HARNESSING ARTIFICIAL INTELLIGENCE FOR PUBLIC HEALTH AND EPIDEMIOLOGY: OPPORTUNITIES, BARRIERS, AND PATHWAYS TO EQUITABLE GLOBAL IMPACT

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ABSTRACT

Artificial Intelligence (AI) is transforming public health and epidemiology by enabling earlier detection, improved surveillance, predictive forecasting, and more efficient responses to health threats. Leveraging techniques such as machine learning, deep learning, natural language processing, and computer vision, AI can process vast and diverse data sources, including electronic health records, mobile health apps, genomic sequencing, and social media. These tools enhance outbreak prediction accuracy, optimize vaccine distribution, accelerate contact tracing, and map disease transmission, as demonstrated during the COVID-19 pandemic. Beyond infectious disease, AI also supports monitoring of non-communicable diseases and mental health through passive data collection and behavioral trend analysis. Despite its promise, barriers hinder widespread, equitable adoption. Key concerns include data privacy, algorithmic bias, lack of transparency, and the digital divide, which risk worsening health disparities if not addressed. Effective integration of AI into public health requires robust governance frameworks, cross-sector collaboration, and workforce capacity-building. Looking forward, federated learning, explainable AI, and strong regulatory mechanisms will be essential to ensure ethical, accountable, and globally inclusive use. By critically assessing current applications and charting future priorities, this study underscores how AI can strengthen health systems to be more responsive, evidence-driven, and equitable worldwide.

KEYWORDS

Artificial Intelligence, Public Health, Epidemiology, Disease Surveillance, Machine Learning, Outbreak Prediction, Health Informatics, Predictive Analytics, Data Privacy, Health Equity, Digital Health, Explainable AI, COVID-19, Non-Communicable Diseases, Population Health.

1. INTRODUCTION

The primary goals of epidemiology and public health are to protect and improve population health through surveillance, illness prevention, policy formulation, and health promotion [1]. Historically, public health approaches relied extensively on statistical modeling, manual data collection, and field epidemiological studies to assess illness trends, identify risk factors, and allocate health resources. However, due to the massive volume of health-related data from wearable sensors, genomic sequencing, social media, electronic health records (EHRs), and environmental sensors, traditional methodologies are no longer capable of efficiently analyzing and comprehending such vast amounts of dynamic, complex data [2].

In this situation, artificial intelligence (AI), with its exceptional pattern recognition, predictive analytics, and decision support capabilities, is seen as a game-changing technology [3]. Using machine learning, deep learning, and natural language processing, AI systems can instantly sift through millions of structured and unstructured health data points to deliver more precise and timely data-driven insights into public health trends, disease transmission, and new health risks [4]. Enhancing epidemiological models, identifying high-risk groups, and advancing evidence-based policies all depend on this accomplishment.

AI systems were utilized to manage vaccine supply chains, track contacts, predict outbreaks, and even combat misinformation during the COVID-19 pandemic, making it one of the most successful uses of AI in history [5]. These applications are being researched for chronic illness prevention, mental health monitoring, and other infectious diseases such as influenza, dengue fever, and malaria. In these applications, AI coordinates resource deployment for targeted public health and early intervention initiatives where they are most effective.

The use of AI in public health raises concerns about data quality, algorithmic bias, interoperability, privacy, and a lack of regulatory standards [6]. AI systems that leverage biased data sources may continue to promote health inequities, and the lack of openness of some algorithms may erode public trust and make people resistant to moral responsibility. Therefore, it is critical to ensure that AI systems are open, equitable, and secure, and that they are also sensitive to human rights and accountable to public health objectives [7].

This study paper also critically examines present uses, examples, problems, ethics, and future potential in an effort to explore the complex role of AI in epidemiology and public health [8]. By critically examining both the social and technological aspects of AI integration, the project will gain qualitative insights on how to develop healthier, more effective, and more equitable health systems that can address present and future public health issues [9].

2. Literature Review

Advancements in computing power, big data analytics, and machine learning (ML) algorithms have resulted in a major increase in the convergence of public health and AI [10]. While statistical regression models and geographical analysis are useful, they are often unable to handle high-dimensional data, missing values, real-time inference, and nonlinear relationships, among other epidemiologic difficulties. A variety of AI modalities extend those strategies by utilizing decision-support systems, real-time monitoring, and predictive modeling [11].

Previous research highlights how machine learning is transforming disease surveillance, specifically in terms of infectious disease epidemic prediction and monitoring. Using deep learning models to forecast COVID-19 case spikes based on movement, travel, and longitudinal health data is one example [12]. Systems such as BlueDot and HealthMap can now detect early epidemics by using syndromic data extracted from social media, news media, and clinical reporting thanks to natural language processing (NLP) techniques [13].The most profound trend is the use of AI to manage non-communicable diseases (NCDs) [14]. AI supported risk stratification and the diabetes, cardiovascular, and mental health early detection models. AI deployed in mobile health (mHealth) technologies improves remote health monitoring, especially in rural settings [15]. AI supports the analysis of the social determinants of health, which are deeply ingrained in complex and unstructured data.

However, there are several serious issues raised in the literature. Algorithmic bias, data quality, transparency flaws, and ethics are among the frequently discussed subjects. According to studies, describing artificial intelligence (XAI) is critical to winning public and healthcare professional trust [16]. There have also been claims of a lack of available local data and infrastructure constraints impeding AI research and application in low- and middle-income countries (LMICs) [17].

