Healthcare Studies, 4(1):1–11, 2026. DOI: 10.58612/hs411

Healthcare Studies

Journal homepage: https://www.fpub.org/journal-details.php?journal-id=42

ISSN (E): 2583-9802
Healthcare Studies

Research Article

Artificial Intelligence as an Integrative Inference Layer in Syndemic Disease Surveillance

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Article Info

Keywords: *Artificial intelligence, Syndemic surveillance, Precision public health, Health equity, Disease surveillance.*

Received: *01.12.2025;*
Accepted: *02.01.2026;*
Published: *10.01.2026*

Abstract

The growing global burden of metabolic diseases alongside recurrent infectious disease outbreaks has exposed fundamental limitations in disease surveillance systems that remain siloed, reactive, and disease specific, despite increasing evidence of syndemic interactions driven by shared biological, social, and structural determinants. This review examines the role of artificial intelligence in enabling integrated metabolic and infectious disease surveillance, critically assessing current methods, identifying sources of bias and ethical risk, and articulating research and policy priorities for equitable and action oriented surveillance. We conducted a narrative scoping hybrid review of peer reviewed literature across public health, biomedical, and computational domains and analyzed studies using a conceptual framework that considered surveillance function, methodological approach, and equity and governance implications. Artificial intelligence methods including machine learning, deep learning, and network based models demonstrate substantial potential for multimodal data integration, early warning, and precision public health, but their real world impact is constrained by structural data inequities, algorithmic bias, limited interpretability, and weak integration into public health decision making. Performance metrics alone are insufficient to evaluate surveillance effectiveness, particularly with respect to equity, trust, and policy relevance. We conclude that artificial intelligence can enhance disease surveillance only if reconceptualized as public health infrastructure rather than isolated technological innovation, requiring equity centered design, interpretable and causal methods, robust governance, and interdisciplinary collaboration to avoid reinforcing existing disparities and to strengthen global health preparedness.

How To Cite: O.F. Olaitan, D.A. Lawal, O.O. Akanbi, N.J. Dashe, O.I. Okeoma, T.O. Fabiyi, M.O. Oyebode, M.D. Mashat. Artificial Intelligence as an Integrative Inference Layer in Syndemic Disease Surveillance. *Healthcare Studies*, 4(1):1–11, 2026. https://doi.org/10.58612/hs411

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1. Introduction

1.1. The Syndemic Convergence of Metabolic and Infectious Diseases

Over the past two decades, the global health landscape has been reshaped by the parallel rise of metabolic diseases such as diabetes, obesity, and cardiovascular disorders, and the persistent threat of infectious diseases. Increasingly, these conditions do not occur in isolation [1]. Rather, they interact in ways that amplify individual and population-level risk, forming what has been described as a *syndemic*: a set of co-occurring epidemics driven by shared biological, social, and structural determinants [2]. Metabolic dysfunction alters immune responses, increases susceptibility to infection, and worsens infectious disease outcomes, while infectious exposures can precipitate or accelerate metabolic derangements through inflammatory and endocrine pathways. These interactions are further intensified by social determinants of health, including poverty, food insecurity, housing conditions, environmental exposures, and inequitable access to care [3].

Recent pandemics have not created these interdependencies but have rendered them unmistakably visible. The disproportionate burden of severe outcomes among individuals with metabolic comorbidities during large-scale outbreaks illustrates how vulnerability accumulates across disease domains and social strata [4]. This convergence challenges long-standing distinctions between communicable and no communicable diseases and calls into question surveillance models that continue to treat them as fundamentally separate phenomena.

1.2. Structural Limitations of Contemporary Surveillance Systems

Despite this evolving reality, most disease surveillance systems remain architecturally siloed, organized around single diseases, programs, or reporting mandates. Such systems excel at enumerating cases within narrowly defined categories but are poorly equipped to capture multimorbidity, interaction effects, or shared upstream drivers of risk. The resulting fragmentation obscures early warning signals that emerge at the intersections of metabolic and infectious disease processes, delays anticipatory public health action, and limits the capacity to identify populations experiencing compounded vulnerability [5].

Moreover, these surveillance paradigms often inadequately represent marginalized communities, where data incompleteness, under diagnosis, and limited digital access are common. As a consequence, surveillance outputs may reinforce existing inequities by rendering some forms of risk visible while systematically overlooking others. In an era characterized by complex disease ecologies, reactive and reductionist surveillance approaches are increasingly misaligned with the realities they seek to monitor [6].

1.3. Artificial Intelligence as an Integrative Surveillance Paradigm

Artificial intelligence offers a potential pathway beyond these limitations, but only if its role is properly conceptualized. Rather than viewing AI narrowly as a predictive or classificatory tool, it is more productively understood as an inferential layer capable of integrating heterogeneous data streams across disease domains, time scales, and social contexts. When thoughtfully designed, AI systems can synthesize clinical, laboratory, digital, environmental, and socioeconomic data to generate surveillance signals that reflect the interconnected nature of metabolic and infectious disease risk [7].

