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Advancing Infectious Disease Surveillance through Digital Epidemiology and Artificial Intelligence-Based Outbreak Prediction

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Abstract

Digital epidemiology has emerged as an important approach for strengthening infectious disease surveillance by integrating large and diverse sources of real-time health information. Digital platforms can provide signals of changing disease activity before conventional surveillance systems detect an outbreak. Artificial intelligence (AI) and machine learning can further analyze these complex datasets and support early outbreak prediction. This review examines the application of digital epidemiology and AI in infectious disease surveillance. Recent studies demonstrate that machine learning, deep learning and natural language processing can improve prediction accuracy. The review also discusses the use of digital approaches during emerging infectious disease outbreaks and their potential to complement conventional surveillance systems. Despite these advances, data quality, algorithmic bias, and limited external validation remain important challenges. Future surveillance systems should therefore combine AI-driven digital signals with established epidemiological methods and expert assessment. Such integration could support earlier detection, improve outbreak preparedness and enable more timely public health responses to emerging infectious disease threats.

1. Introduction

Infectious diseases remain a major threat to global health despite improvements in vaccination, antimicrobial therapy, and public health infrastructure. The emergence of new pathogens and the re-emergence of previously controlled infections continue to challenge existing surveillance systems. The increasing contact between humans and animals have further increased the possibility of rapid disease transmission. Recent outbreaks have shown that the consequences of delayed detection can extend well beyond the initial geographic location of infection. Early recognition therefore remains one of the most important components of infectious disease preparedness. Traditional surveillance systems mainly depend on clinical diagnosis, laboratory confirmation, and communication between healthcare institutions and public health agencies. Such systems remain essential because they provide clinically validated information. However, reporting often occurs after patients develop symptoms and seek healthcare. Additional delays can occur during laboratory testing, data compilation, and communication with public health authorities. These limitations become more important when an infection spreads rapidly or produces mild and asymptomatic cases. A surveillance system based only on confirmed clinical cases may therefore provide an incomplete picture of ongoing transmission. The growth of digital technologies has created a different approach to disease surveillance. Electronic health records, laboratory databases, and pathogen sequencing now generate large amounts of health-related information. Digital epidemiology uses these sources to study population health and disease dynamics. The approach can provide information at a finer temporal and geographic scale than many conventional surveillance systems. Recent reviews indicate that digital data can improve early detection and situational awareness when integrated with established epidemiological surveillance rather than used as an independent replacement (Fallatah & Adekola, 2024; Hassan Nishan, 2026).

Artificial intelligence (AI) has expanded the analytical potential of digital epidemiology. Machine learning (ML) can identify relationships within large datasets that may be difficult to recognize using conventional

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statistical approaches. Deep learning can analyze complex temporal, spatial, genomic, and text-based information. Natural language processing can extract outbreak-related information from unstructured reports and online communication. Network-based approaches can characterize connections between individuals, locations, and transmission events. Recent systematic evidence indicates that ML , deep learning, and natural language processing (NLP) are among the most frequently used AI approaches in infectious disease early warning systems (Villanueva-Miranda et al., 2025). The value of these technologies became particularly visible during the COVID-19 pandemic. Digital systems were used for case monitoring, genomic surveillance, and disease forecasting. Wearable sensors were investigated for identifying physiological changes before conventional diagnosis. In one study involving more than 30,000 participants, combining wearable sensor information with self-reported symptoms produced an area under the curve of 0.80 for distinguishing symptomatic individuals who tested positive from those who tested negative for COVID-19. Symptoms alone produced an AUC of 0.71 (Quer et al., 2021). These developments indicate a transition from passive disease reporting toward continuous and data-driven surveillance. The transition does not mean that traditional epidemiology has become unnecessary. Clinical expertise, laboratory confirmation, and public health decision-making remain central to outbreak control. Digital epidemiology and AI provide additional layers of information that can improve the speed and precision of those activities. This review discusses the development of digital epidemiology, major digital data sources, and AI methods used in infectious disease surveillance. Particular attention is given to previous study findings and to the practical requirements for converting digital signals into reliable public health action.

