

ARTIFICIAL INTELLIGENCE IN DISEASE OUTBREAK PREDICTION AND MODELING: A COMPREHENSIVE REVIEW

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Abstract

Infectious disease outbreaks continue to pose a persistent threat to global health, and the tools used to anticipate them have undergone a rapid transformation over the past decade. Traditional epidemiological approaches, including compartmental models such as SIR and SEIR and classical time-series methods, provided the backbone of outbreak forecasting for much of the twentieth century but are increasingly limited by rigid assumptions, poor scalability, and an inability to absorb heterogeneous real-time data. Artificial intelligence (AI), spanning classical machine learning, deep learning, graph-based architectures, and most recently large language models (LLMs), has emerged as a complementary and in many cases superior tool for outbreak prediction. This review synthesizes recent literature (2022-2026) on AI applications across disease surveillance, forecasting, and modeling. It examines the major technical approaches (machine learning, deep learning, graph neural networks, hybrid physics-informed models, and NLP/LLM-based epidemic intelligence), the data streams that feed them (epidemiological records, mobility and travel data, social media and news text, wastewater signals, and climate/ecological data), and representative case studies including COVID-19, seasonal influenza, avian influenza (H5N1), dengue, and pox. It then

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critically appraises the field's persistent challenges, namely data quality and bias, model interpretability, integration into public health decision-making, and ethical concerns around privacy and equity, before outlining emerging directions such as federated learning, explainable AI, and multimodal LLM-based forecasting systems.

1. Introduction

Infectious disease outbreaks, from seasonal influenza to novel pandemic threats, remain among the most consequential challenges to global public health. The COVID-19 pandemic demonstrated both the scale of damage an uncontrolled outbreak can inflict and the extent to which existing forecasting infrastructure struggled to keep pace with a rapidly evolving, highly heterogeneous stream of data. Public health authorities have historically relied on mechanistic compartmental models, most notably the Susceptible-Infected-Recovered (SIR) and Susceptible-Exposed-Infected-Recovered (SEIR) families, alongside statistical time-series techniques such as ARIMA, to project the trajectory of an outbreak. These approaches remain valuable for their interpretability and grounding in epidemiological theory, but they generally depend on simplifying assumptions about homogeneous mixing, fixed transmission parameters, and limited capacity to incorporate unstructured or high-dimensional real-time data streams. Artificial intelligence has increasingly been proposed as a complementary, and in some domains superior, approach to outbreak prediction. Machine learning (ML) and deep learning (DL) methods can process large, heterogeneous datasets, including clinical records, mobility patterns, environmental indicators, and social media text, to produce more adaptive and often more accurate forecasts (Frontiers in AI, 2025). The COVID-19 pandemic in particular accelerated adoption of AI and digital surveillance technologies across public health systems worldwide, exposing both their promise and their limitations (Johns Hopkins University Hub, 2025). This review aims to:

1. Summarize the principal AI techniques applied to outbreak prediction and modeling.
2. Catalog the data sources that underpin these models.

3. Present representative case studies spanning COVID-19, influenza, avian influenza, dengue, and mpox.

4. Critically evaluate persistent challenges around bias, interpretability, and ethics.

5. Identify emerging directions likely to shape the next generation of epidemic intelligence systems.

2. Traditional Approaches to Outbreak Modeling

Before AI-based methods gained prominence, outbreak modeling relied primarily on two families of techniques. The first, compartmental mechanistic models (SIR, SEIR, and their many extensions such as SIRD and metapopulational variants), divide a population into discrete epidemiological states and describe transitions between them using differential equations calibrated to parameters such as the basic reproduction number. The second, statistical time-series methods such as ARIMA and exponential smoothing, forecast case counts directly from historical incidence data without an explicit mechanistic structure.

Both approaches have well-documented limitations. Compartmental models depend on assumptions of homogeneous mixing and fixed or slowly varying parameters that rarely hold during a real outbreak, particularly one shaped by changing human behavior, evolving variants, and heterogeneous mobility. Statistical time-series models, meanwhile, tend to perform well over short forecasting horizons but degrade rapidly as horizons extend and lack a straightforward mechanism for incorporating exogenous signals such as mobility or climate data. These shortcomings became especially visible during COVID-19, and they form the primary motivation for the growing body of AI-based approaches reviewed in the sections that follow.