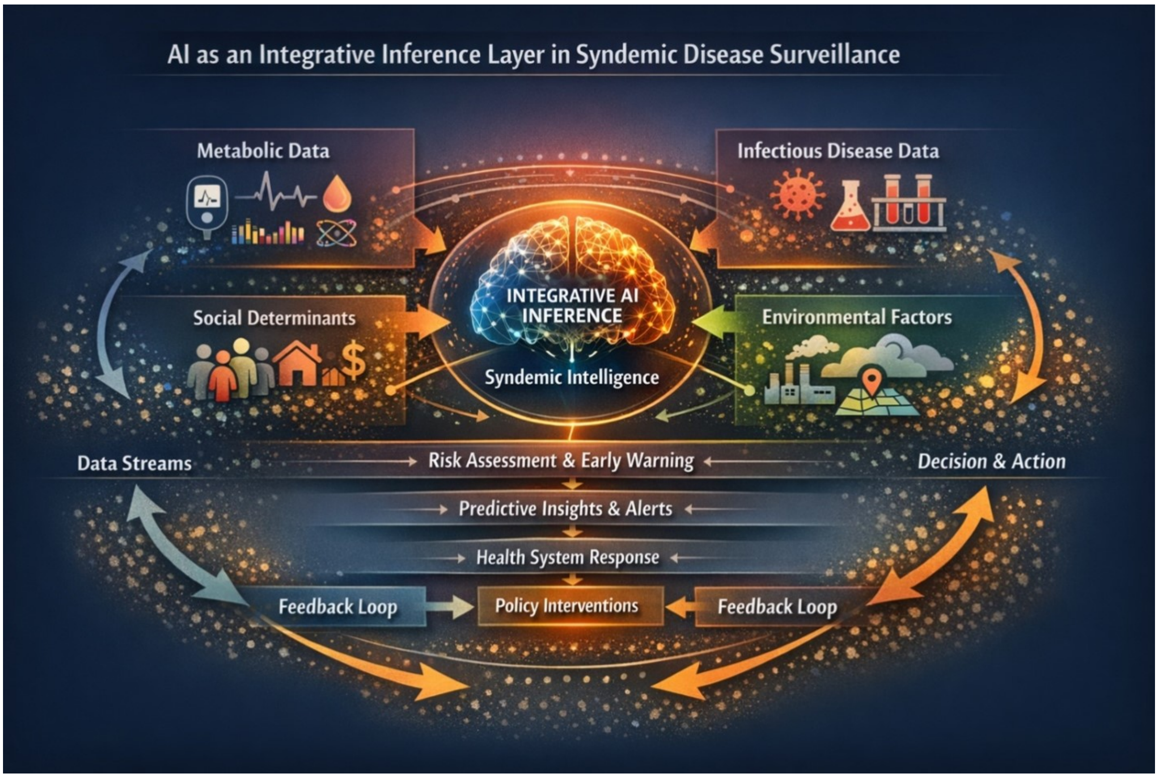

Figure 1: Artificial Intelligence as an Integrative Inference Layer in Syndemic Disease Surveillance

This integrative role of AI is illustrated conceptually in Figure 1, which positions AI as a mediating intelligence linking biological, social, and environmental data into a shared inferential space, while explicitly incorporating feedback loops between surveillance outputs, policy decisions, and subsequent disease trajectories. Such a framing emphasizes that surveillance is not a static data pipeline but a dynamic system in which analytic outputs shape and are shaped by public health action.

However, the promise of AI-enabled integrated surveillance is not guaranteed. Its success depends on treating methodological rigor, equity, and governance as foundational design principles rather than ancillary considerations. Accordingly, this review aims to

1. Critically assess how AI methods are currently applied to metabolic and infectious disease surveillance.
2. Identify sources of bias and structural risk embedded within these systems.
3. Articulate research and policy priorities necessary to realize equitable, integrated, and action-oriented surveillance in the era of syndemics.

Artificial intelligence (AI) is depicted as an integrative inference layer that synthesizes metabolic, infectious, social, and environmental data into a shared analytic space. The figure illustrates dynamic risk assessment, early warning, and decision support across disease domains, with feedback loops linking surveillance outputs to health system and policy responses that shape subsequent data generation and disease trajectories. The figure is intended as a conceptual design checklist for programs planning cross-domain, decision-centered surveillance architectures.

To support this analysis, we conducted a narrative scoping hybrid review of peer-reviewed literature spanning public health, biomedical science, and artificial intelligence. This approach was selected to accommodate methodological heterogeneity and the rapidly evolving nature of AI-enabled surveillance. A detailed description of the search strategy, inclusion criteria, and analytical framework is provided in Section 2.

The remainder of this review proceeds as follows: Section 2 outlines the review methodology; Sections 3 and 4 examine data architectures and AI methods; Section 5 reviews applications; Sections 6 and 7 address equity, ethics, and policy priorities; and Sections 8 and 9 synthesize implications and conclusions.

2. Methods

2.1. Review Design

This review adopts a narratives coping hybrid design, selected to address the conceptual fragmentation and rapid methodological evolution characterizing the application of artificial intelligence (AI) to disease surveillance. A purely systematic approach was deemed insufficient given the heterogeneity of study designs, data sources, and analytic objectives, as well as the emergent nature of integrated metabolic infectious surveillance. The hybrid approach allows for structured mapping of the literature while enabling critical, theory-informed synthesis across disciplinary boundaries, including public health, clinical epidemiology, data science, and health systems research.

2.2. Search Strategy and Study Selection

This review follows a narrative scoping hybrid approach designed to map and critically synthesize heterogeneous literature at the intersection of artificial intelligence, disease surveillance, and public health systems. We conducted structured searches in PubMed, Scopus, and IEEE Xplore, covering publications from January 2010 to December 2024. Representative search strings combined terms related to artificial intelligence (e.g., "machine learning," "deep learning," "AI"), *disease surveillance, metabolic diseases, infectious diseases,* and *population health.*

Peer-reviewed studies were included if they applied AI methods to surveillance, early detection, forecasting, or decision support with relevance to infectious or metabolic diseases and broader public health use. Studies focused solely on technical benchmarking without surveillance or population-level implications were excluded.

Included studies were mapped across three analytical axes:

1. Surveillance function (detection, prediction, or decision support).
2. Methodological approach (e.g., machine learning, deep learning, spatiotemporal or network models).
3. Equity and governance considerations, including data representativeness, bias, transparency, and alignment with public health decision-making.

2.3. Analytical Framework

Included studies were analyzed along three predefined axes:

1. Surveillance function (detection, prediction, or decision support).
2. Methodological approach (including machine learning, deep learning, and spatiotemporal or network-based models).
3. Equity and governance implications, encompassing data representation, bias, transparency, and alignment with public health decision-making. This framework enabled systematic comparison while foregrounding issues central to responsible and integrated AI-enabled surveillance.