2. Evolution of Infectious Disease Surveillance and Digital Epidemiology

Digital epidemiology emerged from this changing information environment. The approach does not depend on a single digital source. Instead, it uses multiple streams of electronically generated information to understand disease patterns. Recent literature describes digital epidemiology as an approach that can combine search activity, social media, electronic health records, wearable devices, mobile applications, and environmental information for disease monitoring (Hassan Nishan, 2026; McClymont et al., 2024). Internet-based surveillance preceded the recent expansion of AI. Platforms such as ProMED-mail, HealthMap, GPHIN, BioCaster, and MedISys demonstrated that information available through news reports and online sources could contribute to epidemic intelligence. A comparative evaluation of six internet-based biosurveillance systems showed that these platforms could detect infectious disease events from informal information sources. The study also demonstrated that system performance differed according to the type of event and the characteristics of the surveillance platform (Barboza et al., 2014). Google Flu Trends provided another important example. Search query information was used to estimate influenza-like illness in near real time. The system could provide information approximately two weeks before conventional surveillance data. However, later analyses showed substantial errors in estimating influenza activity. Combining search information with conventional surveillance data improved prediction compared with relying on search data alone (Butler, 2013; Davidson et al., 2015). This experience provided an important lesson for modern digital epidemiology. A large dataset does not automatically produce an accurate surveillance system. Digital behavior can change because of media coverage, public concern, seasonal trends, or misinformation. Reliable surveillance therefore requires validation against laboratory and epidemiological data. ML provides an alternative approach by allowing algorithms to learn patterns from observed data. Deep learning extends this capability through multilayer neural networks. NLP allows automated extraction of information from text. Geospatial models can identify spatial clusters. Network analysis can describe relationships between individuals and locations. A recent systematic review of AI-based early warning systems identified 67 relevant studies and found frequent use of ML , deep learning, and NLP. Epidemiological records, web-based information, climate variables, and wastewater data were among the commonly integrated sources. Earlier detection and improved prediction were the principal advantages reported across the literature (Villanueva-Miranda et al., 2025).

3. Digital Data Sources for Infectious Disease Surveillance

Smartphones can provide information about symptoms, mobility, exposure events, lifestyle and healthcare seeking behavior. Wearable devices add continuously measured physiological information such as heart rate, activity, and sleep. A notable study by Snyder and colleagues analyzed smartwatch data from 5,300 participants and identified 32 individuals who subsequently developed COVID-19. Physiological or activity changes were observed in 26 participants. A two-tiered warning approach could have identified 63% of cases before symptom onset (Mishra et al., 2020). Another study involving 30,529 participants showed that sensor information improved discrimination between symptomatic COVID-19-positive and COVID-19-negative individuals when compared with symptoms alone (Quer et al., 2021). These findings support the potential role of wearables as an additional surveillance layer. The evidence should not be interpreted as proof that wearable devices can replace diagnostic testing. Physiological changes

are not specific to one infection. Fever, stress, poor sleep, physical activity, and other illnesses can produce similar signals.

Wastewater surveillance has become an important population-level tool in infectious diseases surveillance. Viral or bacterial genetic material released through biological waste can be detected in sewage. This does not require individual participation, and can provide information about infection trends within a defined catchment area. During the COVID-19 pandemic, SARS-CoV-2 RNA was detected in wastewater in several countries. Early investigations suggested that wastewater measurements could provide information about community infection levels and could potentially serve as an early warning signal (Mallapaty, 2020). Wastewater surveillance has also been investigated for poliovirus, antimicrobial resistance genes, gastrointestinal pathogens, and other microorganisms. Combining wastewater measurements with clinical surveillance can strengthen community-level monitoring. Environmental surveillance extends beyond wastewater. Temperature, rainfall, humidity, vegetation, soil moisture, air quality, and water conditions influence many infectious diseases. Such information is particularly important for vector-borne infections (Figure 1).

4.1 Machine learning for disease surveillance

ML can identify relationships between epidemiological variables and disease occurrence. A 2025 scoping review evaluated 77 studies involving ML and AI for infectious disease surveillance, diagnosis and prognosis (Cheah et al., 2025). The review showed that supervised learning, deep learning and ensemble approaches were widely used. Model performance depended strongly on the type and quality of input data. The authors also emphasized the importance of explainable AI when models are used for infectious disease decision-making (Cheah et al., 2025). Machine learning has also been applied directly to healthcare-associated infection surveillance. A systematic review published in 2025 included 121 studies evaluating AI for healthcare-associated infection detection and prediction. Among studies comparing AI with conventional methods, AI models performed better in 81.3% of comparisons (Include reference). More than half of the infection-detection studies achieved an AUROC above 0.90. Performance was more variable for future infection prediction (Barbati et al., 2026). These findings suggest that AI can provide useful automated surveillance when large clinical datasets are available.

