but also political and socio-political one, called upon to be distributed by the governments, research facilities, and even international health organizations (Sharma et al., 2022). AI may provide the tools, but it will be politics, required capacity in the institution, and ethical doctoring which will enable them to be rolled out (Ali, 2024).

Notwithstanding, the loopholes of the conventional surveillance systems have availed fertile grounds for the AI innovations that would presumably overhaul infectious disease surveillance. However, it is not as easy a change. It is characterised in terms of the conflicts among speed/reliability, innovativeness, ethical, and global ambition/local capacity (Tripathi and Rathore, 2025). Therefore, this paper critically assesses Artificial Intelligence (AI) health cloud for real-time infectious disease surveillance with a focus on predicting and preventing future outbreaks.

2. Real-Time Outbreak Detection Using Predictive Analytics

The application of predictive analytics in outbreak detection has been one of the biggest contributions by AI to the modern field of health (Folasole, 2023). Predictive systems are not based on the reactive model (when there is a general pandemic, actions are undertaken) but have shifted to a more drive-on approach which enables early warning and intervention (Ekundayo, 2024; Tripathi and Rathore, 2025). On the basis of multiple datasets, including clinical records, environmental notifications, and human movements, machine learning algorithms can predict anomalies prior to an outbreak, marking potential hotspots like possible basing them on a larger scale than the traditional tools in epidemiology (Folasole, 2023). This model change is, in turn, a sign of a more significant change in patterns of disease surveillance, a shift that does not look at AI as a supportive aspect but as leading infrastructure to react against epidemics (Islam, 2025).

The machine-learning models have demonstrated potentially successful capabilities of predicting the nature of an epidemic in its diversity of settings (Badidi, 2023). Past outbreak data can also be applied in such processes like supervised learning to identify any recurrence of an emerging season or environmental pattern that is correlated with development of disease (Ekundayo, 2024). The hospitalization-based AI models and clues in the social media, as well as weather information are all included in the robust predictive capability of AI models in influenza surveillance (Leites et al., 2021). Similarly, technologies unsupervised will be able to see the anomalies and group them before they are formally reported to the case before they peak abnormally (Tripathi and Rathore, 2025). Such predictions however remain largely reliant on the integrity and representativeness of the input datasets to influence the dependability of such predictions. Reliability of these predictions is however, highly subject to integrity and representativeness of input datasets (Folasole, 2023). In the context of underreporting, or fragmented health infrastructure, the quality of AI predictions decreases, cause of over-confidence in the application of algorithm predictions to low-resource environment (Badidi, 2023).

Moreso, predictive power of AI models has been augmented with the inclusion of Internet of Things (IoT) (Baiense et al., 2025). Regular data streams of wearable items, environment sensors, and community-oriented health trackers accurately reveal the status of the health of an individual, along with threats facing the entire community (Adam Sahib and Bhavani, 2025). As an example, respiratory activity sensing wearable devices and thermotanks have been proposed as a distributed bio surveillance device as they have the prospect to report initial infectious developments within a population being observed (Lawal, et al., 2025). In practice, the outbreaks could be considered at the community level and before spreading on a larger area (Leite et al., 2021). Nevertheless, deeper concerns of privacy and data ownership and scale also emerge because of these strategies since it is believed that the infrastructural and economic opportunities of leveraging IoT technologies are generally not always universally available in all countries (Udegbe, et al, 2025).

In the same vein, predicting an outbreak in real-time can also be provided with additional features introduced by cloud-enabled models and edge AI models (Narla et al., 2020). The sharing of data with various jurisdictions can be helped by cloud environments which support the nation and world-scale modeling through its role in making scales and prediction possible (Islam, 2025). In contrast, edge AI can quickly and locally analyze information, and process data closer to its origin and in such a manner has minimized latency and preserved the privacy data (Badidi, 2023). It is a paradox of localization and centralization, whereby the rippling zone provided by cloud systems on the prospects of a planetary-level integration is given, but with edge AI, a local fulfillment is made, through providing near-real time analysis analysis level (Choudhury et al., 2025). However, both demand an expensive investment and technical capacity as well as securing the system (cybersecurity) to ensure that credibility and trust are established with the population (Islam, 2025; Tripathi and Rathore, 2025).

It should be noted that positive, practical value of the prospects of predictive analytics with regards to the outbreak surveillance, could be illustrated with the cases of wearable health technology and local tracking in the smart community. Indicatively, smart blood pressure monitors based on IoT and located in community-based settings in China demonstrated that not only can the devices enhance the management of a disease but also make the health information available on a population level in China (Li et al., 2024). These tools may be embedded into a system of full-time monitoring of influenza or COVID-like diseases, where continuous information about the physiological parameters of fever, oxygen saturation, respiratory defects, etc. can alert the essential diagnosis long before it occurs (Baiense et al., 2025). This is also applicable to zoonotic surveillance which have the potential to combine environmental data on animal populations and their movement of vectors with human health data and estimate spillover of a species into another coworker (Folasole, 2023). Still, they will succeed when the distribution of wearable and smart technologies is fair, which is not a simple task in the setting where structural imbalance of access to the digital is predetermined (Leite et al., 2021).