3. Integrated Surveillance Architectures: Data, Scale, and Temporal Dynamics

Having established AI as an integrative inferential layer within syndemic surveillance, this section examines the data architectures required to operationalize this role.

3.1. Multimodal Data Ecologies

Integrated surveillance in the era of syndemics depends on the capacity to synthesize heterogeneous data sources that capture complementary dimensions of disease risk. Clinical and laboratory data remain foundational, providing diagnostic confirmation, biomarkers of metabolic dysfunction, and indicators of infectious exposure or severity. However, these data are often episodic, institutionally bounded, and biased toward populations with consistent access to care. On their own, they offer an incomplete and delayed representation of evolving risk [8].

Digital phenotyping and wearable technologies extend surveillance beyond clinical encounters, generating continuous, and high-frequency data on physiological, behavioral, and contextual variables. Metrics such as physical activity, sleep patterns, heart rate variability, and glucose dynamics can reveal early metabolic perturbations and pre-symptomatic responses to infection. While these data streams enhance temporal resolution, they also introduce new inequities related to device access, data ownership, and differential participation [9].

Environmental, geospatial, and socioeconomic data provide critical context for interpreting biological signals. Climate variables, air quality, population mobility, housing density, food environments, and neighborhood deprivation indices shape both metabolic vulnerability and infectious disease transmission. Integrating these upstream determinants enables surveillance systems to move beyond individual pathology toward a population-based understanding of risk embedded within social and ecological systems [10, 11].

3.2. Temporal and Scalar Integration

A defining challenge for integrated surveillance is alignment across temporal and spatial scales. At the individual level, longitudinal data enable the reconstruction of risk trajectories, capturing how metabolic status, exposures, and infections interact over time. At the population level, aggregated signals reveal patterns of clustering, spread, and vulnerability that are invisible in individual records. System-level integration connects these insights to preparedness and response, informing resource allocation, surge capacity planning, and targeted interventions [12].

Artificial intelligence plays a critical role in linking these scales by modeling nonlinear dynamics, detecting early deviations from baseline, and translating granular data into population-relevant indicators. Without such integration, surveillance risks remain either overly individualized or excessively coarse [13, 14].

3.3. Implications for Surveillance Theory

The integration of multi-modal data across scales represents more than a technical advance; it constitutes an epistemological shift in surveillance practice. What becomes knowable and therefore actionable expands from static disease counts to dynamic, relational patterns of risk. Surveillance is redefined as a learning system that generates anticipatory knowledge, challenging traditional boundaries between monitoring, prediction, and intervention in public health [15].

4. Artificial Intelligence Methods: Capabilities, Constraints, and Failure Modes

Building on these integrated data ecologies, this section reviews the principal AI methodologies used in syndemic disease surveillance.

4.1. Machine Learning for Multi-morbidity-Aware Risk Stratification

Machine learning (ML) methods have been widely applied to disease surveillance due to their capacity to identify complex, non-linear patterns across large datasets. In the context of integrated metabolic and infectious disease surveillance, supervised learning approaches such as tree-based models, regularized regression, and ensemble methods have been used to stratify risk, predict adverse outcomes, and identify high-risk subpopulations with coexisting conditions. These methods are particularly effective at handling high-dimensional clinical and laboratory data and can accommodate interactions between metabolic markers, demographic characteristics, and infection-related variables [16–18].

However, their utility in multi-morbidity-aware surveillance is constrained by fundamental limitations. Outcome labels are often poorly defined, inconsistently measured, or temporally misaligned with the processes they are intended to represent. For example, infection severity or metabolic control may be captured only episodically, obscuring dynamic interactions over time. Moreover, most ML models are optimized for association rather than causation, limiting their ability to disentangle correlated risk factors from mechanistic drivers of disease. Interpretability remains a persistent challenge, particularly when models are deployed in public health contexts where transparency and trust are essential for action [19].

4.2. Deep Learning for Multi-modal and Temporal Inference

Deep learning methods have expanded the analytic scope of surveillance by enabling the integration of heterogeneous and unstructured data, including time-series physiological measurements, clinical narratives, imaging, and mobility data. Recurrent and transformer-based architectures are well-suited for modeling temporal dependencies, while multi-modal networks can jointly learn representations across biological, behavioral, and environmental domains. These capabilities are especially relevant for syndemic surveillance, where risk emerges from the interaction of processes operating at different temporal resolutions [20].

Despite their expressive power, deep learning models introduce significant risks. Their internal representations are often opaque, making it difficult to assess how predictions are generated or to identify sources of bias. High performance in retrospective datasets may mask brittleness when models are exposed to shifting disease dynamics, evolving clinical practices, or new populations. Additionally, deep learning systems typically require large, well-curated datasets, conditions that are rarely met in under-resourced settings, thereby limiting their generalizability and equity [21].

4.3. Network and Spatiotemporal Modeling

Network-based and spatiotemporal models offer a complementary perspective by explicitly representing relationships among individuals, locations, and disease processes. Graph-based approaches can capture contact structures, transmission pathways, and comorbidity networks, enabling the coupling of infectious spread with patterns of metabolic vulnerability. Spatiotemporal models integrate geographic and temporal data to detect hotspots, forecast outbreaks, and assess how environmental and social factors modulate risk.

These approaches are particularly valuable for integrated surveillance because they foreground relational dynamics rather than isolated outcomes. However, their effectiveness depends heavily on data quality and completeness. Network structures are often inferred rather than observed, introducing uncertainty and potential bias. Spatiotemporal models may also oversimplify complex social processes or rely on assumptions that do not hold across contexts. Without careful validation, such models risk producing outputs that are precise but misleading [22].

