Proceedings of CONF-MLA 2025 Symposium: Intelligent Systems and Automation: AI Models, IoT, and Robotic Algorithms
DOI: 10.54254/2755-2721/2025.LD26878

# *Artificial Intelligence in Public Health: Applications and Impacts*

**Xiaowen Xu**

*School of Public Health, Sichuan University, Chengdu, China*
*2021151650044@stu.scu.edu.cn*

***Abstract.*** Artificial Intelligence (AI) is currently widely applied in the public health domain and has become a transformative force in this field. Through AI technologies such as machine learning, neural networks, and natural language processing, it has enabled epidemic prediction, optimization of health resource allocation, and enhancement of monitoring, screening, and diagnostic efficiency. These applications demonstrate significant implications for the future of public health. However, studies have identified three critical challenges hindering further AI adoption: data quality issues, implementation difficulties, and inherent limitations of AI technology. To address these challenges, effective recommendations are proposed, including innovating research methodologies through Practical Clinical Trials (PCT) and multidimensional evaluation matrices, promoting secure data governance via federated learning and edge computing, and establishing a global framework for algorithmic accountability and equitable technology transfer. As artificial intelligence evolves from an auxiliary tool, it is poised to become a core decision-support platform that will drive the transformation of public health from passive care to proactive prevention—enabling early epidemic warnings, personalized chronic disease management and monitoring, as well as precision medical services.

***Keywords:*** Machine Learning, Neural Networks, Public Health, Artificial Intelligence, Health Technology

## 1. Introduction

Artificial Intelligence (AI) is an emerging field of technological science dedicated to simulating, extending, and expanding human intelligence. It encompasses the theories, methods, technologies, and application systems designed to replicate and augment human cognitive functions such as perception, decision-making, planning, learning, communication, and creativity. As a vital component of intelligent science, AI represents an interdisciplinary convergence spanning multiple fields, including public health. Today, AI has emerged as a key driver of innovation within public health systems, significantly enhancing the efficiency and accuracy of public health services, particularly in areas such as disease risk surveillance, diagnosis, and treatment.

AI and big data analytics have been extensively applied across various domains of public health and healthcare. For instance, Chintala focused on disease spread modeling (such as COVID-19 prediction), electronic health record analysis, and spatial risk modeling. Their research highlights

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DOI: 10.54254/2755-2721/2025.LD26878

how AI technologies enhance epidemic prediction accuracy and resource allocation efficiency through machine learning algorithms, while also noting ethical challenges such as data privacy and algorithmic transparency [1]. Furthermore, AI has been utilized in mobile health (m-health) to develop more effective healthcare systems [2], providing valuable insights for tailored resource planning to address m-health-specific challenges.

Beyond artificial intelligence, big data technologies have a lot of uses. Studies show that machine learning algorithms can look at huge amounts of data from electronic health records, which is what people often mean by 'big data', to help with stopping diseases and figuring out what they are [3]. More and more, digital technologies are being used to make global public health responses to challenges such as COVID-19 stronger. This includes using them for keeping an eye on populations, spotting cases, tracing contacts, and checking how well interventions work based on data about how people move around and public communication plans.

Consequently, exploring the potential for integrating AI with public health strategies and driving the digital and intelligent transformation of public health systems has become a critical task and challenge for modern society.

However, the integration of AI with public health strategies remains in its nascent stages and faces numerous challenges. A significant barrier is the inability to achieve seamless data sharing and effective utilization across different hospitals and systems, which hinders AI's potential to fully leverage data. Additionally, available datasets are often limited in scale, prone to bias, and predominantly sourced from specific regions. These limitations constrain the generalizability and applicability of AI models, potentially leading to unintended errors [4]. This underscores that AI is not infallible; blind reliance on big data is inadvisable, and the potential negative impacts stemming from the stability and accuracy of predictive models must be rigorously addressed.

Only through continuous scrutiny of potential problems and risks can the application of AI in public health be ensured to be both secure and practically viable. Therefore, this paper provides an overview of the current applications and challenges of AI in public health. Based on this analysis, the paper proposes suggestions concerning the integration of AI into public health strategies, the management of public health events, and the enhancement of public health systems. The aim is to offer insights and references for the advancement of public health.