Nevertheless, humans ought not just to be optimistic regarding the benefits of predictive AI but also consider its shortcomings as well. The information that the predictive models are trained on inherently constrains the predictive models (Ekundake, 2024). The algorithms created in developed countries fail in the settings of resource baseness since the reporting capacity, ecologically particular elements, and healthcare provision vary (Folasole, 2023). In addition, black-box models are ideal in pattern recognition; though, they lack interpretability, as healthcare sector authorities may be reluctant to adopt opaque answers of an algorithm to make life and death decisions (Tripathi and Rathore, 2025). This would jeopardize the decision-making process and the trust that is beheld into it in such a manner that draws accurate predictions inconsistent with what is witnessed locally (Badidi, 2023).

Therefore, AI-based predictive analytics can leave an opportunity for an unprecedented mass to transform the process of detecting outbreaks into an operation based on data and information (Folasole, 2023). Using cloud and edge infrastructures allows predictive systems that take into account a diverse range of data to identify anomalies and forecast outbreaks and early responses to them- IoT sensors, hospital functionality operation, etc (Ekundake, 2024; Islam, 2025; Tripathi and Rathore, 2025). Nevertheless, such basic issues as equity, privacy, interpretability, and infrastructural disparity cannot be addressed as of now (Ogundipe, 2023). These imperatives justify the high value of the governance frames addressed and the cross of sector coherence which would perhaps create a balance between technology advancement and ethical accountability. Without these frameworks, predictive analytics will be used to reinforce injustices in surveillance health across the globe rather than combat it.

3. AI Health Cloud and Geospatial Intelligence for Predicting Disease Hotspots

The introduction of the principle of geospatial intelligence into the AI-based infrastructure of health clouds is a swing in the realm of real-time monitoring of infectious diseases. Unlike traditional mapping systems, which merely provide a fixed visualization of an outbreak (Folasole, 2023), cloud powered AI systems have the ability to process and analyze heterogeneous data including wearable devices, electronic health records (EHRs), and IoT connected health devices and convert them into more dynamic geospatial models which can take into consideration beforehand the direction a disease will take in future (Adam Sahib and Bhavani, 2025; Baiense et al., 2025). These systems take it a notch further as they apply reinforcing learning algorithms and predictive modelling techniques to find out not only where the infections are occurring, but also where they are expected to spread in the future (Abdellatif et al., 2023). The cloud-based geospatial models ensure that real-time dashboards accessed by governments, hospitals, and other health bodies will translate the incoming epidemiological indicators into actionable intelligence and prevent outbreaks (Da Fonseca et al., 2021).

Among the unique benefits of the AI health cloud model, it is possible to note an opportunity to merge patient-level data collected with the help of distributed wearable devices and wireless body area networks (WBANs). Such devices generate continuous health data such as temperature, oxygen levels and heart rate that when aggregated on secure web servers can assist as the initial indicators of the outbreak of an infectious disease (Nyangaresi, 2025). Such data, analyzed together with environmental and movement data, allows AI-based geospatial systems to determine new hotspots with the preferred degree of precision that could not have been afforded to legacy epidemiological surveillance (Rabie et al., 2024). An exemplary case is when the aggregated febrile data of IoT thermometers in a particular district is compared to the rainfall and temperature data to predict dengue or malaria epidemic. However, this predictive functionality is not completely free: collecting and transferring sensitive biometric information creates an urgent problem of privacy and security (Khan and Jilani, 2024) as well as raises issues of patient consent. Without the solid blockchain authentication and privacy preserving protocols, even the systems of the clouds, that have been engineered in order to secure the health of the population endanger becoming the instrument of the overreach of notification and data abuses (Venkata, 2023).

Additionally, AI health clouds together with geospatial mapping ASM, transport network data, and with such additions to clinical surveillance, improve Android-powered smartphones and GPS localization devices (Venkata, 2023). During the COVID-19 pandemic, the surveillance of the flow of people in real-time became useful in predicting the expansion of the virus within cities and, therefore, allowing introducing lockdowns and effectively allocating hospital resources (Hu et al., 2025). This compatibility feature can be integrated with a cloud-based service to support its scaling, responsiveness because the predictive data may be shared on-the-fly among hospitals, ministers of health, and global organizations. However, there are algorithmic and ethical problems surrounding the reliance on the mobility data (Abdellatif et al., 2023). The low-connectivity nature of those locations is one of the causes of data sparsity, resulting in misleading hotspots prediction, not mentioning that AI training models (or other training models) that train mostly in high-changeable settings may have discrepancies in low-resource settings (Baiense et al., 2025). The effectiveness of the AI in monitoring human health on clouds, thus, relies on how unequal is the infrastructures and whether equity is featured in geospatial algorithms.