4.4. Why Technical Performance Is an Inadequate Metric

Across AI methods, technical performance metrics such as accuracy, area under the curve, or mean error remain the dominant benchmarks of success. While necessary, these metrics are insufficient for evaluating surveillance systems intended to inform public health action. Models trained on historical data are vulnerable to model drift, as disease patterns, health behaviors, and data collection practices evolve. *Context collapse* occurs when models developed in one population, health system, or social environment are deployed in another without adequate adaptation, leading to performance degradation and misleading inference.

Most critically, few AI surveillance models undergo prospective, policy-relevant validation. Performance is rarely assessed in terms of timeliness, interpretability, equity impact, or decision utility. As a result, technically sophisticated systems may fail at deployment, producing predictions that are misaligned with institutional workflows or governance constraints. For integrated metabolic–infectious surveillance, success must therefore be judged not by algorithmic performance alone, but by the system's capacity to support equitable, timely, and actionable public health decisions [23].

5. Applications and the Persistent Translation Gap

While these methods demonstrate substantial analytic promise, their value ultimately depends on translation into routine public health practice.

5.1. Early Warning and Anticipatory Surveillance

One of the most frequently cited promises of artificial intelligence in disease surveillance is its capacity to enable early warning and anticipatory action. In integrated metabolic infectious surveillance, AI methods have been used to identify populations at compounded risk by jointly modeling metabolic vulnerability, demographic characteristics, and indicators of infectious exposure. Such approaches move beyond single-disease thresholds to detect subtle deviations in risk trajectories that may precede clinical deterioration or outbreak escalation. By integrating longitudinal metabolic indicators with emerging infectious signals, AI systems can, in principle, support earlier identification of individuals and communities likely to experience disproportionate morbidity [24, 25].

However, the translation of these capabilities into routine public health practice remains limited. Early warning signals are often probabilistic, uncertain, and difficult to interpret within existing surveillance frameworks. Without clearly defined thresholds for action or integration into established response protocols, anticipatory insights risk remaining analytically impressive but operationally inert.

5.2. Precision Public Health

Precision public health refers to the application of data-driven methods to tailor public health interventions to the needs of specific populations while maintaining a population-level focus on equity and prevention.

AI-enabled surveillance has also been positioned as a cornerstone of precision public health, in which interventions are tailored to the needs of specific populations rather than applied uniformly. Risk-stratified models have been proposed to inform targeted prevention strategies, such as prioritizing vaccination, screening, or outreach for populations with high metabolic susceptibility to infectious complications. At the system level, AI-driven forecasts can support preparedness planning by anticipating demand for healthcare resources, guiding stockpiling decisions, and informing geographically targeted responses [26].

Despite these advances, precision public health applications frequently encounter practical constraints. Public health agencies operate within regulatory, ethical, and political environments that may limit the use of individualized risk scores. Moreover, precision approaches can inadvertently exacerbate inequities if risk stratification reflects historical patterns of exclusion or biased data. The promise of precision must therefore be balanced against the imperative to ensure transparency, fairness, and population-level benefit [27].

5.3. Why Most AI Surveillance Systems Do Not Change Practice

The limited impact of AI surveillance on real-world decision-making reflects a persistent translation gap. First, institutional misalignment is common: AI systems are often developed in research settings without sufficient engagement with public health practitioners, resulting in tools that do not align with operational workflows or decision timelines. Second, governance ambiguity, including unclear accountability, data ownership, and legal authority, constrains the adoption of algorithmically informed actions, particularly when decisions carry ethical or political risk [28].

Finally, many AI surveillance initiatives suffer from an overproduction of predictions without corresponding decision pathways. Models generate risk scores or forecasts, but responsibilities for interpreting and acting on these outputs remain undefined. In the absence of clear linkages between analytic insight and intervention, AI risks becoming an additional layer of complexity rather than a catalyst for change.

Bridging this gap requires reorienting AI surveillance from prediction-centric innovation toward decision-centered design, in which analytic outputs are explicitly embedded within governance structures and public health practice [29].

6. Bias, Equity, and Ethical Risk in Integrated AI Surveillance

6.1. Data Inequity as a Structural Phenomenon

Bias in AI-enabled surveillance does not originate solely from technical choices; it is rooted in the structural conditions under which data are generated, collected, and governed. Health data systems systematically under represent marginalized populations, including individuals with limited access to healthcare, those living in informal settlements, migrants, and communities in low-resource settings. In the context of integrated metabolic–infectious surveillance, these exclusions are particularly consequential, as metabolic disorders and infectious risks are often concentrated among populations least visible to formal data infrastructures [30].

Digital data sources, while expanding surveillance reach, frequently reproduce and intensify existing inequities. Wearable devices, mobile health applications, and digital symptom reporting platforms disproportionately capture data from younger, wealthier, and more technologically connected individuals. At a global scale, surveillance data remain heavily skewed toward high-income countries, creating asymmetries in model development and validation. As a result, AI systems trained on these data may systematically underestimate risk in populations already experiencing disproportionate disease burden, embedding structural inequity into analytic outputs [31, 32].

6.2. Algorithmic Bias and the Illusion of Generalizability

Algorithmic bias often arises when models trained on inequitable data are assumed to be generalizable across populations and contexts. In integrated surveillance, this risk is amplified by the interaction of multiple disease domains. Biases affecting metabolic disease prediction such as under diagnosis or delayed diagnosis in marginalized group scan propagate into infectious disease risk estimates, compounding error across domains. Machine learning models may inadvertently amplify these biases by optimizing performance on majority populations, thereby masking poor performance in subgroups that are epidemiologically critical [30, 33].

The illusion of generalizability is further reinforced by reliance on aggregate performance metrics that obscure heterogeneity. Models may demonstrate high overall accuracy while performing poorly in specific demographic, geographic, or socioeconomic contexts. When such models are deployed across settings without recalibration or contextual adaptation, performance degradation is inevitable. This degradation is not merely a technical concern; it has direct implications for equity, as misclassification and delayed detection disproportionately affect those already under served. Without systematic bias auditing and subgroup-specific evaluation, AI-enabled surveillance risks reinforcing the very disparities it purports to address [34].