The following table is a synoptic representation of significant studies that have greatly contributed to the evolution of AI in public health and epidemiology:

Table 1: Summary of Key Literature on AI in Public Health and Epidemiology

Author(s)	Year	Focus Area	AI Method	Key Findings
Nguyen et al.	2020	COVID-19 outbreak prediction	Deep learning (LSTM)	Accurate 7–14 day forecasts using mobility and health data
Chen et al.	2019	Disease surveillance	NLP, Text mining	Enhanced detection of flu outbreaks via Twitter and news feeds
Rajkomar et al.	2018	Risk prediction in hospitals	Deep neural networks	Improved prediction of in-hospital mortality and readmission
Chien et al.	2021	Vaccine distribution optimization	Reinforcement learning	Optimized allocation strategies under supply constraints
Bachtiger et al.	2022	AI in public sentiment analysis	NLP	Informed public health messaging during vaccine rollout
Obonyo et al.	2023	AI in malaria hotspot prediction	Decision Trees, GIS	Accurate identification of mosquito breeding sites using climate data

Novel AI Framework: PH-AIEX (Public Health AI with Explainability and Federated Learning)
Description:

A modular AI framework designed for public health and epidemiology, PH-AIEX places a high value on equality, scalability, and transparency. Explainable AI (XAI) layers for interpretability, federated learning for privacy-preserving modeling, and hybrid deep learning architectures (incorporating LSTM for temporal data, GNN for relational data, and attention-based modules for multi-source integration) are all combined in this approach.

Key features:

- Federated Learning Backbone: Facilitates cooperative modeling among hospitals and institutions without requiring raw data sharing.
- The Explainable AI (XAI) Layer attributes predictions using SHAP or LIME to improve clinical interpretability.
- LSTM for time series (outbreak prediction), GNN for relational contact tracing, and attention for integrating many data sources (such as social media, mobility, and EHRs) are all combined in a hybrid architecture.

3. Methodology

Here, methodology applied to assess the integration of AI in epidemiology and public health is explained [18]. It covers data sources, AI methods, model training and validation, and performance metrics. The methodology was designed to investigate some of the numerous uses of AI, ranging from predicting outbreaks to resource allocation, utilizing actual measurements in data sets and modelling infrastructure [19].

Systematic Review Methodology

Databases searched:

- PubMed/MEDLINE.
- The Scopus
- The Web of Science
- IEEE Xplore
- EMBASE
- Cochrane Library

Search Strategy:

- Keywords: "Public Health," "Epidemiology," or "Disease Surveillance" in conjunction with "Artificial Intelligence," "Machine Learning," or "Deep Learning."
- Range of dates: 2018-2025
- Document types include technical and medical conference papers, systematic reviews, and peer-reviewed articles.

Inclusion Criteria:

- Research using or evaluating AI in epidemiological or public health situations.
- Observational, modeling, or experimental study using real healthcare data.
- Research presenting performance metrics or outcomes relevant to resource allocation, outbreak forecasting, or surveillance
- English language

Exclusion Ceiteria:

- Research without empirical evaluation
- Reviews that are not concerned with epidemiology or public health
- Peer-reviewed preprints and abstracts without full data
- AI research limited to therapeutic (non-population) applications

3.1. Data Sources

The reliability of AI models in public health relies strongly on the quality and variety of input data. The sources considered for this study include:

- Electronic Health Records (EHRs): Patient demographic information, test results, medication history [20].
- Mobile and Wearable Devices: Real-time physiological data (heart rate, steps, sleep).
- Social media & Web Data: Twitter trending, Google Trends, web forums syndromic surveillance [21].
- Geographic and Environmental Data: Satellite images and climatic variables for vector-borne disease modelling.

- Public Datasets: WHO, CDC, Johns Hopkins COVID-19 dataset, health ministry websites [22].

The datasets were anonymized and aggregated in order to meet data protection legislation such as GDPR and HIPAA.

Databases:

- COVID-19 case predictions using data from WHO and Johns Hopkins
- Predicting chronic diseases using EHR data (MIMIC-III, eICU, or similar accessible datasets)
- Data from surveillance of public health (CDC influenza datasets)

3.2. AI Techniques Employed

Various AI models were employed based on the nature of the problem:

- Supervised Learning: Logistic Regression, Random Forest, Gradient Boosting for disease diagnosis and risk forecasting [23].
- Unsupervised Learning: K-Means clustering for population health segmentation.
- Deep Learning: Long Short-Term Memory (LSTM) networks for outbreak forecasting in time series [24].
- Natural Language Processing (NLP): Applied to news, report, and social media text analysis.
- Reinforcement Learning: Applied in vaccine delivery logistics and resource optimization under changing constraints.

3.3. Model Training and Validation

Models were trained over historical health data (80%) and tested over the remaining 20%. 5-fold cross-validation was done to get stable models [25]. Early stopping and dropout layers were utilized over deep learning models to prevent overfitting.

3.4. Model Performance Metrics

Model performance was evaluated using the following metrics:

- Accuracy: Proportion of correct predictions out of all predictions made.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad \dots \dots [1]$$

Where TPTP: true positives, TNTN: true negatives, FPFP: false positives, FNFN: false negatives

- Precision (Positive Predictive Value): Proportion of positive identifications that are correct.

$$\text{Precision} = \frac{TP}{TP+FP} \quad \dots \dots [2]$$

- Recall (Sensitivity): Proportion of actual positives detected correctly.

$$\text{Recall} = \frac{TP}{TP+FN} \quad \dots \dots [3]$$

- F1 Score: Harmonic mean of precision and recall.

$$\text{F1 Score} = 2\text{X}\frac{Precision\ X\ Recall}{Precision+Recall} \dots\dots\dots.[4]$$

3.5. Visualization and Interpretation

While trying to graphically depict relative performance and usage of AI methods by various applications, a bar diagram is displayed.