3. AI Techniques Used in Outbreak Prediction

3.1. Classical Machine Learning

Classical supervised learning methods, including random forests, gradient boosting machines (e.g., XGBoost), and support vector machines, have been widely applied to outbreak risk classification and short-term case forecasting. These methods are valued for their relatively strong performance on tabular, structured epidemiological data and for being comparatively easier to interpret than deep neural architectures. Gradient boosting classifiers, for example, have been used to model highly pathogenic avian influenza (HPAI) H5N1 outbreak risk by integrating county-level detection records with satellite-derived climate metrics, storm event data, and wild bird activity indices, allowing researchers to characterize which environmental predictors most strongly shape spillover risk at landscape scale (Jindal et al., 2026).

3.2. Deep Learning and Hybrid Physics-Informed Models

Deep learning architectures, particularly recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) networks, have been extensively applied to epidemic time-series forecasting because of their ability to capture nonlinear temporal dependencies that classical statistical models miss. A growing and particularly promising subfield combines these architectures with the mechanistic structure of compartmental models, producing hybrid physics-informed neural networks. One such approach paired a simple artificial neural network for regional disease incidence with a graph convolutional network to capture spread to adjacent regions; when applied to COVID-19 incidence data in Spain, the model achieved a correlation of 0.9679 with test data while using fewer parameters than prior approaches (Scientific Reports, 2025). Related architectures, including SIR-INN, a physics-informed neural network that integrates real-time influenza data into a modified SIR framework, and the Physics-Informed Spatial Identity (PISID) network for multi-region forecasting (PLOS ONE, 2025), illustrate a broader trend toward models that retain

epidemiological interpretability while gaining the predictive flexibility of deep learning.

3.3. Graph Neural Networks (GNNs)

Graph neural networks have emerged as one of the most active research directions in AI-driven epidemic modeling because they naturally represent the relational structure of disease spread across regions, populations, or contact networks. A comprehensive 2024 review organized the field into a taxonomy of epidemic-related tasks and GNN methodologies, arguing that traditional mechanistic models often suffer from oversimplified or fixed assumptions that limit predictive power and fail to capture complex relational information between locations (Liu et al., 2024). Specific architectures include Graph Attention-based Spatial Temporal (GAST) networks, Recurrent Graph Gate Fusion Transformers, CausalGNN (which incorporates causal structure into spatio-temporal forecasting), and EpiLLM, a dual-branch architecture that fuses spatio-temporal epidemic trends with mobility data to generate localized disease spread predictions. More recent work has extended this line of research to dynamic hypergraph neural networks, which model higher-order interactions among more than two nodes simultaneously, a structure well suited to representing group-level transmission events such as households, schools, or workplaces.

3.4. Natural Language Processing and Large Language Models

Natural language processing has long played a role in epidemic intelligence through the automated mining of news reports, health bulletins, and social media for early outbreak signals. The emergence of large language models has substantially expanded this capability. Multilingual LLM ensembles have been used to extract outbreak-related signals from unstructured health reports and news sources, improving both detection speed and contextual accuracy relative to earlier keyword-based systems (Frontiers in AI, 2025). More ambitiously, PandemicLLM is a multi-modal LLM architecture for outbreak forecasting that integrates policy, genomic, and

behavioral data and has been reported to outperform traditional time-series models on these combined tasks (Nature Medicine, 2026). Collectively, LLM-enhanced systems represent the newest and fastest-moving layer of the AI outbreak-prediction stack, though as discussed in Section 6, they also introduce new interpretability and validation challenges.

3.5. Reinforcement Learning and Intervention Optimization

A smaller but notable body of work applies reinforcement learning (RL) to the problem of

optimizing non-pharmaceutical interventions, such as the timing and intensity of lockdowns or vaccination campaigns, by framing epidemic control as a sequential decision-making problem in which an agent balances health outcomes against social and economic cost. While less mature than the forecasting-focused literature above, RL-based intervention optimization is likely to become more prominent as forecasting models improve and policymakers seek quantitative decision-support tools.