4.2 Artificial intelligence for healthcare-associated infection detection

Hospital infection surveillance represents an important application of AI because conventional surveillance can require extensive manual review of clinical records. AI can examine structured and unstructured clinical information and identify patients who fulfil infection surveillance criteria (Table 1). Cozzolino et al. performed a systematic review and meta-analysis of AI-based hospital-acquired infection surveillance systems. The pooled sensitivity was 0.835, while pooled specificity was 0.899 and pooled AUC was 0.864. Only nine studies had tested their systems in real clinical practice. The limited number of real-world evaluations indicates that high technical accuracy does not automatically translate into clinical implementation (Cozzolino et al., 2025). A separate 2024 study evaluated two AI systems for identification of central line-associated bloodstream infection and catheter-associated urinary tract infection. Both systems correctly identified the infections in six National healthcare safety network training scenarios when clear prompts were provided. Errors occurred when scenarios contained ambiguous dates, abbreviations or special characters (Wiemken & Carrico, 2024). The findings demonstrate that AI-assisted surveillance can reduce manual workload but still requires appropriate data formatting and human verification.

Table 1: AI approaches and their applications in infectious disease surveillance

AI approach	Primary function	Application	Outcomes	Limitation	Reference
Random forest	Classification and prediction	Outbreak and risk prediction	Handles multiple predictors	Can be less interpretable	(Qasrawi et al., 2025; Villanueva-Miranda et al., 2025)
Support vector machine	Classification	Disease detection and risk classification	Effective with complex datasets	Sensitive to parameter selection	(Villanueva-Miranda et al., 2025)
LSTM networks	Temporal prediction	Epidemic forecasting	Captures sequential patterns	Requires substantial training data	(Villanueva-Miranda et al., 2025; Wang et al., 2026)
Convolutional neural networks	Pattern recognition	Medical and epidemiological classification	Strong feature extraction	Requires large datasets	(Cheah et al., 2025)

Natural language processing	Text extraction and classification	News, social media and clinical text surveillance	Processes unstructured information	Language and contextual bias	(Li et al., 2026; Villanueva-Miranda et al., 2025)
Ensemble learning	Combined prediction	Outbreak risk estimation	Can improve predictive robustness	More complex interpretation	(Villanueva-Miranda et al., 2025)
Anomaly detection	Identification of unusual patterns	Early outbreak alerts	Detects unexpected changes	False-positive alerts	(Villanueva-Miranda et al., 2025)
Deep learning	Complex pattern modelling	Epidemic forecasting and multimodal surveillance	Handles high-dimensional data	Computationally demanding	(Cheah et al., 2025)

4.3 Deep learning for temporal outbreak prediction

Deep learning models are particularly useful for infectious diseases that show temporal variation. Long Short-Term Memory (LSTM) networks can analyse sequential observations and retain information from previous time points. This property allows the model to identify temporal relationships that may not be captured by simpler statistical approaches. A 2025 real-time epidemic forecasting study developed a transferable machine learning model for predicting epidemic dynamics and pre-trigger warning events. The model was designed to use wastewater-based epidemiological information for early warning. The study addressed the difficulty of translating wastewater pathogen concentrations into future clinical case numbers because viral shedding and transmission patterns can vary over time (Chen & Yu, 2025). The study demonstrates an important advantage of combining AI with environmental surveillance. Wastewater provides a population-level signal while machine learning can model the relationship between pathogen concentration and subsequent disease activity.

4.4 Natural language processing (NLP) for outbreak surveillance

NLP can extract epidemiological information from large volumes of text which could be structured, semi-, unstructured. NLP can analyse public health reports, online news and other digital information sources to identify disease-related signals. A 2026 review of AI in infection surveillance described the integration of electronic health records, social media, spatiotemporal information and wearable technologies as an emerging approach to real-time surveillance (Li et al., 2026). The review concluded that AI can support earlier outbreak detection and disease transmission prediction when heterogeneous datasets are integrated (Li et al., 2026). NLP is particularly useful when conventional surveillance data are delayed. Text-based signals can provide information about unusual disease activity before formal case counts become available. The signal still requires epidemiological validation because changes in media attention can alter the volume of disease-related information without representing a true increase in incidence.

5. AI-Based Outbreak Prediction and Forecasting

Wastewater surveillance provides an opportunity to monitor pathogen circulation at the population level. AI can extend this approach by converting wastewater measurements into predictions of future epidemic activity. A 2024 study monitored SARS-CoV-2 and influenza A virus in wastewater from three major port cities in China between February 2023 and January 2024. Wastewater measurements showed approximately one week of lead time compared with clinical data. The investigators then developed a machine learning approach combining Gaussian modelling and random forest algorithms to predict epidemic trajectories. The predicted trends for SARS-CoV-2 and influenza A were highly consistent with subsequent observations (Fu et al., 2024). This study provides direct evidence that wastewater surveillance can be combined with machine learning to generate forecasts rather than simply detect the presence of a pathogen. The predictive value of wastewater has also been examined in rural populations. A 2025 study developed an epidemiological model using SARS-CoV-2 wastewater measurements to forecast COVID-19 outbreaks in rural communities (Meadows et al., 2025). Wastewater trends generally preceded clinical cases. The model generated forecasts approximately 9–15 days ahead, although interpretation was affected by noise in wastewater viral measurements (Meadows et al., 2025). The findings are important for areas where clinical surveillance infrastructure is limited. Wastewater monitoring can provide community-level information without requiring every infected individual to undergo diagnostic testing.