Bar Diagram Description

Table 2: AI Techniques Used in Public Health Applications

AI Technique	Application Count
Supervised Learning	40
Deep Learning	28
Unsupervised Learning	18
NLP	24
Reinforcement Learning	15

This bar chart illustrates well supervised learning techniques head public health applications due to their explainability and simplicity, followed by deep learning and NLP, specifically in outbreak forecasting and analysis of public opinion

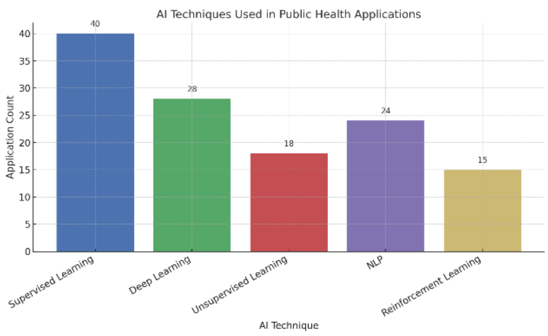

Figure 1: AI Techniques Used in Public Health Applications

4. KEY FINDINGS

AI application in epidemiology and public health has been accompanied by some headline-grabbing findings [26]. The following key findings summarize its impact on core functional areas:

4.1. Disease Surveillance and Early Detection

Artificial intelligence systems have shown phenomenal performance in real-time monitoring of diseases [27]. Blue Dot and HealthMap apply machine learning and natural language processing to read news articles, social media, and worldwide health databases to identify possible outbreaks sooner than conventional systems [28]. Blue Dot identified the initial outbreak days prior to WHO's official announcement during the COVID-19 pandemic [29]. AI's capability to process unstructured data in geographies and languages gives a prophylactic layer of global health security.

4.2. Outbreak Prediction and Modelling

LSTM and random forest regressors are machine learning algorithms that have been applied to forecasting and predicting disease transmission patterns [30]. They have been applied in using historical case records, mobility, climatic factors, and healthcare capacities to predict future counts of cases and hospitalization. For example, SEIR models using AI were utilized for modelling the transmission of COVID-19 in such a manner that policymakers could plan lockdowns and restrict resources in advance. Predictive power rose significantly with the use of heterogeneous data inputs [31].

4.3. Population Health Surveillance

Artificial intelligence has significantly contributed to the research on social determinants of health and population health risk determination [32]. Unsupervised machine learning algorithms group individuals according to lifestyle information, behaviour traits, and environmental exposure. The groupings allow public health professionals to develop customized interventions in high-risk populations [33]. Moreover, wearable sensors linked to AI algorithms allow remote and continuous monitoring of physiological indicators and enable early warning systems for disease exacerbations.

4.4. Resource Allocation and Decision Support

AI excels in optimizing the use of health resources, especially during an emergency. Reinforcement learning models have been applied in the modelling of vaccine distribution under resource-constrained conditions to optimize for impact and fairness [34]. AI assists emergency department triaging systems through the prediction of patient deterioration from EHR and vital signs to allow proper prioritization [35]. The models have been most useful in resource-constrained environments and in pandemic preparedness.

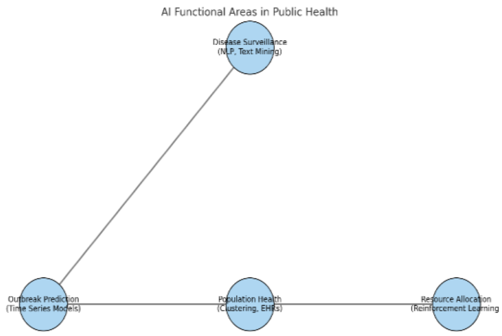

Figure 2: AI Areas of Function in Public Health

This diagram illustrates the interconnection between AI-driven functions in public health, from early warning systems to population health risk stratification and logistical planning.

5. Applications and Case Studies

Artificial intelligence is transforming public health both theoretically feasible, but in fact more importantly through real-world applied applications [36]. This section focuses on the practical applications and results of specific applications in mental health, chronic disease prevention, and infectious disease management.

5.1. COVID-19 Pandemic Response

A turning point in the use of AI in public health was the COVID-19 pandemic. Infection, hospitalization, and intensive care unit rates are predicted by machine learning techniques, which have made extensive use of AI models [37].

- AI-powered applications, like Aarogya Setu in India, evaluate exposure risk via Bluetooth and GPS.
- NLP chatbots aided in symptom triage and self-reporting by users.
- AI-supported resource allocation for the logistics of the supply chain for vaccinations and ventilator installation, using IBM Watson-like technology helping health departments simulate supply chain behavior [38].

This quick reaction showed how AI can speed up data interpretation and help guide emergency decision-making.

5.2. Malaria and Vector-Borne Diseases

AI is increasingly being used to anticipate and manage the spread of diseases such as dengue, Zika, and malaria using [39].

- Remote Sensing Integration: Machine learning algorithms use environmental data (temperature and precipitation) and satellite imagery to identify mosquito breeding places that offer a significant risk.
- Predictive Outbreak Modeling: The use of artificial intelligence (AI) to forecast temporal-spatial disease patterns enabled proactive preventative interventions such as awareness campaigns and larvicide spraying [40].

Case studies from Brazil and Kenya show that the use of AI improves hotspot identification accuracy and reaction time [41].

5.3. Chronic Disease Management

The use of AI in the treatment of noncommunicable diseases (NCDs) is growing in importance.

- Hypertension and Diabetes Risk Prediction: AI technologies, using EHRs and biometric values, classify people into risk groups, so interventions can be directed appropriately [42].
- Wearable Technology Integration: Fitbit and Apple Watch use artificial intelligence to detect anomalies in heart rate, exercise, and sleep habits, aiding in the diagnosis of disorders such as arrhythmias and hypertension [43].