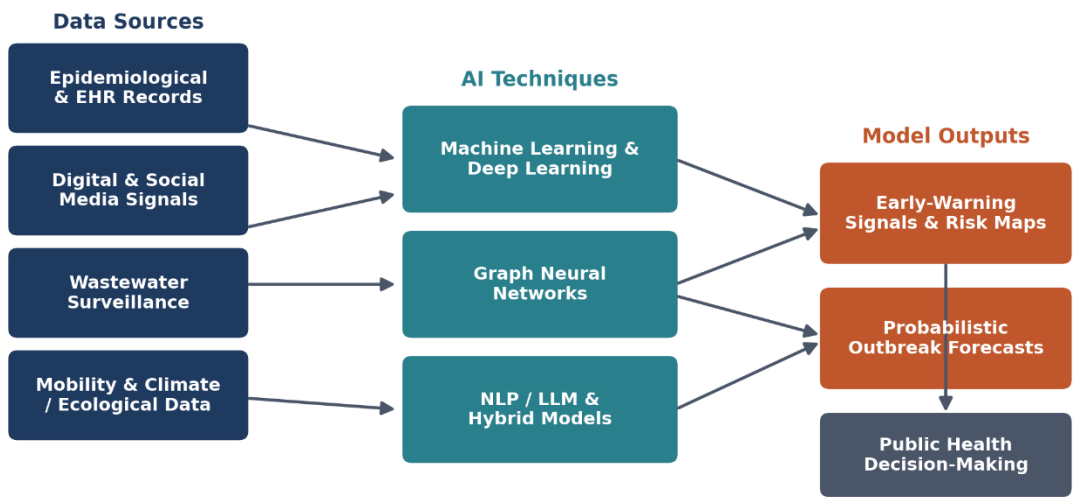


Figure 1. Conceptual pipeline linking data sources, AI techniques, and public health outputs in AI-driven outbreak prediction.

Table 1. Summary of AI Techniques Used in Outbreak Prediction

Technique	Representative Architectures	Primary Use Case	Illustrative Reference
Classical machine learning	Random forests, gradient boosting (XGBoost), SVM	Outbreak risk classification; zoonotic spillover risk mapping	Jindal et al., 2026
Deep learning (RNN/LSTM)	LSTM, attention-based RNN	Epidemic time-series forecasting	Scoping review, medRxiv, 2025

Technique	Representative Architectures	Primary Use Case	Illustrative Reference
Hybrid physics-informed neural networks	SIR-INN, PISID, diffusion-informed NN + GCN	Combines mechanistic structure with data-driven flexibility	Scientific Reports, 2025
Graph neural networks	GAST, CausalGNN, EpiLLM, hypergraph GNNs	Spatio-temporal, multi-region spread modeling	Liu et al., 2024
NLP / large language models	Multilingual LLM ensembles, PandemicLLM	Mining unstructured text; multimodal forecasting	Frontiers in AI, 2025
Reinforcement learning	RL-based intervention policies	Optimizing NPIs and vaccination strategy	General RL-epidemiology literature

4. Data Sources for AI-Driven Outbreak Prediction

4.1 Epidemiological Surveillance and Electronic Health Records

The most direct data source for outbreak modeling remains structured epidemiological surveillance, including case counts, hospitalizations, and laboratory-confirmed diagnoses reported through public health systems. A growing body of work also mines electronic health records (EHRs) directly for early signals. One large-scale study trained machine learning models on 4.5 million longitudinal patient records to predict, within 24-hour intervals, the likelihood of a patient being diagnosed with an infectious or non-specific gastrointestinal, respiratory, or neurological disease; combining these predictions with spatiotemporal anomaly detection allowed the system to detect roughly a third of outbreaks earlier than conventional surveillance, with lead times ranging from one to 24 days (Goncalves et al., 2025).