ML can also be used to combine wastewater measurements with other epidemiological variables. Pagsuyoin et al. reviewed data-driven approaches for wastewater-based epidemiology and described the use of machine learning to process multimodal data, predict disease trends and evaluate public health scenarios. This review identified several limitations that can influence prediction accuracy. These include variation in viral shedding,

wastewater characteristics, data quality and temporal alignment between wastewater measurements and clinical outcomes. Model interpretability also remains an important consideration when predictions are used for public health decisions (Pagsuyoin et al., 2025). These findings indicate that wastewater-based AI forecasting should not be considered a direct substitute for clinical surveillance. The strongest application is likely to involve wastewater as an early population-level signal that is interpreted together with laboratory and epidemiological information. Recent AI systems have begun to combine multiple digital surveillance sources within a single prediction framework. One 2025 study developed an AI-assisted real-time monitoring framework integrating wearable health information, wastewater surveillance, smart pharmacy data, IoT-based information and public health reports (Alwakeel, 2025). The framework used LSTM networks for temporal forecasting, isolation forests for anomaly detection and NLP for extracting epidemiological information from text. The reported system achieved 92.4% accuracy for outbreak detection, while wearable-based fever detection reached 93.5% accuracy and wastewater pathogen classification reached 94.1% accuracy (Alwakeel, 2025). These results demonstrate the potential of multimodal surveillance. However, the study represents a system-level experimental evaluation rather than evidence that such a platform has already improved population-level health outcomes.

6. Integration of Digital Epidemiology into Public Health Response

Digital epidemiology becomes more useful when surveillance signals can be translated into an actionable early warning. Wastewater provides an important example because pathogen concentrations can change before clinical surveillance detects a comparable increase. The 2024 study of SARS-CoV-2 and influenza A in three Chinese port cities demonstrated approximately one week of lead time from wastewater surveillance compared with clinical data (Fu et al., 2024). The subsequent machine learning model reproduced the observed epidemic trajectories with high consistency. Such information could allow public health authorities to increase diagnostic capacity or strengthen surveillance before clinical cases reach their peak. Digital surveillance can also improve disease monitoring in communities where clinical reporting is limited. A 2025 rural COVID-19 study found that wastewater trends could precede clinical cases and that an epidemiological model could provide 9–15-day forecasts (Meadows et al., 2025) This approach has particular relevance for rural settings because wastewater sampling can capture community-level transmission without depending entirely on individual healthcare attendance. The approach may therefore reduce gaps in surveillance coverage between large urban centres and smaller communities. AI can support infection prevention teams by reducing the amount of manual clinical information that must be reviewed. A 2024 study showed that AI systems could identify CLABSI and CAUTI from standardized surveillance scenarios. Correct identification was achieved across all six training scenarios when the prompts were clear (Wiemken & Carrico, 2024). The clinical value of automated surveillance was evaluated more broadly in a 2025 systematic review and meta-analysis. Although AI systems showed pooled sensitivity of 0.835 and specificity of 0.899, only nine studies had evaluated systems in real clinical practice (Cozzolino et al., 2025). The limited implementation evidence indicates that technical accuracy alone is insufficient. Workflow compatibility, interpretability and prospective evaluation are also required.