The other geospatial intelligence of the AI health clouds is the possibility to optimize resource allocation and priorities of interventions. Predictive hot springs cannot just allow health authorities to predict an outbreak location, but can also predetermine resources, including vaccines, personal protective gear (PPE), and medical staff, to respond to locations at high risk (Da Fonseca et al., 2021; Anupriya and Devi, 2024). The fact that these predictions are hosted in the cloud does allow access to frequent and interoperable dashboards which can be updated in real-time with the response teams and this reduces delays in the introduction of an emergency response. Each of these promises is, however, cast aside by the continuing issues of health system fragmentation with interoperability (Anupriya and Devi, 2024). The majority of low-resource countries are operating siloed data models of health systems with limited possible capacity to integrate cloud-based tree models analytics (Rabie et al., 2024). Furthermore, lack of connectivity in rural regions also challenges the credibility of real-time mapping, and the increased need to ensure resilient and inclusive digital health ecosystems is urgent (Baiense et al., 2025).

Better still, the case of applying geospatial AI to the medical clouds forces one to reconsider the idea of surveillance ethics. While the adoption biometric surveillance, predictive profiling of individuals, and excessive policing of the marginated groups cannot be disregarded (Khan and Jilani, 2024), the idea that outbreaks can be detected early on helps save millions of lives (Liu et al., 2024). Without privacy protection systems, health cloud AI systems must encompass privacy protection methods, such as blockchain-based data sharing, aggregation with anonymity, and differential privacy (Nyangaresi, 2025; Rabie et al., 2024). Ensuring that some of the training datasets also include epidemiological and demographic data of a diverse variety of contexts is also important to prevent the imposition of further structural inequalities in algorithmic predictions (Hu et al., 2025). Eventually, AI health cloud surveillance may be realized to succeed not only because of the degree of technological development, but also through the establishment of governance measures to moderate predictive possibilities and ethical responsibility.

4. Challenges in Deploying AI Health Cloud for Real-Time Infectious Disease Surveillance

One of the most immediate concerns in AI health cloud implementation continues to be the privacy of the data to track infectious diseases in real-time (Li et al., 2024). Relative to standard solutions, health earnings, healthcare prototypes are now collecting, storing, and analyzing masses of sensitive data generated by IoT-based wearables and wireless body-area networks (WBANs), and electronic wellness records (Baiense et al., 2025). The information of this kind is not only essential in predictive analytics but also it can expose people to unauthorized access, over-surveillance, and identity exposure within a very short time. According to Nyangaresi (2025), secure communication schemes are obligatory in WBANs, and with it, remote monitoring will receive an opportunity to become legit. The design of cloud-system needs to follow then with encryption, anonymization and detailed access-control.

Regardless of the fact that the new developments do not merely indicate to the solution, they pose new intricate problems. As an illustration, it has been proposed that blockchain-enhanced transmission can be able to secure health data in the clouds where decentralized authentication can be provided and also prevented tampering can occur (Khan and Jilani, 2024). Similarly, generative deep learning models have also been suggested to expand data security in a medical IoT environment where AI itself is capable of not only preserving sensitive patient information but can also protect it (Anupriya and Devi, 2024). These technical solutions do not however work in the governance level entirely. The main issue to rise is that the people are still agency to the data in the collection, storage, and its reuse across various jurisdictions with varying rules. Whereas the efforts such as Health Insurance Portability and Accountability Act (HIPAA) and General Data Protection Regulation (GDPR) offer the privacy standards, health cloud systems operate on a global scale, typically overstepping the jurisdictions of legal actions (Liu et al., 2024). The notion of data security is skewed unless there are harmonization efforts in attempting the same which is likely to have negative implications on the citizens as well as their capacity to enroll in disease surveillance systems.

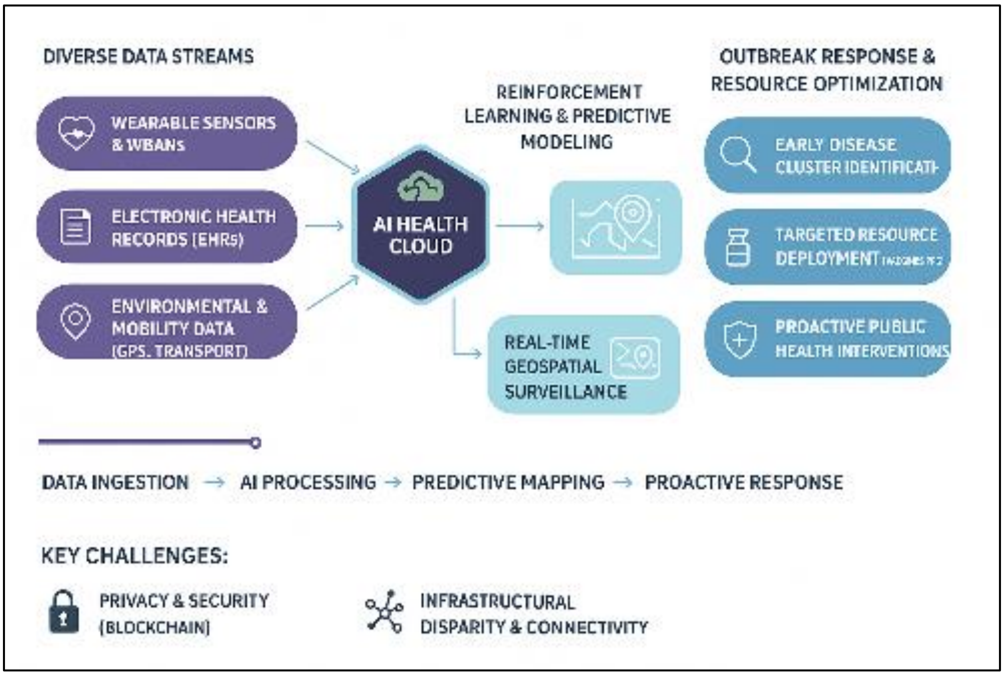
On the other hand, an algorithm can favor some countries and hurt others in its health prediction, and the situation is automatically wrong as it comes with prejudice in the outcomes and fabricated interpretations (Abdellatif et al., 2023). The quality or utility of AI models developed on health clouds is equivalent to the inputs that they are engineered. When there is skewness in input data, there are biased predictions that will enhance dishonesties in disease tracking (Leite et al., 2021). As an example, predictions will fail to identify the rural regions where disease fires can begin and remain unseen will fail disproportionately when the urban population is overrepresented in the training data that have access to these constant and unstable digital infrastructure (Abdellatif et al., 2023). The extent of the bias has drastic effects on the observation of outbreaks, as the most vulnerable groups among the target population are likely to be under-represented in the information feeds. And also, the predisposed biases of wearable against more privileged groups will potentially produce a more skewed version of geospatial hotspots map, which will impact even less represented yet more vulnerable groups unfavorably (Baiense et al., 2025).