4.2 Digital and Social Media Surveillance

Digital epidemiology platforms mine online news, informal reports, and social media to detect outbreak signals ahead of official reporting. ProMED-mail, a moderated global disease reporting network operated by the International Society for Infectious Diseases, and HealthMap, which aggregates news, blogs, and official alerts

onto an interactive map, are among the most established such systems; both contributed to the Epidemic Intelligence from Open Sources (EIOS) system developed by the World Health Organization (PMC, 2020). The commercial platform BlueDot has become a widely cited example of AI-augmented epidemic intelligence: using airline travel data alongside news and climate signals, BlueDot alerted its clients to the novel coronavirus outbreak in Wuhan several days before the World Health Organization's public announcement, and its model correctly flagged Bangkok, Hong Kong, Tokyo, Taipei, and Seoul as likely early destinations for imported cases (PMC, 2021). These systems are not without important caveats, however: BlueDot's algorithm is proprietary and cannot be independently validated, is costly to license, and still requires human epidemiologists to verify automated alerts. A cautionary counterexample is Google Flu Trends, an early and widely publicized effort to estimate influenza prevalence from search query patterns. The system initially performed well but later significantly overestimated flu levels due to model overfitting and a failure to account for media-driven changes in search behavior, a case that is now widely cited as a lesson in the importance of rigorous validation and contextual awareness when building digital surveillance tools (Cureus, 2025). More recent scoping reviews of social media and digital surveillance report that

signals derived from search engines or platforms such as X (formerly Twitter) can anticipate official case reporting for diseases including COVID-19 and influenza by one to three weeks, particularly when combined across multiple digital sources and validated against traditional surveillance data from the CDC, WHO, or national health ministries (International Journal of Environmental Research and Public Health, 2025).

4.3 Wastewater-Based Epidemiology

Wastewater-based epidemiology (WBE) has emerged as a cost-effective, population-level surveillance tool that does not depend on individual healthcare-seeking behavior, making it especially valuable in settings with limited clinical testing capacity. Machine learning models trained on wastewater biomarker concentrations have been used to generate multi-community COVID-19 outbreak predictions (Ai et al., 2022), and more recent work has paired genome sequencing of wastewater samples with machine learning to detect emerging SARS-CoV-2 variants before they are identified through clinical surveillance (Zhuang et al., 2025). Dual-branch deep learning frameworks combining frequency-domain transforms with wastewater signal data have also been developed for tiered early-warning systems,

and similar approaches have been extended to non-COVID pathogens such as norovirus and rotavirus (Discover Public Health, 2026). A recurring theme across this literature is that while WBE offers valuable lead time, its predictive models must contend with substantial noise introduced by variation in sewershed characteristics and sample collection methods (Risk Analysis, 2025).

4.4 Mobility, Climate, and Ecological Data

Mobility data, drawn from airline ticketing records, mobile phone location data, or platforms such as Apple Mobility, is frequently combined with case data to model geographic spread, particularly for respiratory pathogens. Climate and ecological variables, including temperature, precipitation, land cover, and wild bird migration patterns, are especially important for zoonotic and vector-borne diseases. Geospatial machine learning frameworks integrating satellite-derived climate metrics and bird movement data have been used to characterize outbreak risk for highly pathogenic avian influenza across the United States, China, and globally (medRxiv, 2026), while similar climate-integrated approaches have been applied to dengue and other climate-sensitive infectious diseases (Inam, 2025).