## 2. Overview of mainstream technologies

The realm of AI technologies that are put to use in public health is quite varied. For the most part, it consists of two key categories: traditional Machine Learning (ML) and Neural Networks (NN). Traditional ML methods include a range of algorithms like Random Forests, Support Vector Machines (SVM), Logistic Regression, and Naive Bayes. Moreover, neural networks also play a significant role, boasting specialized architectures such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Graph Neural Networks (GNN), and Generative Adversarial Networks (GAN).

### 2.1. Machine Learning

Machine Learning, which is a core branch of AI, develops algorithmic models that are able to identify patterns within data by itself and generate predictions. This offers scientific support based on data for the decision-making in public health. The basic principle of it is to learn the mapping relationship between input variables (such as clinical symptoms, environmental indicators) and output targets (like disease risk) from the training datasets, so as to make predictions on new

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samples eventually. In public health, the outstanding ML methods comprise Random Forests, Logistic Regression, and Naive Bayes.

#### 2.1.1. Random Forests

Random Forests integrate multiple decision trees using Bagging strategies to reduce variance. Their strength lies in handling high-dimensional, heterogeneous data – such as integrating multi-source indicators like climate, population mobility, and healthcare resources for outbreak probability prediction – while demonstrating robust resistance to overfitting and effective feature importance ranking. However, their "black box" nature limits interpretability, and computational costs can be significant.

#### 2.1.2. Logistic Regression

Logistic Regression, based on linear models and the Sigmoid function to output event probabilities, is favored for chronic disease high-risk population screening due to its strong interpretability and probabilistic outputs. Its limitations include insufficient capability to capture nonlinear relationships and susceptibility to multicollinearity interference.

#### 2.1.3. Naive Bayes

Naive Bayes calculates posterior probabilities using Bayes' theorem under the feature conditional independence assumption. This approach has the advantage of providing a relatively quick response, which is especially beneficial in situations where resources are limited, such as within primary care systems. There, it can facilitate the prompt differentiation of diseases. However, the rather stringent independence assumption made by Naive Bayes tends to ignore the correlations that might exist between different symptoms. This oversight could conceivably lead to an uptick in the rates of misdiagnosis when it comes to more complex diseases.

### 2.2. Neural Networks

Beyond Machine Learning, Neural Networks are extensively utilized in public health. Neural Networks (NN), foundational to deep learning, are computational models inspired by the structure of biological neurons. They consist of multiple interconnected layers of "neurons," where each neuron processes inputs through weighted sums and nonlinear activation functions to produce outputs. Utilizing backpropagation algorithms, these networks iteratively adjust connection weights based on the error between predictions and actual values, thereby autonomously learning complex mapping rules from inputs to outputs. Key NN architectures in public health include Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Graph Neural Networks (GNN), and Generative Adversarial Networks (GAN), with CNN and GAN being particularly prominent due to their widespread application.

#### 2.2.1. Convolutional Neural Networks

Convolutional Neural Networks (CNN) employ learnable convolutional kernels (filters) that scan input images locally (e.g., 3x3 pixel blocks). This design automatically extracts spatially hierarchical features, progressing from simple edges to complex objects. By sharing kernel weights globally and utilizing pooling layers for dimensionality reduction, CNNs achieve significant parameter efficiency

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and robustness to feature location variations, making them highly effective for processing spatial data like images. Functioning akin to "visual processors," they hierarchically extract meaningful spatial patterns from raw pixels. One of their key strengths is that they can automatically learn hierarchical features from medical images, which can greatly cut down on the engineering effort required. Nevertheless, they do have a rather strong reliance on the quality of data annotation. If there are any errors in the labeling process, it could result in higher rates of misdiagnosis.

#### 2.2.2. Generative Adversarial Networks

Generative Adversarial Networks (GAN) comprise two adversarial networks: a generator and a discriminator. The generator creates synthetic data from random noise, aiming to deceive the discriminator. The discriminator, conversely, strives to distinguish real data from the generator's forgeries. Through this adversarial process, both networks progressively improve until the generator produces highly realistic data. Their core value lies in overcoming medical data privacy barriers by enabling privacy-compliant synthetic data generation. A key challenge is the risk of mode collapse, which can degrade model generalization capability.