These risks are mitigated on the basis of explainability and transparency. In fact, AI schemes can be used to support the process of clarifying how it arrived at predictions, whereby clinics and policymakers can doubt the outcomes, rather than adhere to the directions of algorithms (Abdellatif et al., 2023). Likewise, the predictive models must also be audited periodically and feature varying collections of epidemiological data with an aim of reducing systemic errors (Nwankwo, 2024). The question of representative datasets to be constructed is however a problem. The practice of health data collection delivered in the majority of non-resource settings is unstable and renders things piecemeal which implies that predictive algorithms operate using unfinished biased information (Hu et al., 2025). Structural injustice in the circulation of data may also put the prospects of AI-based disease prediction at risk in this manner (Narla, Valivarthi and Peddi, 2020).

Also, the naturally questionable success of the AI health clouds only depends on itself and the extent of integration with the existing healthcare systems. Even though predictive modeling and geospatial intelligence can be used to warn about future outbreaks, the extent to which health outcomes are improved is possible only provided local healthcare facilities can act on the intelligence (Leite et al., 2021). Nonetheless, the digital infrastructure, workforce, and interoperability criteria (i.e., standards) needed to support smooth integration are lacking in most health systems and, in particular, in the ones of low- and middle-income countries (Da Fonseca et al., 2021). The technologies within the clouds typically cover high-bandwidth network connections and high-intensity computing, which is absent in resource-organized practices with the highest resource burden on infectious illnesses (Nwankwo, et al, 2024). This means that capacity building is required. Therefore, healthcare professionals should be trained as well, which would not only allow them to comprehend AI-driven wisdom but would also allow them to make it a part of their everyday clinical routine. It involves institutional practice reform, and scaling and long-term infrastructures pilot projects (Abdellatif et al., 2023). In addition, the overbearing burden by interoperability is also glowing. Many hospitals on their EHR systems are siloed systems that do not enable their data to traverse local, national, and global environments. Ways to go include such concerns as safe and extendable guidelines on EHR-sharing (Liu et al., 2024), which are quite realistic to implement but rather slow. The predictive potential of the health clouds risks being an insulated technology layer in the sense it cannot influence decision-making in real-time because it is not interoperable.

Another challenge in deploying AI health cloud for real-time infectious disease surveillance is finding balance between innovation and public trust. AI health clouds will have to grapple with the innovation and technological trust dilemma. Wearables, WBANs, and AI-based surveillance devices will provide an unrivaled grid layout of consumption of an outbreak (Baiense et al., 2025; Li et al., 2024). However, although such systems in absence of an obvious protection can be an object of the profile of surveillance facilities, where the extraction of data has a priority over human values (Nyangaresi, 2025). It is easy to lose little trust but once lost one may not regain it. The open control, open design and participatory processes in developing a system are therefore non-replaceable (Rabie et al., 2024). Nevertheless, policy makers and developers can achieve this through one specific design of privacy, fairness, and equity to constitute an effective and socially justifiable structure of health cloud systems by ensuring on its part real-time disease surveillance will be achieved.

The below figure describes how the combination of different types of data the AI Health Cloud facilitates (wearable sensors, electronic health records, and environmental/mobility data) can be provided as a predictive analytics platform that can aid in helping to identify clusters of disease earlier, deploy resources directly to those clusters, and create any proactive actions to help improve the overall health of the population. It highlights the whole lifecycle of data ingestion, predictive mapping inspired by AI and response optimization, and lists key concerns including privacy matters related to data, security and structural differences.