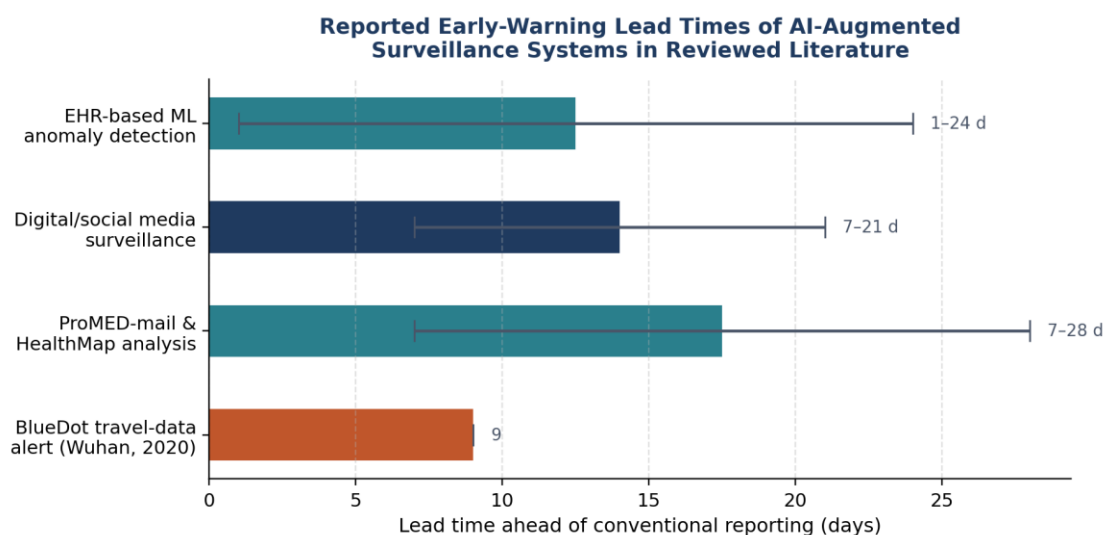


Figure 2. Reported early-warning lead times of selected AI-augmented surveillance systems, drawn from ranges reported in the reviewed literature.

Table 2. Summary of Data Sources for AI-Driven Outbreak Prediction

Data Source	Examples / Platforms	Strengths	Limitations
Epidemiological & EHR records	CDC case reports; Kaiser Permanente EHR data	High specificity; established ground truth	Reporting lag; incomplete or non-specific coding
Digital & social media surveillance	ProMED-mail, HealthMap, GPHIN, BlueDot	Early signal, 1-3+ weeks ahead of official reports	Noise; requires human verification; language barriers
Wastewater-based epidemiology	RT-qPCR biomarkers; ML-assisted variant sequencing	Population-level; independent of care-seeking behavior	Sewershed variability; limited cross-site generalizability
Mobility & travel data	Airline ticketing, mobile location, Apple Mobility	Captures geographic spread patterns	Privacy concerns; restricted access
Climate & ecological data	Satellite climate metrics; bird migration GPS tracks	Critical for zoonotic/vector-borne disease risk	Requires integration with biological/case data

5. Case Studies

5.1 COVID-19 Forecasting

COVID-19 catalyzed the largest coordinated forecasting effort in the history of infectious disease epidemiology. The US COVID-19 Forecast Hub, launched in April 2020 in partnership with the CDC (CDC Epidemic Prediction Initiative, 2025), aggregated weekly probabilistic forecasts of cases, hospitalizations, and deaths from dozens of independent modeling teams using a wide range of approaches, from mechanistic to purely statistical to machine-learning-based, into a single ensemble forecast used in official CDC communications. Studies evaluating these ensembles found that combined forecasts provided precise short-term predictions that declined in accuracy as the forecasting horizon extended toward four weeks (Cramer et al., 2024), underscoring a limitation shared across nearly all approaches reviewed in this paper. Beyond the Forecast Hub, hybrid deep learning approaches, including diffusion-informed neural networks and graph-based spatio-temporal models, have reported strong correlations with observed COVID-19 incidence in specific regional contexts such as Spain (Scientific Reports, 2025) and multi-

region settings incorporating intervention-strategy simulations (Wang & Jin, 2025).

5.2 Seasonal Influenza and the FluSight Initiative

The CDC's FluSight initiative, running since 2016, served as a direct model for the later COVID-19 Forecast Hub and continues to coordinate ensemble forecasts of seasonal influenza activity across US states. Recent scoping reviews of AI and computational methods for influenza forecasting document an expanding toolkit that spans classical ARIMA-based approaches, attention-based recurrent neural networks, and, increasingly, GNN-based nowcasting models that exploit the interplay between temporal, geographic, and functional spatial features to improve influenza-like-illness prediction (medRxiv, 2025).