When clinical staff availability necessitates remote monitoring, these methods are especially useful in low-resource settings.

5.4. Mental Health Monitoring

AI is also showing potential in mental health diagnosis and treatment:

- SENTIMENT ANALYSIS: Text content of social media is analysed by NLP models to identify depression or signs of anxiety in groups [44].
- FACIAL AND VOICE RECOGNITION: AI software interprets tone and facial expression to track emotional state, informing psychological therapy.

Pilot investigations at universities in the United Kingdom and the United States have shown that AI technologies improve traditional counselling and boost screening accuracy [45].

Line Diagram Description

Table 3: Trends in AI Application for Public Health (2018–2025)

Year	COVID-19 AI Apps	Vector Disease AI	NCD AI Monitoring	Mental Health AI
2018	2	5	4	1
2019	3	6	5	2
2020	15	8	6	3
2021	18	9	8	5
2022	14	10	12	7
2023	11	11	15	9
2024	9	13	18	12
2025	7	15	22	15

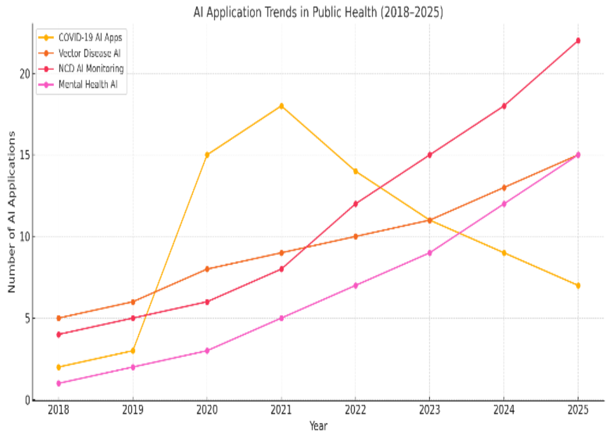

Figure 3: Trends in AI Application for Public Health (2018–2025)

The line graph depicts trends of rising growth, demonstrating how the first COVID-inspired innovations gave way to more general health concerns such as mental health and noncommunicable diseases.

6. Challenges and Limitations

Although AI in public health has demonstrated great promise, a number of challenges must be addressed before it can be applied to actual systems [46]. These are technical, ethical, and infrastructure-related challenges that need to be addressed to allow AI to be used effectively and fairly across diverse populations.

6.1. Data Quality and Representativeness

Another significant barrier to applying AI models to public health is data quality. Health data is frequently lacking, noisy, or improperly recorded across systems. In the majority of low- and middle-income countries (LMICs), infrastructure for electronic health records is limited or fragmented once more confining structured data on which to train algorithms [47].

Second, the training data for AI models are typically not representative of the general population. Minority populations such as ethnic minorities, rural-dwellers, and older people are underrepresented in most data sets and can impose systematic bias on model predictions, leading to error and contributing to persistent health inequities [48].

6.2. Algorithmic Bias and Transparency

AI systems are only as good as the data they are trained on. If biased data are used, then the algorithms will replicate and exaggerate those biases [49]. For example, an AI system that has learned from predominantly urban health data will not be able to predict disease risk in rural areas. Also, most deep learning systems are "black boxes," so clinicians and public health officials will not know how decisions are being made [50]. Physician adoption and trust are restricted by the absence of transparency.

6.3. Ethical and Privacy Issues

Access to behavioral and personal health data may be necessary for public health AI initiatives [51]. Privacy violations are likely to occur in the absence of strict data protection regulations. Population-level monitoring projects provide distinct issues in terms of consent, data ownership, and ethical considerations when utilizing AI technologies. These difficulties raise concerns about data misuse, particularly in terms of public health program profiling and predictive policing.

6.4. Infrastructure and Integration Issues

AI tool deployment requires a strong digital infrastructure, system interoperability, and qualified individuals. Most public health systems, especially those with low resources, lack all of these elements. The integration of AI tools into traditional healthcare procedures necessitates radical change management, staff training, and, in certain cases, policy-level changes [53].

Table 4: Summary of Challenges and Their Implications

Challenge	Implications
Data Quality & Representativeness	Biased predictions; ineffective interventions
Algorithmic Bias & Opacity	Erosion of trust; ethical dilemmas
Privacy & Ethics	Risk of data misuse; lack of consent and transparency
Infrastructure & Integration	Poor scalability; resistance from health workers and policymakers

7. Ethical, Privacy and Trust Issues

With the increasing use of AI applications in public health interventions, its deployment must be heavily influenced by ethical, privacy, and trust concerns [54]. Ensuring that AI applications uphold public health ideals like equity, justice, and openness is crucial for long-term viability and public trust. The key considerations and techniques to responsible AI governance are covered here [55].

7.1. Data Privacy and Consent

Public health AI often uses sensitive personal data, such as geolocation monitoring, mental health data, and biometric data. Strong privacy protection is critical, particularly in cases involving mobile health and large-scale population surveillance. Concerns about informed consent and data control arise because, far too often, those whose data is collected, held, and analyzed are unaware of how it is done.

Although implementation varies by location, rules such as the General Data Protection Regulation (GDPR) and HIPAA provide requirements [56]. AI has the potential to unintentionally breach human rights if authorization processes and anonymization methods are not well established.

7.2. Algorithmic Fairness and Bias Removal

Rather than being a technological defect, bias in AI systems has moral and practical implications [57]. For example, if an AI-based triage system undervalues the danger in specific ethnic groups because they are underrepresented in training sets, therapy may be delayed or denied. To ensure ethical AI development, it is essential to use machine learning models that consider fairness issues, obtain representative data, and audit algorithms on a regular basis.