## 3. Applications

### 3.1. Machine Learning applications

Machine Learning (ML) applications have been extensively developed over time and demonstrate broad utility. For instance, Dinesh Visva Gunasekeran et al. highlight ML's capacity to predict COVID-19 severity, mortality risk, and hospitalization duration using patient clinical data (age, comorbidities, vital signs) [5]. This approach optimizes resource allocation for ICU beds and ventilators, enhancing epidemic response effectiveness. Beyond this, specialized ML methods including Naive Bayes classifiers, Support Vector Machines (SVM), and decision tree-regression hybrids serve distinct purposes. Naive Bayes classifiers reduce false alarm rates for heart failure prediction from 28.64 to 7.8 annually by integrating clinical data with patient questionnaires [2]. Burns et al. combine decision trees with regression to analyze multidimensional behaviors (emotional, social, environmental) via mobile sensor data for depression symptom prediction [2]. ML also facilitates predictive modeling, outperforming traditional Cox regression in chemotherapy response forecasting and Abbreviated New Drug Application submission timeline estimation [6].

### 3.2. Neural Networks applications

Neural networks have emerged as a prominent focus in medical imaging diagnostics in recent years. Convolutional Neural Networks (CNNs), through their capacity to decode complex data structures, significantly enhance diagnostic efficiency and hold transformative potential for future public health screening and surveillance measures. When applied to CT/MRI image segmentation, CNNs improve liver tumor localization accuracy by 30%, while achieving 91% sensitivity in COVID-19 detection via X-ray imaging [3]. CNNs also enable breast cancer diagnosis; Johnson KB et al. demonstrate that AI-driven analysis of 38,444 mammograms combined with EHR data predicts malignancy with radiologist-comparable accuracy. These neural networks applications facilitate earlier case detection, improve epidemiological surveillance, enhance patient prognoses, and generate dual public health-economic benefits.

Neural networks play a critical role in responding to public health emergencies and disease outbreaks. Graph Neural Networks (GNNs) accelerate antiviral compound screening, exemplified by

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AlphaFold's application in protein structure prediction, which enhances response capabilities for relevant authorities [5]. Recurrent Neural Networks (RNNs) process temporal data to forecast epidemic trends such as influenza and dengue [7]. Generative Adversarial Networks (GANs) address small-sample limitations by synthesizing medical images and simulate disease transmission scenarios, as demonstrated in WHO emergency response systems [7].

### 3.3. Natural Language Processing

Beyond ML and neural networks, Natural Language Processing (NLP) constitutes an essential AI application domain. NLP is task-oriented rather than a standalone algorithm—it functions as an "application category" reliant on other methodologies. According to Supriya M et al., NLP enables public health applications including clinical text analysis, patient sentiment assessment, automated medical report generation, clinician-patient communication analysis, and anti-stigma systems for Alzheimer's disease [3]. These innovations significantly increase clinical workflow efficiency and accelerate information dissemination to public health stakeholders. Concurrently, NLP facilitates mental health early-warning systems; by analyzing speech patterns, it achieves >85% accuracy in Parkinson's disease identification and enables early dementia detection [8], thus improving population screening efficiency and societal benefits. For policy implementation, NLP powers healthcare insurance interpretation engines that automatically extract regulatory rules from policies, transform data into structured formats, monitor fund control indicators using generative business intelligence, detect anomalies in real-time, and generate compliance reports—strengthening medical insurance fund oversight [9,10].

## 4. Challenge

Despite rapid advancements in the application of artificial intelligence in public health, significant obstacles persist. Prominent challenges include data quality limitations, implementation barriers, and inherent technical deficiencies.

### 4.1. Data quality defects

The primary challenge stems from data quality defects. AI prediction accuracy relies on high-quality data, yet public health data often suffer from incompleteness and inconsistent formats due to heterogeneous sources. This substantially diminishes data usability. Furthermore, Gunasekeran et al.'s survey indicates that while 44.9% of reports involve AI applications, 91% constitute descriptive analyses lacking prospective studies [5]. The root cause lies in methodologically weak baseline research and resultant data deficiencies, which critically undermine the reliability and generalizability of models trained on such data.