Source: Developed by the researcher

Figure 1 AI Health Framework for Real-Time Infectious Disease Surveillance

5. Predictive Analytics in Infectious Disease Surveillance through AI Health Clouds

With a large number of companies developing predictive analytics into infectious disease surveillance programs, it is now considered that in the future, AI health clouds can act as a scalable platform onto which machine learning models could be deployed in real-time (Islam, 2025). Unlike conventional statistical frameworks, machine learning platforms in clouds empower the organization to absorb heterogeneous data flows, such as electronic health records and biosensors founded on the Internet of Things, as well as mobility and climate intelligence, thereby, encompassing non-linear dynamics of the disease outbreak (Narla, Valivarthi, and Peddi, 2020). Cloud applications based on supervised learning models have been created, as an example, to detect influenza-like infection using a combination of patient records and web factor information such as web search results providing advance warning compared to conventional reporting systems (Ekundayo, 2024). Likewise, the distributed cloud-based computation has been deployed in discovering unknown outbreak warnings of high-dimensional data using deep belief networks trained on metaheuristics neighborhood techniques (Narla, Valivarthi, and Peddi, 2020). However, such predictive designs have enduring disadvantages because they may face the problem of overfitting and inability to generalize in irregular data employed in dissimilar populations. On the one hand, transparency is the key to the success of real-time predictions, and without any doubt, on the other, the predictions that the cloud system offers have some resolution and transparency, respectively (Islam, 2025).

Even more predictive characteristics of the AI health clouds are the HR historical epidemiological and environmental data. The medium permit to study existing facts about old data about past diseases and demography, climatic changes against the present indicators that have been taken by the IoT networks and city surveillance systems. For example, predictive models, based on rainfall data and mosquito vectors, are established to predict outbreaks of dengue in tropical regions, which serve as an active platform on which the control measures against the mosquito vectors can be grounded (Folasole, 2023). Cloud systems put more reserve on this capability through the offering of scalable reconfigurable systems in which models would be repeatedly refreshed along with the influx of new information (Islam, 2025). The threat of such a strategy is, however, the integration of old assumptions when forecasting engines in particular in the scenario of new epidemics wherein past patterns may be irrelevant to the new pattern of contagion. According to Choudhury et al., (2025), this could be done by making use of epidominated learning on cloud platforms, which trains a single model at different times on various institutions and spaces in order to offer a flexible provision that does not breach privacy. Nonetheless, even standardized data governance and cross-international commitment that further divide the predictive aptitudes and lessen the capacity to obstruct with cloud-based systems were not set.

Besides the traditional machine learning, reinforcement learning (RL) in AI health clouds is emerging as one of the extreme solutions to prevalent models. Instead of considering existing data as RS morbidity to further inquire, they can look into the interdependency between outbreak dynamics and intervention strategies, such as vaccination determinacies and mobility limitations intra tonium recommender system (RS) before their actual implementation rather than act as a find-aid or reason checks. Abdellatif et al. (2023) point to the fact that the optimization associated with the presence of the reinforcement learning (RL) feedback creates the conditions of dynamically adjusting to the uncertain factors that define an epidemic state. In the past, urban contexts have observed certain opportunities in RL-based epidemic simulators to simulate the risks (mobility-based) given its capability of offering specific advice on containment in conditions where transmission networks and devices are too complex (Alwakeel, 2025). Nevertheless, there are no unlimited applications of RL using a cloud-computed surveillance. These types of systems require loads of good training information to be utilized which can only happen in the early phases of an epidemic.

The opportunity of providing healthcare prevention and the systemic burden of AI health cloud systems can be highlighted by analyzing the application of predictive analytics through the previous pandemics. During the COVID-19 crisis, it was possible to use AI models built on the cloud to forecast spikes in cases and allocate resources in hospitals to optimise asset utilisation, allowing the planning of peak case scenarios by the policymakers (Sharma et al., 2022). As well as an example, the use of predictive systems (along with the current surveillance system of the outbreak of Zika virus) integrating epidemiological intelligence and social media indicators to distinguish hotspots of transmission and implement an effective intervention in the mosquito-rearing control (Choi et al., 2016). Moreso, Ebola in West Africa was also tracked using mobility-informed predictive models, which visualized the risk of the Ebola spread across borders and predicted it using cloud-based analytics (Leite, Albuquerque, and Pinheiro, 2021). These triumphs were, however tainted by huge failures. Many COVID-19 predictive models had failed to stay predictive because disruptions in testing like the mutating of the virus and the under-reporting of the cases had an impact on the streams of input data (Ali, 2024). AI tools were even interpreted contextually within the number of epidemiological interpretations and therefore led to the overestimation and underestimation of risks thus compromising the trust of this population (Tripathi and Rathore, 2025). It is implied by these experiences that, whereas AI health clouds have the potential to enhance the capacity of the predictive analytics, the preventive strength of the technology relies just as much on a well-designed data governance platform, effective communication, and system integration as robust public health systems.