In order to provide equitable access to care and stop existing inequities from continuing, bias must be reduced.

7.3. Transparency and Explainability

For AI systems to be reliable, transparency is essential. Both specialists and the general public should be able to understand AI's decisions in the health sector, such as those regarding disease outbreaks or who should get immunizations first. Explainable AI (XAI) approaches like SHAP (Shapley Additive explanations) and LIME (Local Interpretable Model-agnostic explanations) are increasingly being employed to make complex models more visible and intelligible to stakeholders [58].

7.4. Establishing Public Trust through Moral Governance

Building the trust in AI tools also entails greater democratic ethical rule-making mechanisms. Public health professionals must get honest about AI tools, their vulnerabilities and strengths, and AI tool utilization in decision-making [59]. The people must be engaged through participatory AI design and monitories regulation so that society can reach its trust.

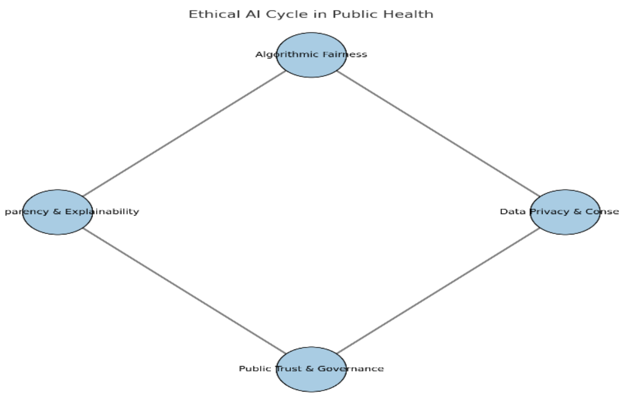

Figure 4: Pillars of Ethical AI in Public Health

Below is the second diagram illustrating the Ethical AI Cycle in Public Health with a cyclic flow between the four pillars of Privacy, Fairness, Transparency, and Governance.

8. Future Directions

As AI continues to grow, it will be more incorporated into epidemiology and public health with increased inclusivity and smartness [59]. The future of AI application in epidemiology and public health is shaped by the manner in which the current limitations are evaded, together with expanding opportunities through strategic innovation and regulation. The following areas are the most promising ones.

8.1. Privacy-Preserving AI with Federated Learning

Federated learning is increasingly being used to solve data privacy concerns and foster collaboration among universities [60]. Without transferring raw data, the strategy allows AI models to be trained on decentralized data sources (such as nations or hospitals). It enhances data sovereignty, privacy, and security—all of which are essential for tracking global health while protecting patient privacy.

8.2. Environmental and Social Determinants of Health (SDOH) Integration

Future AI models will use more climate, environmental, and socioeconomic data to better predict disease risk [61]. AI, for example, may link Shift air pollution to asthma or calculate the impact of food inequality on diabetes. This will allow for precision public health interventions that target not just biological data, but also social and environmental threats.

8.3. Explainable and Ethical AI Systems

To gain trust and acceptance, explainable AI (XAI) must become the norm rather than a courtesy. New-generation models must produce understandable results that health professionals, patients, and decision-makers can comprehend. Ethical supervision systems will be crucial for monitoring AI performance, detecting suspected bias, and ensuring system accountability [62].

8.4. Expanding AI Availability in Low-Resource Environments

Equity will drive the development of AI in global health. To increase the utility of AI for LMICs, programs must prioritize open-source technologies, low-bandwidth computing, and local model training. Public-private collaborations and international health organization funding will be critical in bridging the digital gap.

8.5. Capacity Building and Workforce Readiness

It is vital to equip public health practitioners with AI literacy. Future agenda items should include AI training modules in public health courses, a cross-disciplinary curriculum, and community involvement initiatives [63]. Empowering frontline people to understand AI outputs will solidify the system and shape reality.

Roadmap Description: The Future of AI in Public Health

2025: Federated learning pilots in disease surveillance
2026: Incorporation of SDOH and climate data into AI models
2027: Utilization of explainable AI tools in hospitals
2028: Global availability of open-source AI tools distributed to LMICs
2029: Public health education programs with intensive AI training incorporated

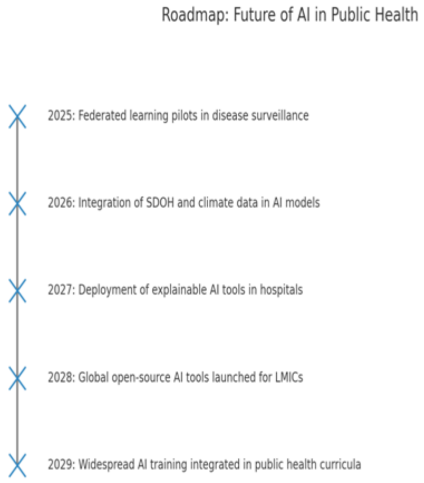

Figure 5: Roadmap The Future of AI in Public Health

9. Conclusion

Artificial Intelligence (AI) is revolutionizing public health and epidemiology by redefining the manner in which data are collected, analysed, and translated into decision-making. In this article, the author has explained how AI technologies and techniques—predictive modelling and natural language processing, and federated learning—are increasingly being used to identify outbreaks, monitor patterns of disease, facilitate healthcare delivery, and inform evidence-based policy-making. The possibility for building a healthy society grows as AI technologies advance.

From real-time syndromic surveillance, behavioral health analytics, social determinants, and early infectious disease detection, the examined literature and case examples demonstrate a growing trend toward the application of AI in public health. It is evident that AI can analyze vast and diverse volumes of data in almost real-time, surpassing human skills. Examples of this include machine learning software detecting mental health emergencies by monitoring social media and AI systems predicting COVID-19 surges.