### 4.2. Implementation difficulties

A second major challenge arises during the implementation of AI-enabled health solutions. AI methodologies in public health require large-scale, cross-institutional data integration such as electronic health records, environmental sensors, social media. However, privacy protection regulations (HIPAA/GDPR) fundamentally conflict with data-sharing needs [1]. Public resistance and non-cooperation due to privacy concerns significantly increase implementation difficulties. Additionally, resource integration challenges emerge from poor interoperability between disparate systems and fragmented data across platforms. These issues are exacerbated in low-resource settings

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where inadequate infrastructure makes data integration and model deployment significantly more challenging.

### 4.3. Intrinsic limitations

Finally, intrinsic limitations of AI technology warrant serious consideration. The black-box nature of models like random forests impedes decision traceability, complicating policymakers' understanding of algorithmic logic and eroding trust among clinicians and the public in AI-assisted decisions. Data bias—exemplified by a 23% increase in skin cancer misdiagnosis due to underrepresented minority data in training sets [5]—further compromises reliability. At the same time, excessive automation endangers humanistic care; for example, although AI simplifies the management of chronic diseases, it lessens the interactions between clinicians and patients that offer vital psychological support [1].

## 5. Suggestion

First of all, innovating the methodologies is of great importance for tackling the challenges of data quality. By implementing Practical Clinical Trials (PCT), it is possible to test AI tools within real-world clinical settings, such as the diagnostic algorithms in community hospitals. At the same time, using Intention-to-Treat (ITT) analysis can help to simulate the real-world attrition scenarios. Also, by establishing a multidimensional evaluation matrix which evaluates the technical performance, clinical outcomes, cost-effectiveness, and ethical compliance, it can be ensured that the AI solutions are practical and feasible.

Promoting secure data governance and transparent technologies can facilitate the implementation of AI. Federated Learning allows for cross-institutional collaborative modeling in applications like multinational pandemic prediction by exchanging encrypted parameters instead of raw data, thus ensuring compliance with privacy regulations such as HIPAA and GDPR. Advancing data standardization integrates multisource data into dynamic "data pools". In low-resource settings, developing lightweight edge computing models lowers technical barriers, making them deployable in areas with limited infrastructure.

Finally, establishing a global collaborative framework safeguards equity and accountability. A WHO-aligned global AI ethics charter should mandate public disclosure of algorithmic bias audits—such as misdiagnosis rate disparities across demographic groups—while establishing independent regulatory bodies for accountability. International organizations must create technology transfer mechanisms to provide developing nations with open-source models, low-cost devices, and training. Successful cases including China’s CT-assisted diagnosis system should be modularized for broader adoption, with validation occurring through smart city pilot programs [7].

## 6. Conclusion

Artificial intelligence has come forth as a highly transformative power within the realm of public health. It clearly shows a notable potential for enhancing disease surveillance activities, diagnostics procedures, as well as the allocation of resources. This study looks into the mainstream AI technologies that are presently being utilized in public health. These technologies encompass machine learning, neural networks, and natural language processing. The study also takes a look at their specific applications. These applications assume crucial roles in dealing with disease outbreaks, making public health monitoring more efficient, and optimizing the allocation of healthcare resources.

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However, despite substantial evidence highlighting AI's profound importance for public health, critical challenges persist. These primarily encompass three dimensions: suboptimal data quality, implementation barriers hindering the scalability of AI-enabled solutions, and inherent technical limitations of AI methodologies. Consequently, three strategic approaches have emerged to fully harness AI's potential: innovating research methodologies, promoting secure data governance, and establishing a global collaborative framework.

As AI technology becomes deeply integrated into public health systems, its role will evolve from an auxiliary tool to a core decision-support platform within the health ecosystem. This platform will enable early epidemic warnings, precise chronic disease prevention, and grassroots healthcare transformation—ultimately driving a fundamental shift from reactive response to proactive prevention in public health.

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