6. Preventing Real-Time Infectious Disease through AI Health Cloud for Surveillance in Future

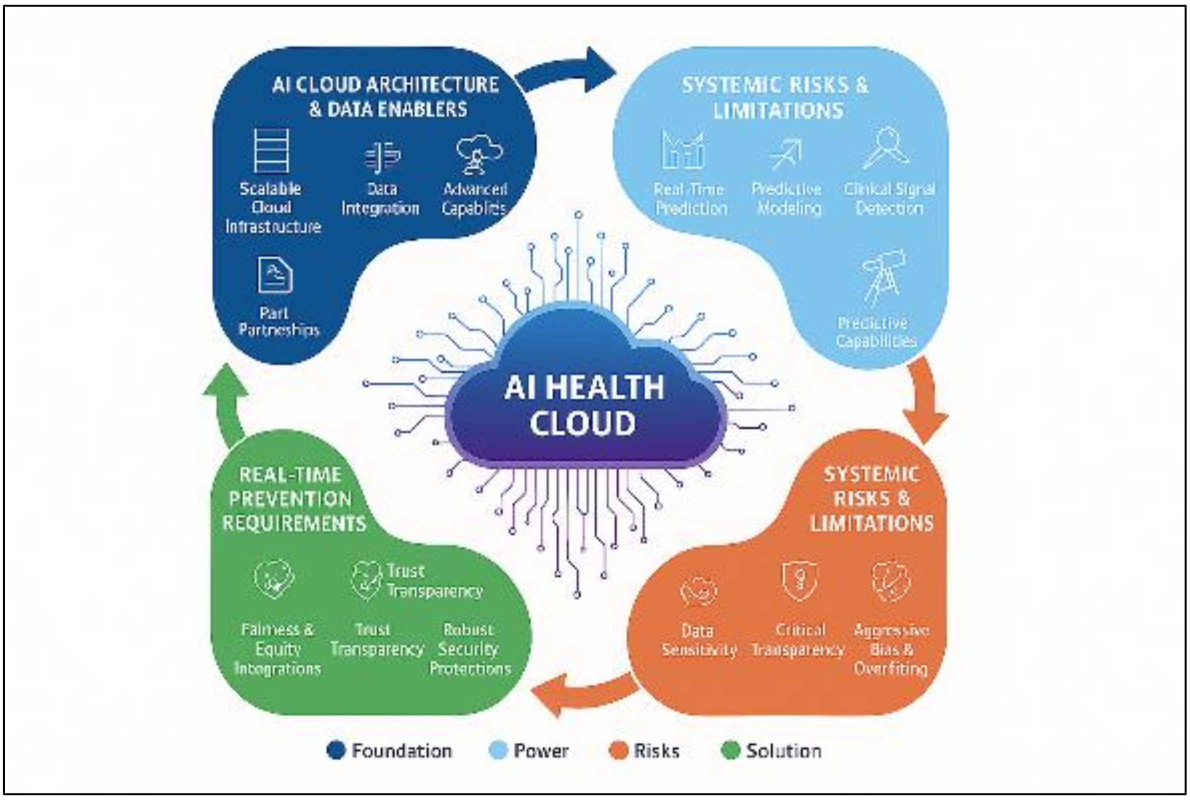
The impact of any AI health cloud system towards the prevention of infectious diseases in real time cannot be achieved without prior preparation measures that include fairness, equity, as well as trust at every level of surveillance (Hu et al., 2025). Whereas AI models have in the past been shown to have enormous potential when it comes to prediction of outbreaks, their preventive potential largely depends on the inclusivity and the responsibility of its design. Anupriya and Devi (2024) note that one of the greatest risks of preventive surveillance is the problem of algorithmic bias, since underrepresented groups fail to be reflected in predictive data, limiting the amendments of the system to deploy time-sensitive warnings to disadvantaged groups. In Hu et al. (2025), the technological aspects of African public health is traditionally not sufficient to incorporate rural and low resource regions, which leads to inequality of access to prevention tools. Similarly, Ekundayo (2024) indicates that AI-based health clouds cannot serve the preventative role to rural or underserved populations since predictive models generated using urban and high-income data are incapable of yet benefiting to prevent the outbreak.

Once several demographics combined with separated geographic and social-economic data can be discovered in AI health clouds, early-warning systems may detect an outbreak in a larger context and predict prevention actions. Khan and Jilani (2024) suggest that blockchain-based cloud models may potentially facilitate safe but massive data-sharing because it can also allow the additional layers of the population to be included in the predictive processes. Likewise, low data also can be borne in mind by carrying out an extrapolation of about the data holes with the help of generative neural model as revealed by Anupriya and Devi (2024), thus preventing the system. However, it can be prevented not only by larger datasets, but by more patient-the datasets an integration of the social determinants of health into prevention operations that would not only target the increased indicators on the early outbreaks, but also on conditions which promote their flourishing (Leite, Albuquerque, and Pinheiro, 2021).

The argument that the lapses about the response to an outbreak should also be used to answer the question of what should be the measure of such preventive control. To capture the active components of preventive (including resource arrangement) and vaccination and rather specific preventive health intervention is much more advisable than to predict such projections (Khan and Jilani, 2024). The price of the learning based on reinforcement will be that those strategies, which isolate the conditions will cause the formation of a continuous response to these changing conditions, such that the diseases will order everything crowded together in a brief period before these conditions go out of control (Khan and Jilani, 2024). Similarly, Rabie et al. (2024) show that the process of wearable health device verification executed by the privacy protection type can lead to the heightened presence at the preventive service, especially among groups that are exposed to various dangers where confidential data transfer might be one of the primary factors. However, Tripathi and Rathore (2025) affirm that, in practice, AI schemes are effective but not just fair enough to lead to the preventive strategies and intervention before rising the cohort who will gain the most out of the programmes. In this regard, preventive models should be techno savvy as well as socially accommodative.