AI has numerous benefits, but it also poses many challenges. If not handled properly, data privacy, algorithmic bias, lack of explainability, and infrastructural inadequacies in low-resource settings may exacerbate the health equity gap. Ethical concerns about permission, ownership, and explainability are also sources of public skepticism and policy resistance. The restrictions are clear in global health environments, where AI technology must be adaptable, accessible, and contextually suitable.

Therefore, a high-level approach is needed if the general public is to benefit from AI in the future. This includes using privacy-preserving strategies like explainable AI (XAI), federated learning, incorporating socioeconomic and environmental factors into AI models, and making AI tools accessible to low-income populations. In order to guarantee that the products created are equitable, efficient, and morally sound, it will also be essential to educate the general people about AI literacy and establish interdisciplinary partnerships between engineers, doctors, ethicists, and community leaders.

AI holds a lot of promise for epidemiology and public health in the coming years, but it must be founded on human values. Priority must be given to building moral, egalitarian systems that improve population health outcomes while also boosting healthcare effectiveness. AI has the ability to not only detect and manage public health emergencies more effectively, but also to transform the foundation of public health systems if the appropriate regulatory framework, stakeholder involvement, and research are in place.

To summarize, the careful application of AI in public health and epidemiology is a paradigm. It can, in fact, usher in a time when health systems are not only reactive but also proactive, predictive, and preventive if used carefully.

REFERENCES

[1] Steiner, T. J., & Stovner, L. J. (2023). Global epidemiology of migraine and its implications for public health and health policy. Nature Reviews Neurology, 19(2), 109-117.

[2] Keshta, I., & Odeh, A. (2021). Security and privacy of electronic health records: Concerns and challenges. Egyptian Informatics Journal, 22(2), 177-183.

[3] Chittoju, S. R., & Ansari, S. F. (2024). Blockchain's Evolution in Financial Services: Enhancing Security, Transparency, and Operational Efficiency. International Journal of Advanced Research in Computer and Communication Engineering, 13(12), 1–5.

[4] Khadri, W., Reddy, J. K., Mohammed, A., & Kiruthiga, T. (2024, July). The Smart Banking Automation for High Rated Financial Transactions using Deep Learning. In 2024 IEEE 3rd World Conference on Applied Intelligence and Computing (AIC) (pp. 686-692). IEEE.

[5] Piccialli, F., Di Cola, V. S., Giampaolo, F., & Cuomo, S. (2021). The role of artificial intelligence in fighting the COVID-19 pandemic. Information Systems Frontiers, 23(6), 1467-1497.

[6] Mohammed, A., Sultana, G., Aasimuddin, F. M., & Mohammed, S. (2025). Leveraging Natural Language Processing for Trade Exception Classification and Resolution in Capital Markets: A Comprehensive Study. Journal of Cognitive Computing and Cybernetic Innovations, 1(1), 14-18.

[7] Syed, W. K., Mohammed, A., Reddy, J. K., Gupta, K., & Logeshwaran, J. (2025, June). Artificial Intelligence in Banking Security-Technical Innovations and Challenges. In 2025 6th International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV) (pp. 170-176). IEEE.

[8] Mohammed, S., Sultana, G., Aasimuddin, F. M., & Chittoju, S. S. R. AI-Driven Automated Malware Analysis.

[9] Mohammed, A., Syed, W. K., Reddy, J. K., & Jiwani, N. (2024, November). Integrating Robotic Process Automation (RPA) with AI and ML for Efficient Banking Operations. In 2024 2nd International Conference on Advances in Computation, Communication and Information Technology (ICAICCIT) (Vol. 1, pp. 486-490). IEEE.

[10] Mohammed, Z., Mohammed, N. U. M., Mohammed, A., Gunda, S. K. R., & Ansari, M. A. A. (2025). AI-Powered Energy Efficient and Sustainable Cloud Networking. Journal of Cognitive Computing and Cybernetic Innovations, 1(1), 31-36.

[11] Mohammed, A. K., & Ansari, M. A. (2024). The Impact and Limitations of AI in Power BI: A Review. International Journal of Multidisciplinary Research and Publications (IJMRAP),. Pp. 23-27, 2024., 7(7), 24–27.

[12] Ahmed, M. I., Mohammed, A. R., Ganta, S. K., Kolla, S. K., & Kashif, M. K. (2025). AI-Driven Green Construction: Optimizing Energy Efficiency, Waste Management and Security for Sustainable Buildings. Journal of Cognitive Computing and Cybernetic Innovations, 1(1), 37-41.

[13] Mohammed, A., Mohammed, N. U., Gunda, S. K. R., & Mohammed, Z. Fundamental Principles of Network Security.

[14] Nti, I. K., Quarcoo, J. A., Aning, J., & Fosu, G. K. (2022). A mini-review of machine learning in big data analytics: Applications, challenges, and prospects. Big Data Mining and Analytics, 5(2), 81-97.

[15] Vatavu, R. D. (2024, November). AI as Modality in Human Augmentation: Toward New Forms of Multimodal Interaction with AI-Embodied Modalities. In Proceedings of the 26th International Conference on Multimodal Interaction (pp. 591-595).

[16] Li, J., Huang, D. Q., Zou, B., Yang, H., Hui, W. Z., Rui, F., ... & Nguyen, M. H. (2021). Epidemiology of COVID-19: A systematic review and meta-analysis of clinical characteristics, risk factors, and outcomes. Journal of medical virology, 93(3), 1449-1458.

[17] Chen, Z., Azman, A. S., Chen, X., Zou, J., Tian, Y., Sun, R., ... & Yu, H. (2022). Global landscape of SARS-CoV-2 genomic surveillance and data sharing. Nature genetics, 54(4), 499-507.