5.3 Avian Influenza (H5N1)

The ongoing H5N1 highly pathogenic avian influenza panzootic, which has affected several hundred bird and mammal species and produced nearly a thousand documented human cases since 1997, has become a major proving ground for

geospatial AI risk modeling. Gradient boosting classifiers trained on climate, storm event, and wild bird activity data have been used to predict county-level HPAI outbreak risk in the United States (Jindal et al., 2026), while interpretable machine learning frameworks using two decades of outbreak data have mapped H5 outbreak risk across China (medRxiv, 2026), and global geospatial modeling frameworks combining ecological, environmental, and anthropogenic variables have characterized H5N1 risk internationally using presence data from the World Animal Health Information System (Nature Medicine, 2026). Complementary empirical approaches have combined long-term GPS tracking data from migratory waterfowl with ground-level surveillance data to model the spatiotemporal spread of the virus via wild bird migration, though these models have shown better predictive performance for wild waterfowl than for poultry facilities or non-migratory species (PMC, 2025).

5.4 Dengue and Climate-Sensitive Diseases

Because dengue transmission is strongly modulated by temperature, rainfall, and vector abundance, AI-based dengue forecasting has become a flagship application for climate-integrated outbreak prediction. Recent reviews highlight the design of spatiotemporal AI models specifically for dengue early warning that incorporate vector surveillance and, in some cases, citizen-participation data alongside case and climate records, with the explicit goal of providing timely predictions that support vector-control interventions (Inam, 2025).

5.5 Mpox

Following the 2022 and subsequent mpox outbreaks, researchers developed machine learning models for both clinical diagnosis, using symptom-based data, and image-based detection from photographs of skin lesions. Several of these diagnostic models have incorporated explainable AI (XAI) techniques specifically to improve clinician trust and transparency, reflecting a broader shift in the field toward interpretability-aware design discussed further in Section 6 (Alkhanbouli et al., 2025).

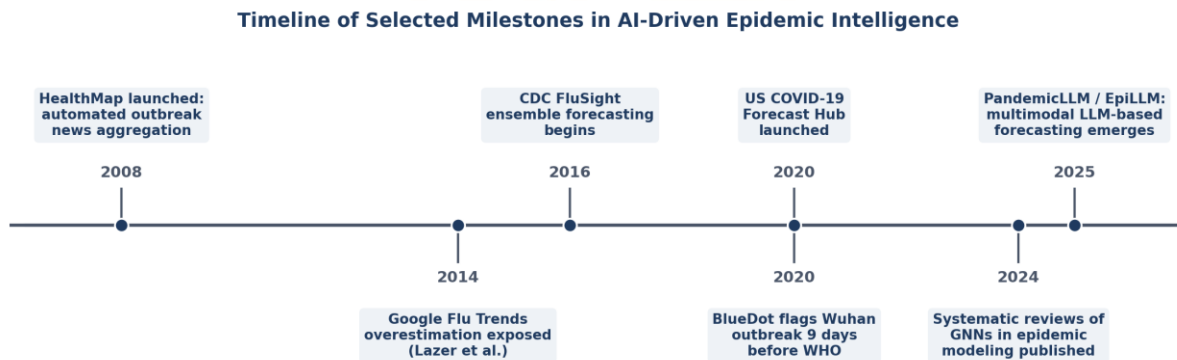


Figure 3. Timeline of selected milestones in the development of AI-driven epidemic intelligence, 2008-2025.