Building trust and advocacy of AI prevention devices is also considered to be important in accomplishing a successful prevention of an outbreak. Nyangaresi (2025) adds that, anonymity protocols in any health monitoring system, makes it more participatory since the population gains a feeling that they indeed will get the information, which in turn automatically means preventive participation. Even the most effective preventative models, at that, would be of no use in terms of keeping vulnerable groups safe since the mistrust will largely not allow spreading the needed information in a timely way by this point. Da Fonseca et al. (2021) state that preventive technologies must be both culturally and community-correct, so their means are as accessible as they could be. Ali (2024) is not the only one to suggest that the challenge of an outbreak prevention Precautionary measure involves a question of establishing human confidence in AI systems, including technical prediction. The open governance components, moral protection, and considerations of participation involved hence are impregnable to ensure the AI health clouds perform as responsive resources yet serve as potential restraining mechanisms whenever the next outbreaks may emerge (Villanueva-Miranda, et al, 2025).

Fig 2 below represents the full ecosystem of the AI Health Cloud, such as the underlying infrastructure, prediction abilities, and system risks along with ethical and governance remedies. It points out that a scalable cloud solution and additionally more powerful analytics can anticipate outbreaks in real time, yet since the subject of inequality has been raised because of the issues of fairness, trust, and high percentage of security, this will require to deal with the problems of fairness, trust, and a very high level of security to make a sustainable and equal implementation.



Source: Developed by researcher

Figure 2 AI Health Cloud Ecosystem-Architecture, Risk, and Governance Framework

7. Conclusion

Implementing AI health cloud infrastructure on real-time infectious diseases surveillance systems is a decisive move towards preventing infectious diseases proactively instead of responding to them. These systems have unmatched capabilities to identify abnormalities, predict outbreaks and prescriptive actions using machine learning, reinforcement learning, geospatial intelligence and streams enabled by IoT, in such a way that relevant interventions are implemented in real-time. Their commitments to preventive measures, however, is contingent on redress of serious concerns of prejudice, equity, privacy and trust. AI health clouds will fail to eradicate inequality without supportive datasets, open governance, and the systematic changes to the current system. The key to effective prevention of the outbreaks lies in the fact that the potential to offer the balance between social legitimacy and technological innovation might enable offering the predictive systems to the entire populations of the country, irrespective of the geography or the socio-economic factors.

In the future there are two recommendations at the heart of things. To begin with, models like these that ensure that predictive datasets are representative and that project social and demographic diversity onto AI health clouds are not discriminatory or exclusionary and should be institutionalized by state health agencies. Second, other health-focused organizations and international states would be interested in seeking to build a trust relationship through transparent governance, participatory design and high privacy standards to influence the overall trust levels of the population in AI-enhanced preventive surveillance. At best, predictive power will supplement ethical stewardship of AI health clouds, so that the communities can preclude future outbreaks.

References

[1] Abdellatif, A. A., Mhaisen, N., Mohamed, A., Erbad, A., & Guizani, M. (2023). Reinforcement learning for intelligent healthcare systems: A review of challenges, applications, and open research issues. *IEEE Internet of Things Journal, 10*(24), 21982–22007.

[2] Adam Sahib, R. B., & Bhavani, R. (2025). IoT-based smart healthcare using efficient data gathering and data analysis. *Peer-to-Peer Networking and Applications, 18*(1), 43.

[3] Ali, H. (2024). AI for pandemic preparedness and infectious disease surveillance: Predicting outbreaks, modeling transmission, and optimizing public health interventions. *International Journal of Research Publication and Review, 5*(8), 4605–4619.

[4] Alwakeel, M. M. (2025). AI-assisted real-time monitoring of infectious diseases in urban areas. *Mathematics, 13*(12), 1911.

[5] Anupriya, J., & Devi, R. R. (2024). Artificial intelligence-based security improvement in medical-IoT health care system using generative deep belief neural network. *SN Computer Science, 5*(8), 1027.

[6] Badidi, E. (2023). Edge AI for early detection of chronic diseases and the spread of infectious diseases: Opportunities, challenges, and future directions. *Future Internet, 15*(11), 370.

[7] Baiense, J., Zdravevski, E., Coelho, P., Pires, I. M., & Velez, F. J. (2025). Driving healthcare monitoring with IoT and wearable devices: A systematic review. *ACM Computing Surveys, 57*(11), 1–38.

[8] Chakilam, C. (2022). AI-driven insights in disease prediction and prevention: The role of cloud computing in scalable healthcare delivery. *Migration Letters, 19*(S8), 2105–2123.

[9] Choi, J., Cho, Y., Shim, E., & Woo, H. (2016). Web-based infectious disease surveillance systems and public health perspectives: A systematic review. *BMC Public Health, 16*(1), 1238.