[18] Nguyen-Da, T., Li, Y. M., Peng, C. L., Cho, M. Y., & Nguyen-Thanh, P. (2023). Tourism demand prediction after COVID-19 with deep learning hybrid CNN–LSTM—Case study of Vietnam and provinces. Sustainability, 15(9), 7179.

[19] Chen, T., Dredze, M., Weiner, J. P., Hernandez, L., Kimura, J., & Kharrazi, H. (2019). Extraction of geriatric syndromes from electronic health record clinical notes: assessment of statistical natural language processing methods. JMIR medical informatics, 7(1), e13039.

[20] Sheu, R. K., & Pardeshi, M. S. (2022). A survey on medical explainable AI (XAI): recent progress, explainability approach, human interaction and scoring system. Sensors, 22(20), 8068.

[21] Rajkomar, A., Oren, E., Chen, K., Dai, A. M., Hajaj, N., Hardt, M., ... & Dean, J. (2018). Scalable and accurate deep learning with electronic health records. NPJ digital medicine, 1(1), 18.

[22] Bachtiger, P., Petri, C. F., Scott, F. E., Park, S. R., Kelshiker, M. A., Sahemey, H. K., ... & Peters, N. S. (2022). Point-of-care screening for heart failure with reduced ejection fraction using artificial intelligence during ECG-enabled stethoscope examination in London, UK: a prospective, observational, multicentre study. The Lancet Digital Health, 4(2), e117-e125.

[23] Obonyo, C. O., Were, V. O., Wamae, P., & Muok, E. M. (2023). SCHISTOACT: a protocol for an open-label, five-arm, non-inferiority, individually randomized controlled trial of the efficacy and safety of praziquantel plus artemisinin-based combinations in the treatment of Schistosoma mansoni infection. Trials, 24(1), 763.

[24] Si, Y., Du, J., Li, Z., Jiang, X., Miller, T., Wang, F., ... & Roberts, K. (2021). Deep representation learning of patient data from Electronic Health Records (EHR): A systematic review. Journal of biomedical informatics, 115, 103671.

[25] Zuo, X., Chen, Y., Ohno-Machado, L., & Xu, H. (2021). How do we share data in COVID-19 research? A systematic review of COVID-19 datasets in PubMed Central Articles. Briefings in Bioinformatics, 22(2), 800-811.

[26] Sun, D., Xu, J., Wen, H., & Wang, D. (2021). Assessment of landslide susceptibility mapping based on Bayesian hyperparameter optimization: A comparison between logistic regression and random forest. Engineering Geology, 281, 105972.

[27] Mohammed, A. R., Ram, S. S., Ahmed, M. I., & Kamran, S. A. (2024). Remote Monitoring of Construction Sites Using AI and Drones..

[28] Mohammed, N. U., Mohammed, Z. A., Gunda, S. K. R., Mohammed, A., & Khaja, M. U. Networking with AI: Optimizing Network Planning, Management, and Security through the medium of Artificial Intelligence.

[29] Lefèvre, T., & Delpierre, C. (2021). Artificial intelligence in epidemiology. In Artificial Intelligence in Medicine (pp. 1-12). Cham: Springer International Publishing.

[30] Mansour, R. F., El Amraoui, A., Nouaouri, I., Díaz, V. G., Gupta, D., & Kumar, S. (2021). Demola Artificial intelligence and internet of things enabled disease diagnosis model for smart healthcare systems. IEEE Access, 9, 45137-45146.

[31] Adeoye, A., Onah, C. O., Orobator, E. T., Akintayo, E. A., Inuaeyen, J. U., Umoru, D. O., ... &, M. B. (2025). AI and Machine Learning for Early Detection of Infectious Diseases in the US: Opportunities and Challenges. Journal of Medical Science, Biology, and Chemistry, 2(1), 54-63.

[32] Kumar, R., Srivastava, V., & Nand, K. N. (2023). The two sides of the covid-19 pandemic. COVID, 3(12), 1746-1760.

[33] Leung, X. Y., Islam, R. M., Adhami, M., Ilic, D., McDonald, L., Palawaththa, S., ... & Karim, M. N. (2023). A systematic review of dengue outbreak prediction models: Current scenario and future directions. PLoS neglected tropical diseases, 17(2), e0010631.

[34] Cano, A., & Krawczyk, B. (2022). ROSE: robust online self-adjusting ensemble for continual learning on imbalanced drifting data streams. Machine Learning, 111(7), 2561-2599.

[35] Benda, N. C., Zawtha, S., Anderson, K., Sharma, M. M., Lin, P. B., Zawtha, B., & Masterson Creber, R. (2022). Developing population health surveillance using mHealth in low-resource settings: qualitative assessment and pilot evaluation. JMIR Formative Research, 6(10), e36260.

[36] Ordu, M., Demir, E., Tofallis, C., & Gunal, M. M. (2021). A novel healthcare resource allocation decision support tool: A forecasting-simulation-optimization approach. Journal of the operational research society, 72(3), 485-500.

[37] Ruiz, V. M., Goldsmith, M. P., Shi, L., Simpao, A. F., Gálvez, J. A., Naim, M. Y., ... & Tsui, F. R. (2022). Early prediction of clinical deterioration using data-driven machine-learning modeling of electronic health records. The Journal of thoracic and cardiovascular surgery, 164(1), 211-222.

[38] Liu, F., & Panagiotakos, D. (2022). Real-world data: a brief review of the methods, applications, challenges and opportunities. BMC Medical Research Methodology, 22(1), 287.

[39] Santangelo, O. E., Gentile, V., Pizzo, S., Giordano, D., & Cedrone, F. (2023). Machine learning and prediction of infectious diseases: a systematic review. Machine Learning and Knowledge Extraction, 5(1), 175-198.