AI prediction can help identify locations or populations that require increased surveillance. Wastewater forecasting provides one example. If pathogen concentrations indicate an increasing probability of an outbreak, public health authorities can intensify diagnostic testing and epidemiological investigation in the affected region (Fu et al., 2024; Meadows et al., 2025). Healthcare-associated infection prediction provides another application. AI models can identify patients who have a higher probability of developing an infection. Infection prevention personnel can then prioritize these patients for closer monitoring (Barbati et al., 2026). Such approaches may improve the efficiency of public health programmes because resources can be directed toward locations and populations with the highest predicted risk. AI-generated alerts should not be treated as confirmed outbreaks. The value of an AI system depends on the ability of public health professionals to investigate and validate the signal. Wastewater measurements can be influenced by viral shedding, population changes and sampling conditions (Meadows et al., 2025; Pagsuyoin et al., 2025) AI-based healthcare surveillance can also produce errors when clinical information is ambiguous (Wiemken & Carrico, 2024). These findings support a human-in-the-loop model in which AI identifies potentially important patterns while epidemiologists and infection-control specialists determine whether the signal represents a genuine public health event. Recent research is moving toward surveillance systems that combine several digital signals rather than relying on one data source. AI can integrate wastewater measurements, wearable information, clinical data and epidemiological reports within a common analytical framework. The advantage of this approach is that each data source provides a different type of information. Wastewater provides community-level pathogen activity. Clinical records provide patient-level information. Wearable devices provide continuous physiological measurements. Digitized text can serve as the primary unit to provide early information about unusual events through underlying patterns, which are mostly hidden. AI and ML can analyse these signals together and generate a more comprehensive estimate of outbreak risk (Alwakeel, 2025; Li et al., 2026). The transition from experimental models to operational public health platforms will require

prospective validation, standardized data structures and clear procedures for responding to AI-generated alerts. Current evidence shows strong technical potential but limited evidence that AI surveillance systems consistently improve real-world public health outcomes (Cozzolino et al., 2025)

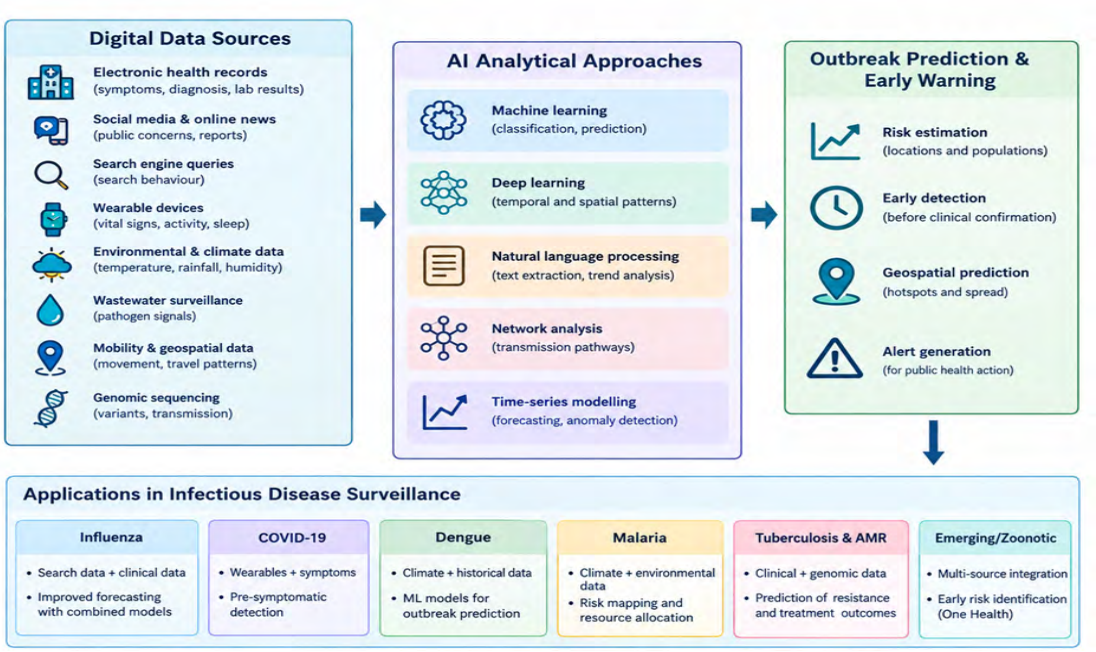


Figure 1: AI-based infectious disease surveillance using digital epidemiology. These approaches support outbreak detection, risk estimation, spatial prediction, and early warning.

7. Conclusion

Digital epidemiology has expanded infectious disease surveillance beyond conventional clinical and laboratory reporting. AI can integrate epidemiological, environmental, wastewater, wearable and digital information to identify emerging signals and predict outbreak patterns. Evidence from COVID-19, influenza, dengue and other hospital acquired infections demonstrates the potential of AI-and ML-powered approaches for earlier detection and improved risk assessment. However, AI should complement rather than replace established surveillance systems. Future progress will depend on validated multimodal models, reliable data, transparent algorithms and close collaboration between AI specialists and public health professionals.

Declarations

Ethics approval statement

Not applicable

Consent to participate

Not applicable

Consent to publish

Not applicable

Data Availability Statement

The data are available from the corresponding author upon reasonable request.

Competing Interests

The authors declare that they have no conflict of interest.

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Author contribution

S.W and E.J involved in preparation of this manuscript. All authors have read and agreed to the published version of the manuscript.

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