[10] Choudhury, A., Sarma, K. K., Gulvanskii, V., Kaplun, D., & Dutta, L. (2025). Leveraging federated learning and edge computing for pandemic-resilient healthcare. *Scientific Reports, 15*(1), 20497.

[11] Da Fonseca, M. H., Kovaleski, F., Picinin, C. T., Pedroso, B., & Rubbo, P. (2021). E-health practices and technologies: A systematic review from 2014 to 2019. *Healthcare, 9*(9), 1192.

[12] Ekundayo, F. (2024). Using machine learning to predict disease outbreaks and enhance public health surveillance. *World Journal of Advanced Research and Reviews, 24*(3), 794–811.

[13] Folasole, A. (2023). Data analytics and predictive modelling approaches for identifying emerging zoonotic infectious diseases: Surveillance techniques, prediction accuracy, and public health implications. *International Journal of Engineering Technology Research & Management, 7*(12), 292.

[14] Hu, S., Oppong, A., Mogo, E., Collins, C., Occhini, G., Barford, A., & Korhonen, A. (2025). Natural language processing technologies for public health in Africa: Scoping review. *Journal of Medical Internet Research, 27*, e68720.

[15] Islam, S. (2025). Cloud-enabled AI system for early epidemic surveillance. *Journal of Advanced Research, 1*(2), 26–41.

[16] Khan, A. R., & Jilani, A. K. (2024). Privacy-enhanced heart disease prediction in cloud-based healthcare systems: A deep learning approach with blockchain-based transmission. *Fusion: Practice & Applications, 15*(1).

[17] Lawal, O. P., Igwe, E. P., Olosunde, A., Chisom, E. P., Okeh, D. U., Olowookere, A. K., ... & Orobator, E. T. (2025). Integrating real-time data and machine learning in predicting infectious disease outbreaks: Enhancing response strategies in Sub-Saharan Africa. *Asian Journal of Microbiology and Biotechnology, 10*(1), 147–163.

[18] Leite, G. S., Albuquerque, A. B., & Pinheiro, P. R. (2021). Applications of technological solutions in primary ways of preventing transmission of respiratory infectious diseases—A systematic literature review. *International Journal of Environmental Research and Public Health, 18*(20), 10765.

[19] Li, C., Fan, S., & Li, H. (2024). Study on the effectiveness of a community hypertension management model based on home smart blood pressure monitoring using IoT technology. *Frontiers in Public Health, 12*, 1428310.

[20] Liu, Z., Hu, L., Cai, Z., Liu, X., & Liu, Y. (2024). Secose: Toward searchable and communicable healthcare service seeking in flexible and secure EHR sharing. *IEEE Transactions on Information Forensics and Security, 19*, 4999–5014.

[21] Narla, S., Valivarthi, D. T., & Peddi, S. (2020). Cloud computing with artificial intelligence techniques: GWO-DBN hybrid algorithms for enhanced disease prediction in healthcare systems. *Journal of Current Science & Humanities, 8*(1), 14–30.

[22] Nwankwo, E. I., Emeihe, E. V., Ajegbile, M. D., Olaboye, J. A., & Maha, C. C. (2024). Artificial intelligence in predictive analytics for epidemic outbreaks in rural populations. *International Journal of Life Science Research Archive, 7*(1), 078–094.

[23] Nyangaresi, V. O. (2025). Anonymity-preserving security protocol for wireless body area networks: Towards the secure remote patient healthcare monitoring. In *Sensor Networks for Smart Hospitals* (pp. 293–312). Elsevier.

[24] Ogundipe, O. O. (2023). Using AI and big data to predict and prevent disease outbreaks. *Journal of Science, Technology and Engineering Research, 1*(4), 1–14.

[25] Rabie, O. B. J., Selvarajan, S., Hasanin, T., Mohammed, G. B., Alshareef, A. M., & Uddin, M. (2024). A full privacy-preserving distributed batch-based certificate-less aggregate signature authentication scheme for healthcare wearable wireless medical sensor networks (HWMSNs). *International Journal of Information Security, 23*(1), 51–80.

[26] Sharma, S., Gomes, J., Sarkar, S., Chakraborty, A., & Kumar, S. (2022). Analyzing the effective healthcare management model for a COVID-19 pandemic: A suggestive study. *International Journal of Health Sciences, 6*(S3), 6245–6266.

[27] Tripathi, A., & Rathore, R. (2025). AI in disease surveillance—An overview of how AI can be used in disease surveillance and outbreak detection in real-world scenarios. In *AI in Disease Detection: Advancements and Applications* (pp. 337–359).

[28] Udegbe, F. C., Nwankwo, E. I., Igwama, G. T., & Olaboye, J. A. (2023). Real-time data integration in diagnostic devices for predictive modeling of infectious disease outbreaks. *Computer Science & IT Research Journal, 4*(3), 525–545.

[29] Venkata, S. S. M. G. N. (2023). AI-driven data engineering for real-time public health surveillance and early outbreak detection. *Engineering International, 11*(2), 85–98.

[30] Villanueva-Miranda, I., Xiao, G., & Xie, Y. (2025). Artificial intelligence in early warning systems for infectious disease surveillance: A systematic review. *Frontiers in Public Health, 13*, 1609615.