Table 3. Summary of Case Studies in AI-Driven Outbreak Prediction

Disease	AI Approach	Key Data Inputs	Reported Outcome
COVID-19	Ensemble forecasting; hybrid GCN + ANN	Case, hospitalization, and mobility data	0.9679 correlation with test data (Spain); ensemble forecasts accurate over short horizons

Disease	AI Approach	Key Data Inputs	Reported Outcome
Seasonal influenza	FluSight ensembles; GNN-based nowcasting	Weekly influenza-like-illness surveillance	Ongoing CDC-coordinated ensemble since 2016
Avian influenza (H5N1)	Gradient boosting; geospatial ML risk mapping	Climate, storm events, bird migration, WAHIS records	County- and global-level outbreak risk maps
Dengue	Spatiotemporal AI with climate integration	Vector surveillance, climate, citizen-reported data	Earlier warnings supporting vector-control interventions
Mpox	ML diagnostic models with XAI	Clinical symptoms; lesion images	Improved diagnostic accuracy and clinician trust

6. Challenges and Limitations

6.1 Data Quality, Availability, and Bias

AI models are only as reliable as the data on which they are trained, and infectious disease data streams are frequently incomplete, delayed, or systematically biased (PMC, 2025). Underreporting, uneven healthcare-seeking behavior, and limited digital or internet access can each introduce bias into the datasets that feed AI systems, and a systematic review of AI-based early warning systems found that such biases can intensify existing health inequities rather than correct for them (Frontiers in Public Health, 2025). This concern is especially acute in low-resource settings, where sparse surveillance infrastructure limits both the volume and the representativeness of training data; a related critique describes a pattern of digital colonization in which low-income countries function primarily as data sources for models whose benefits accrue disproportionately elsewhere, deepening rather than narrowing global health disparities (Public Health AI Handbook, 2026).

6.2 Interpretability and the Black-Box Problem

Many of the highest-performing AI architectures, particularly deep neural networks and complex ensemble models, are difficult for clinicians, epidemiologists, and policymakers to interpret, a limitation widely referred to as the black-box problem. This lack of transparency complicates efforts to identify errors, detect embedded biases, or establish accountability when model outputs

inform high-stakes public health decisions. In response, a growing subfield applies explainable AI (XAI) techniques, such as SHAP (Shapley Additive Explanations) values and Grad-CAM visualizations, to make model reasoning more transparent (Alkhanbouli et al., 2025); one review of AI for climate-driven outbreak forecasting notes that SHAP-based explanations of how temperature influences model predictions can help balance predictive complexity with the demand for transparency, thereby strengthening trust in AI-informed public health decisions (Inam, 2025).

6.3 Generalizability Across Regions and Diseases

Models trained and validated in one geographic or epidemiological context frequently generalize poorly to others. Ecological niche models trained on pre-2020 H5N1 and H5Nx data, for example, showed reduced predictive accuracy when applied to occurrence patterns in the 2020-2022 period, illustrating how rapidly evolving pathogen ecology and shifting environmental conditions can erode model performance over time (medRxiv, 2026). Similarly, wastewater-based prediction frameworks validated on a single region's sewershed characteristics have shown limited generalizability to other locations and time periods without further validation (Discover Public Health, 2026).

6.4 Ethical and Privacy Concerns

The data streams most useful for AI-driven outbreak prediction, including mobility records, EHR data, and social media content, raise

substantial privacy concerns. A 2025 analysis of the ethics of AI in infectious disease epidemiology frames the field as a double-edged sword (Ethox Centre, University of Oxford, 2025): the same techniques that enable earlier outbreak detection also create new avenues for privacy erosion and surveillance overreach, and argues that maintaining public trust requires that data remain anonymized and secure, that AI decision-making be made more explainable to policymakers and the public, and that ethical AI frameworks explicitly prioritize diverse and representative training data. These concerns have motivated growing interest in privacy-preserving architectures, discussed in Section 7.

6.5 Integration into Public Health Decision-Making

Even highly accurate AI forecasting systems face substantial barriers to real-world adoption. Automated epidemic intelligence platforms often generate large volumes of unfiltered alerts that still require human analysts to validate and contextualize, and existing surveillance systems frequently lack integration with operational public health infrastructure, such as emergency department resource allocation (Public Health AI Handbook, 2026). Bridging this gap will likely require closer collaboration between AI developers and public health practitioners, alongside clearer regulatory and reporting standards for validating AI-based surveillance tools before deployment.