6.3. Surveillance Ethics and Public Trust

The ethical risks of integrated AI surveillance extend beyond bias to questions of consent, privacy, and accountability. Surveillance systems increasingly rely on data generated outside traditional healthcare encounters, often without explicit informed consent or clear mechanisms for individual control. The aggregation of metabolic, infectious, social, and environmental data heightens concerns about re-identification, stigmatization, and misuse, particularly when surveillance outputs are linked to policy actions affecting specific communities [35, 36].

Public trust is further challenged by the opacity of many AI systems and by unclear lines of responsibility when algorithmically informed decisions cause harm. In the absence of transparent governance frameworks, surveillance risks becoming technocratic, privileging algorithmic authority over democratic deliberation and community engagement. This risk is especially pronounced in public health emergencies, where the urgency of action may override safeguards for accountability and inclusion [37].

Table 1 synthesizes these concerns by tracing bias propagation pathways across the AI surveillance life cycle. By mapping how biases emerge at the data, model, and deployment stages and how they manifest differently in metabolic and infectious disease surveillance,the table illustrates how technical design choices translate into population-level equity outcomes. Importantly, it also identifies potential mitigation strategies, underscoring that bias is not an inevitable consequence of AI but a challenge that can be addressed through deliberate, equity-centered design and governance.

Together, these considerations underscore that equity and ethics must be treated as core dimensions of surveillance architecture rather than downstream constraints. Integrated AI surveillance will only be legitimate and effective if it is designed to recognize, measure, and actively counteract structural inequities, while maintaining public trust through transparency, accountability, and inclusive governance.

7. Research and Policy Priorities for the Next Decade

The limitations identified across methods and applications point to the need for a reorientation of research and policy priorities.

7.1. Methodological Priorities

Over the next decade, progress in AI-enabled integrated surveillance will depend less on incremental gains in predictive accuracy than on advances in how inference is conducted and evaluated. A central priority is the development of causal and multi modal inference frameworks capable of disentangling correlated risk factors from underlying mechanisms. Integrated metabolic–infectious surveillance requires models that can distinguish shared drivers of vulnerability from coincidental associations, particularly when informing interventions that may have far-reaching social and economic consequences. Causal approaches combined with multi modal data integration offer a pathway toward more robust and policy-relevant inference [46].

Equally critical is the routine incorporation of uncertainty-aware and interpretable modeling. Surveillance outputs are inherently probabilistic, yet uncertainty is rarely communicated in ways that support decision-making. Models that explicitly quantify uncertainty, surface assumptions, and provide interpretable rationales for their outputs are better aligned with the needs of public health practitioners and

Table 1: Bias Propagation Pathways in AI-Enabled Integrated Disease Surveillance

Surveillance Stage	Source of Bias	Manifestation in Metabolic Disease Surveillance	Manifestation in Infectious Disease Surveillance	Equity Consequences	Potential Mitigation Strategies
Data Generation	Structural inequities in healthcare access	Underdiagnosis of metabolic disorders in marginalized populations; delayed clinical detection	Missed or late identification of infections due to limited testing access	Systematic underestimation of compounded risk in underserved groups	Invest in community-based data collection; integrate non-clinical data sources [38]
Data Collection	Digital divide and selective participation	Wearable and digital health data skewed toward affluent, urban populations. connectivity	Digital symptom reporting excludes populations with limited	Biased risk profiles that privilege digitally connected groups	Equity-aware sampling; adjustment for data missingness; alternative data modalities [39]
Data Labeling	Inconsistent or proxy outcome definitions	Crude indicators of metabolic control that miss disease severity or progression	Case definitions influenced by testing availability and reporting practices	Misclassification disproportionately affects high-risk populations	Standardized, context-sensitive labeling; uncertainty annotation [40]
Model Training	Optimization for majority populations	Models perform well for common metabolic phenotypes but poorly for atypical or advanced disease.	Reduced sensitivity in detecting outbreaks in marginalized or low-incidence settings	Amplification of existing health disparities	Subgroup-specific evaluation; fairness constraints during training [41]
Model Validation	Limited external and prospective validation	Apparent accuracy masks poor performance across socioeconomic or ethnic subgroups	Failure to generalize across regions with different transmission dynamics	False confidence in model outputs	Mandatory external validation; stratified performance reporting [42]
Deployment	Context collapse across settings	Models developed in high-income settings misestimate risk elsewhere	Imported models fail to account for local transmission drivers	Inappropriate allocation of surveillance attention and resources	Contextual recalibration; local stakeholder involvement [43]
Decision Support	Opacity and lack of interpretability	Clinicians and policymakers are unable to interrogate metabolic risk drivers.	Limited trust in outbreak alerts without a transparent rationale	Reduced uptake of AI-informed decisions	Explainable AI methods; decision-support co-design [44]
Policy Response	Unequal capacity to act on surveillance outputs	Preventive interventions benefit already-resourced populations	Delayed or insufficient outbreak response in marginalized areas	Reinforcement of structural inequities	Equity-focused response planning; accountability mechanisms [45]

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policymakers. Without such features, AI systems risk overconfidence, misinterpretation, and erosion of trust, particularly in high-stakes contexts.

7.2. Equity as a Design Constraint, Not an Outcome

A defining priority for future surveillance systems is the repositioning of equity from an aspirational outcome to a non-negotiable design constraint. This requires making bias auditing and subgroup performance evaluation standard practice throughout the AI life cycle, rather than post hoc assessments conducted only after deployment. Models should be evaluated not only on aggregate performance but also on their capacity to detect risk accurately among populations experiencing the greatest burden of disease.