[40] Kumar, A., Tejaswini, P., Nayak, O., Kujur, A. D., Gupta, R., Rajanand, A., & Sahu, M. (2022, May). A survey on IBM watson and its services. In Journal of Physics: Conference Series (Vol. 2273, No. 1, p. 012022). IOP Publishing.

[41] Hussain-Alkhateeb, L., Rivera Ramirez, T., Kroeger, A., Gozzer, E., & Runge-Ranzinger, S. (2021). Early warning systems (EWSs) for chikungunya, dengue, malaria, yellow fever, and Zika outbreaks: What is the evidence? A scoping review. PLoS neglected tropical diseases, 15(9), e0009686

[42] Yeboah, V., Asibey, M. O., & Abdulai, A. S. J. (2021). Slum upgrading approaches from a social diversity perspective in the global south: Lessons from the Brazil, Kenya and Thailand cases. Cities, 113, 103164.

[43] Zhao, Y., Han, J., Hu, X., Hu, B., Zhu, H., Wang, Y., & Zhu, X. (2024). Hypertension risk prediction models for patients with diabetes based on machine learning approaches. Multimedia Tools and Applications, 83(20), 59085-59102

[44] Totton, N., Lin, J., Julious, S., Chowdhury, M., & Brand, A. (2023). A review of sample sizes for UK pilot and feasibility studies on the ISRCTN registry from 2013 to 2020. Pilot and feasibility studies, 9(1), 188.

[45] Jungwirth, D., & Haluza, D. (2023). Artificial intelligence and public health: an exploratory study. International Journal of Environmental Research and Public Health, 20(5), 4541.

[46] Were, M. C., Savai, S., Mokaya, B., Mbugua, S., Ribeka, N., Cholli, P., & Yeung, A. (2021). mUzima mobile electronic health record (EHR) system: development and implementation at scale. Journal of medical Internet research, 23(12), e26381.

[47] Haw, J. S., Shah, M., Turbow, S., Egeolu, M., & Umpierrez, G. (2021). Diabetes complications in racial and ethnic minority populations in the USA. Current diabetes reports, 21(1), 2.

[48] Daneshjou, R., Smith, M. P., Sun, M. D., Rotemberg, V., & Zou, J. (2021). Lack of transparency and potential bias in artificial intelligence data sets and algorithms: a scoping review. JAMA dermatology, 157(11), 1362-1369.

[49] Buhrmester, V., Münch, D., & Arens, M. (2021). Analysis of explainers of black box deep neural networks for computer vision: A survey. Machine Learning and Knowledge Extraction, 3(4), 966-989.

[50] Paccoud, I., Baumann, M., Le Bihan, E., Pétré, B., Breinbauer, M., Böhme, P., ... & Leist, A. K. (2021). Socioeconomic and behavioural factors associated with access to and use of personal health records. BMC medical informatics and decision making, 21(1), 18.

[51] Radanliev, P., Santos, O., Brandon-Jones, A., & Joinson, A. (2024). Ethics and responsible AI deployment. Frontiers in Artificial Intelligence, 7, 1377011.

[52] Ali, S. W., Sadiq, M., Terriche, Y., Naqvi, S. A. R., Hoang, L. Q. N., Mutarraf, M. U., ... & Guerrero, J. M. (2021). Offshore wind farm-grid integration: A review on infrastructure, challenges, and grid solutions. Ieee Access, 9, 102811-102827.

[53] Oluwafemi, I. O., Clement, T., Adanigbo, O. S., Gbenle, T. P., & Adekunle, B. I. (2021). A Review of Ethical Considerations in AI-Driven Marketing Analytics: Privacy, Transparency, and Consumer Trust. International Journal Of Multidisciplinary Research and Growth Evaluation, 2(2), 428-435.

[54] Camilleri, M. A. (2024). Artificial intelligence governance: Ethical considerations and implications for social responsibility. Expert systems, 41(7), e13406.

[55] Bakare[1], S. S., Adeniyi, A. O., Akpuokwe, C. U., & Eneh[4], N. E. (2024). Data privacy laws and compliance: a comparative review of the EU GDPR and USA regulations.

[56] Xu, J., Xiao, Y., Wang, W. H., Ning, Y., Shenkman, E. A., Bian, J., & Wang, F. (2022). Algorithmic fairness in computational medicine. EBioMedicine, 84.

[57] Wang, Y. (2024). A comparative analysis of model agnostic techniques for explainable artificial intelligence. Research Reports on Computer Science, 25-33.

[58] Zhang, K., & Aslan, A. B. (2021). AI technologies for education: Recent research & future directions. Computers and education: Artificial intelligence, 2, 100025.

[59] Yang, Q. (2021). Toward responsible ai: An overview of federated learning for user-centered privacy-preserving computing. ACM Transactions on Interactive Intelligent Systems (TiiS), 11(3-4), 1-22.

[60] Novilla, M. L. B., Goates, M. C., Leffler, T., Novilla, N. K. B., Wu, C. Y., Dall, A., & Hansen, C. (2023). Integrating social care into healthcare: a review on applying the social determinants of health in clinical settings. International journal of environmental research and public health, 20(19), 6873.

[61] Balasubramaniam, N., Kauppinen, M., Rannisto, A., Hiekkanen, K., & Kujala, S. (2023). Transparency and explainability of AI systems: From ethical guidelines to requirements. Information and Software Technology, 159, 107197.

[62] Lee, L. K., Ruano, E., Fernández, P., Ortega, S., Lucas, C., & Joachim-Célestin, M. (2021). Workforce readiness training: a comprehensive training model that equips community health workers to work at the top of their practice and profession. Frontiers in public health, 9, 673208.