Table 4. Key Challenges in AI-Driven Outbreak Prediction and Emerging Solutions

Challenge	Description	Emerging Solution
Data quality & bias	Underreporting, uneven care-seeking, digital divide	Federated learning; diverse, representative data collection
Black-box interpretability	Complex models are difficult to trust or validate	Explainable AI (SHAP, Grad-CAM, causal inference)
Generalizability	Poor transfer across regions, diseases, and time periods	Continual validation; hybrid mechanistic-AI models
Privacy	Sensitive mobility, EHR, and behavioral data	Differential privacy; federated, decentralized learning
Operational integration	Alert fatigue; disconnect from public health infrastructure	Human-AI collaboration; standardized reporting frameworks

7. Future Directions

7.1 Federated and Privacy-Preserving Learning

Federated learning (FL) allows multiple institutions or jurisdictions to jointly train a shared predictive model without centralizing sensitive patient-level data, addressing many of the privacy concerns discussed above. A systematic review of federated learning in public health identified nineteen studies applying FL to surveillance, outbreak detection, risk prediction, and policy support between 2020 and mid-2025, concluding that FL offers a genuinely transformative opportunity for decentralized, real-

time early-warning systems, while cautioning that federated learning does not automatically guarantee privacy or robustness on its own (Healthcare (Basel), 2025). More advanced implementations combine FL with differential privacy, adding statistical noise to model updates so that no single contributing site's data can be inferred from the shared model; recent work applying this combination to county-level COVID-19 forecasting demonstrated that local health authorities could jointly improve short-term forecasts while keeping sensitive case data entirely local (Agrawal et al., 2025).

7.2 Explainable AI and One Health Integration

As explainable AI techniques mature, several researchers have called for their integration into a broader One Health framework that jointly models human, animal, and environmental health data, particularly for zoonotic spillover events such as avian influenza. A 2026 review argues that scalable XAI methods capable of handling spatiotemporal and multimodal data, including explainability techniques adapted specifically for graph neural networks, represent a key technical priority for shifting explainable AI from retrospective interpretation toward prospective, cross-sectoral decision support (ScienceDirect, 2026).

7.3 Multimodal and LLM-Based Epidemic Intelligence

The integration of large language models with structured epidemiological data represents perhaps the most rapidly evolving direction in the field. Systems such as PandemicLLM and EpiLLM point toward a future generation of epidemic intelligence platforms capable of synthesizing genomic, behavioral, policy, and mobility data alongside unstructured text from news and health reports into a single forecasting or decision-support system (University of Florida Emerging Pathogens Institute, 2025). Realizing this potential responsibly will require parallel investment in validation methodology, since LLM-based systems introduce their own interpretability and hallucination-related risks that are not yet as well characterized as those of more established statistical and machine learning approaches.

7.4 Toward Real-Time, Integrated Surveillance

A recurring theme across the literature reviewed here is the need for greater integration between the many disparate data streams and modeling approaches currently in use. Future systems are likely to combine wastewater signals, digital and social media surveillance, mobility and climate data, and clinical records within unified, continuously updating platforms, supported by explainable AI methods and privacy-preserving architectures, in order to close the gap between

technical forecasting capability and actionable, trusted public health decision-making.

8. Conclusion

Artificial intelligence has meaningfully expanded the toolkit available for predicting and modeling infectious disease outbreaks, moving the field beyond the constraints of classical compartmental and statistical models toward architectures capable of ingesting heterogeneous, high-volume, real-time data. Machine learning, deep learning, graph neural networks, and increasingly large language models have each demonstrated concrete value across a range of case studies, from COVID-19 and seasonal influenza to avian influenza, dengue, and mpox. At the same time, the literature reviewed here makes clear that these gains come with unresolved challenges: data quality and representativeness, model interpretability, cross-regional generalizability, and the ethical management of sensitive health data all remain active areas of concern rather than solved problems. The most promising path forward lies not in any single technique but in the thoughtful integration of complementary approaches, mechanistic grounding paired with data-driven flexibility, explain ability paired with predictive power, and privacy-preserving architectures paired with genuinely collaborative, cross-institutional data sharing, so that AI-driven epidemic intelligence can be deployed as a trusted and equitable tool for global health resilience.

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