Beyond technical measures, equity-oriented surveillance demands community-governed data infrastructures. Meaningful participation by affected communities in decisions about data collection, use, and governance is essential for legitimacy and sustainability. Such approaches challenge extractive data practices and help ensure that surveillance serves public health goals rather than institutional or commercial interests. In the absence of inclusive governance, even technically sophisticated systems risk reinforcing historical patterns of exclusion [47].

7.3. From Prediction to Prevention

Perhaps the most consequential priority is the transition from prediction-centric innovation to decision-centered surveillance design. AI systems must be embedded within institutional decision architectures, with clearly defined roles, responsibilities, and response pathways. This includes aligning analytic outputs with policy timelines, clarifying accountability for action, and ensuring that surveillance insights translate into preventive interventions rather than retrospective explanations.

Regulatory and ethical alignment will be central to this transition. Clear frameworks are needed to govern data use, algorithmic accountability, and the appropriate scope of surveillance, particularly as systems increasingly integrate non-clinical data sources. Rather than constraining innovation, well-articulated governance can enable responsible deployment by setting expectations for transparency, oversight, and public benefit [48].

These priorities are synthesized in Figure 2, which presents a strategic, time-sequenced roadmap linking methodological innovation, equity safeguards, governance readiness, and public health impact. By situating technical advances alongside institutional and regulatory milestones, the roadmap emphasizes that effective AI-driven surveillance is not a singular technological achievement but a coordinated, longitudinal endeavor.

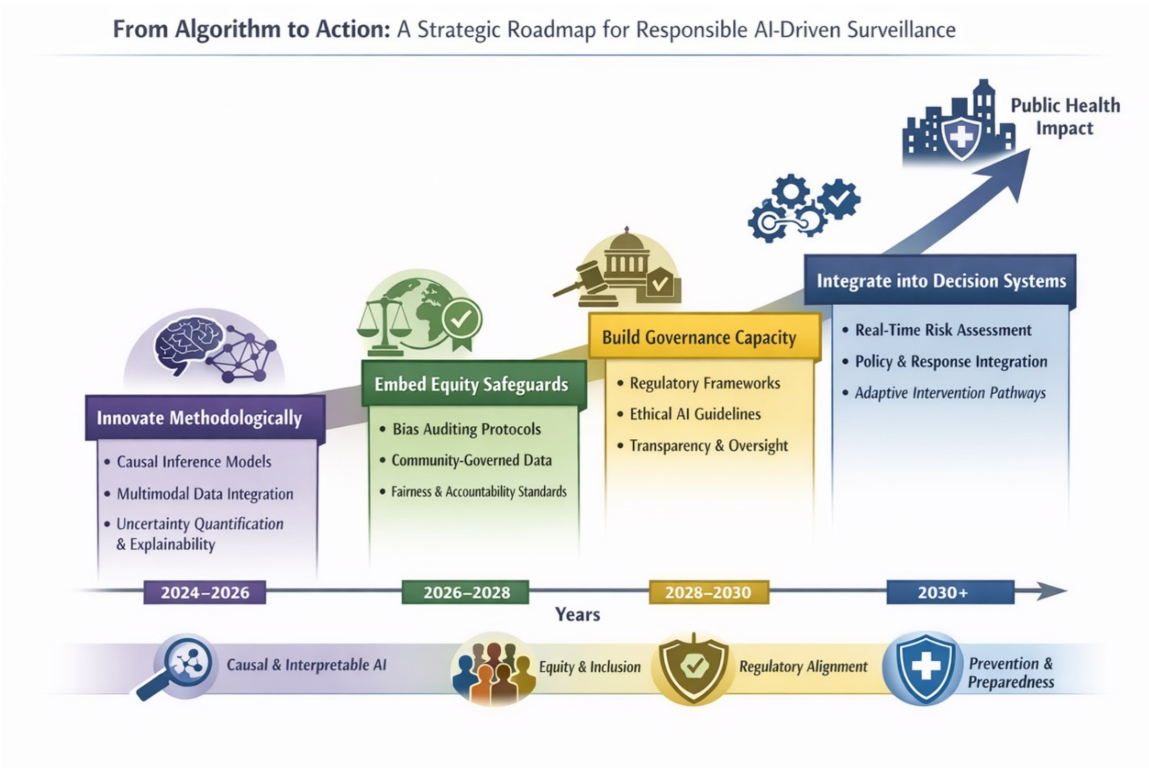

Figure 2: From Algorithm to Action: A Strategic Roadmap for Responsible AI-Driven Surveillance

Conceptual roadmap illustrating staged priorities for AI-enabled surveillance over the next decade, linking advances in causal and interpretable methods with equity-centered design, governance readiness, and integration into public health decision-making. The roadmap is intended to guide policymakers and public health agencies in aligning technical innovation with institutional capacity and ethical oversight.

8. Discussion

This review highlights that the transformative potential of artificial intelligence (AI) for disease surveillance lies not in isolated methodological advances but in its capacity to reconfigure how public health systems generate, interpret, and act on knowledge. Across methods, applications, and ethical considerations, a consistent theme emerges: integrated metabolic–infectious surveillance demands analytic approaches that are responsive to complexity, attentive to equity, and embedded within institutional decision-making structures. Machine learning, deep learning, and network-based models each offer distinct capabilities, yet their effectiveness is contingent on data quality, interpretability, and alignment with public health objectives rather than technical performance alone [31].

Ethical and equity considerations are not peripheral constraints but central determinants of system legitimacy and effectiveness. Structural data inequities, algorithmic bias, and governance gaps threaten to undermine the benefits of AI-enabled surveillance if left unaddressed. As demonstrated in the analysis of bias propagation, technical design choices can translate directly into population-level harms, particularly for communities already experiencing disproportionate disease burden. Addressing these risks requires reorienting surveillance design toward transparency, accountability, and inclusive governance, ensuring that AI systems serve public health goals rather than exacerbate existing disparities [30].

Crucially, the findings of this review support a reconceptualization of integrated AI surveillance as public health infrastructure rather than episodic innovation. Like laboratory networks or immunization registries, surveillance systems must be durable, interoperable, and governed in the public interest. Treating AI as infrastructure foregrounds long-term sustainability, workforce capacity, regulatory alignment, and institutional trust, shifting emphasis away from short-term predictive gains toward enduring public value. This perspective also clarifies why many AI surveillance initiatives fail to influence practice: innovations developed in isolation cannot compensate for weak institutional integration or ambiguous decision pathways [49].

Several limitations warrant consideration. The rapid evolution of AI methods constrains comprehensive coverage, and much of the existing literature remains retrospective and concentrated in high-income settings. Additionally, unresolved tensions persist between innovation and regulation, precision and equity, and individual-level prediction versus population-level action. These tensions are not obstacles to progress but defining challenges that must be navigated deliberately. Advancing integrated AI surveillance will therefore require sustained interdisciplinary collaboration, iterative evaluation, and a commitment to treating surveillance as a collective public good rather than a purely technical endeavor.

9. Conclusion

Artificial intelligence has the potential to fundamentally transform disease surveillance by enabling integrated, anticipatory, and systems-oriented approaches to monitoring metabolic and infectious diseases. When conceived as an inferential layer capable of synthesizing biological, social, and environmental data, AI offers tools to move beyond reactive case counting toward a more nuanced understanding of population vulnerability and risk dynamics. Such capabilities are increasingly essential in an era characterized by syndemic interactions and recurrent public health threats.

Yet this potential will remain unrealized and may prove harmful if AI-enabled surveillance is deployed in a technocratic or inequitable manner. Systems developed without attention to data representativeness, algorithmic bias, and governance risk, reinforce existing disparities while eroding public trust. The concentration of technical capacity in high-income settings further threatens to widen global inequities unless deliberate efforts are made to support inclusive data infrastructures and locally relevant model development.

Realizing the promise of integrated AI surveillance, therefore, requires interdisciplinary leadership that bridges public health, data science, ethics, and policy. It also demands global inclusivity, with meaningful participation from low- and middle-income countries and marginalized communities in shaping surveillance priorities and governance. By treating AI-enabled surveillance as a shared public health infrastructure grounded in equity, transparency, and accountability, the global health community can harness its transformative potential while safeguarding against unintended harm.

Declarations

This article is a review of published literature and did not involve human participants, primary data collection, or identifiable personal data; therefore, ethics approval was not required. The authors note that future deployments of AI-enabled disease surveillance systems should incorporate privacy-by-design principles, subgroup fairness audits, and clearly defined oversight and crisis-response pathways to ensure ethical and equitable use.

Article Information

Disclaimer (Artificial Intelligence): The author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.), and text-to-image generators have been used during writing or editing of manuscripts.

Competing Interests: Authors have declared that no competing interests exist.

References

[1] S. Swarup, I. Ahmed, Y. Grigorova, and R. Zeltser. Metabolic Syndrome, December 2025. URL http://www.ncbi.nlm.nih.gov/books/NBK459248/.

[2] H. Zhang, X. D. Zhou, M. D. Shapiro, G. Y. H. Lip, H. Tilg, and L. Valenti. Global burden of metabolic diseases, 1990-2021. *Metabolism*, 160:155999, November 2024.

[3] Islam MdS, S. B. Monir, N. Haque, M. A. Vabna, J. Fan, and Y. Li. Immunometabolic crossroads: infections as bidirectional modulators in diabetes and metabolic syndromes. *Front Endocrinol (Lausanne)*, 16:1710157.

[4] S. U. Khan, K. K. Hagan, and Z. Javed. Disproportionate Impact of COVID-19 Among Socially Vulnerable Patients. *Circ Cardiovasc Qual Outcomes*, 15(8):e009294, July 2022.

[5] N. Maddah, A. Verma, M. Almashmoum, and J. Ainsworth. Effectiveness of Public Health Digital Surveillance Systems for Infectious Disease Prevention and Control at Mass Gatherings: Systematic Review. *J Med Internet Res*, 25:e44649, May 2023.

[6] Z. S. Y. Wong and M. Rigby. Identifying and addressing digital health risks associated with emergency pandemic response: Problem identification, scoping review, and directions toward evidence-based evaluation. *Int J Med Inform*, 157:104639, January 2022.

[7] J. Yang, A. Amrollahi, and M. Marrone. Harnessing the Potential of Artificial Intelligence: Affordances, Constraints, and Strategic Implications for Professional Services. *The Journal of Strategic Information Systems*, 33(4):101864, December 2024.

[8] A. Jackson-Morris, S. Masyuko, L. Morrell, I. Kataria, E. L. Kocher, and R. Nugent. Tackling syndemics by integrating infectious and noncommunicable diseases in health systems of low- and middle-income countries: A narrative systematic review. *PLOS Glob Public Health*, 4(5):e0003114, May 2024.

[9] Y. Zhang, J. Wang, H. Zong, R. K. Singla, A. Ullah, X. Liu, et al. The comprehensive clinical benefits of digital phenotyping: from broad adoption to full impact. *NPJ Digit Med*, 8:196, April 2025.

[10] C. Chiziba, L. D. Mercer, O. Diallo, A. Bertozzi-Villa, D. J. Weiss, J. Gerardin, et al. Socioeconomic, Demographic, and Environmental Factors May Inform Malaria Intervention Prioritization in Urban Nigeria. *Int J Environ Res Public Health*, 21(1):78, January 2024.

[11] O. Lawal, J. Stephen, V. O. David, T. C. Ajayi, P. O. Okunola, N. Atiku, et al. Malaria-Typhoid Fever Diagnostic Confusion in Nigeria and Its Impact on Treatment Delays and Mortality Among Pregnant Women and Children. Epidemiology and Health Data Insights. *1(2):ehdi008*, July 2025.

[12] K. Hu, C. Li, X. Yang, S. Ou, X. Zhang, D. Xiao, et al. From infectious diseases to chronic diseases: the paradigm shift of spatial epidemiology in disease prevention and control. *Front Public Health*, 13:1698964, October 2025.

[13] A. Sasinthiran, S. Gnanasekaran, and R. Ragala. A review of artificial intelligence applications in wind turbine health monitoring. *International Journal of Sustainable Energy*, 43(1):2326296, December 2024.

[14] Lauretta Ekanem Omale, Victor Akachukwu Ibiam, Lasisi Wuraola Sidikat, and Oladimeji Taiwo. Transformative applications of Artificial Intelligence in infectious disease forecasting and public health decision support systems. *World J Adv Res Rev*, 25(3):2250–8, March 2025.

[15] Y. Hao, C. Cheng, J. Li, H. Li, X. Di, X. Zeng, et al. Multimodal Integration in Health Care: Development With Applications in Disease Management. *J Med Internet Res*, 27:e76557, August 2025.

[16] N. H. Alhumaidi, D. Dermawan, H. F. Kamaruzaman, and N. Alotaiq. The Use of Machine Learning for Analyzing Real-World Data in Disease Prediction and Management: Systematic Review. *JMIR Med Inform*, 13:e68898, June 2025.

[17] Victor Akachukwu Ibiam, Lauretta Ekanem Omale, and Oladimeji Taiwo. The role of Artificial Intelligence models in clinical decision support for infectious disease diagnosis and personalized treatment planning. *Int J Sci Res Arch*, 14(3):1337–47, March 2025.

[18] O. P. Lawal, E. P. Igwe, A. Olosunde, E. P. Chisom, D. U. Okeh, A. K. Olowookere, et al. Integrating Real-Time Data and Machine Learning in Predicting Infectious Disease Outbreaks: Enhancing Response Strategies in Sub-Saharan Africa. *Asian Journal of Microbiology and Biotechnology*, 10(1):147–63, May 2025.

[19] S. Cuschieri, S. Stranges, and T. T. Makovski. The different definitions of multimorbidity and their implications for research, surveillance, and policy. *Eur J Public Health*, 35(2):197–8, December 2024.

[20] A. Rahman, T. Debnath, D. Kundu, Khan MdSI, A. A. Aishi, S. Sazzad, et al. Machine learning and deep learning-based approach in smart healthcare: Recent advances, applications, challenges and opportunities. *AIMS Public Health*, 11(1):58–109, January 2024.

[21] A. M. Almosti and M. M. H. Rahman. Analysis of Data Privacy Breaches Using Deep Learning in Cloud Environments: A Review. *Electronics. [cited*, 2025(13):23, December 2025. URL `https://www.mdpi.com/2079-9292/14/13/2727.`

[22] J. McKee and T. Dallas. Structural network characteristics affect epidemic severity and prediction in social contact networks. *Infect Dis Model*, 9(1):204–13, December 2023.

[23] E. S. Andersen, J. B. Birk-Korch, R. S. Hansen, L. H. Fly, R. Röttger, D. M. C. Arcani, et al. Monitoring performance of clinical artificial intelligence in health care: a scoping review. *JBI Evid Synth*, 22(12):2423–46, October 2024.

[24] I. Villanueva-Miranda, G. Xiao, and Y. Xie. Artificial intelligence in early warning systems for infectious disease surveillance: a systematic review. *Front Public Health*, 23(13):1609615, June 2025.

[25] Adeseun Kafayat Balogun, Julie Alaere Atta, Oreoluwa Mary Oyetubo, Victor Akachukwu Ibiam, Kehinde Abiola Bakare-Adesokan, and Taiwo Ololade Ojo. Developing culturally competent models for inclusive social work and healthcare interventions. *Int J Sci Res Arch*, 14(1):1396–406, January 2025.

[26] R. Aswini, B. Saranya, K. Gayathri, and E. Karthikeyan. Revolutionizing infectious disease surveillance: Multi-omics technologies and AI-driven integration. *Decoding Infection and Transmission*, 3:100061, January 2025.

[27] F. Kee and D. Taylor-Robinson. Scientific challenges for precision public health. *J Epidemiol Community Health*, 74(4):311–4, April 2020.

[28] A. Abd-Alrazaq, B. Solaiman, Y. M. Mekki, D. Al-Thani, F. Farooq, M. Alkubeyyer, et al. Hype vs Reality in the Integration of Artificial Intelligence in Clinical Workflows. *JMIR Form Res.*, 9:e70921, December 2025.

[29] S. Ansari, B. Baur, K. Singh, and A. J. Admon. Challenges in the Postmarket Surveillance of Clinical Prediction Models. *NEJM AI*, 2 (5):10, May 2025. doi: 10.1056/AIp2401116.

[30] J. Joseph. Algorithmic bias in public health AI: a silent threat to equity in low-resource settings. *Front Public Health*, 13:1643180, July 2025.

[31] A. Osonuga, A. A. Osonuga, S. C. Fidelis, G. C. Osonuga, J. Juckes, and D. B. Olawade. Bridging the digital divide: artificial intelligence as a catalyst for health equity in primary care settings. *International Journal of Medical Informatics*, 204:106051, December 2025.

[32] A. K. Balogun, V. A. Ibiam, O. A. Otesanya, and B. E. Agbo-Adediran. Policy advocacy for inclusive healthcare access from a social work perspective. *International Journal of Science and Research Archive*, 14(1):1407–15, 2025.

[33] M. A. Sufian, L. Alsadder, W. Hamzi, S. Zaman, Sagar Asms, and B. Hamzi. Mitigating Algorithmic Bias in AI-Driven Cardiovascular Imaging for Fairer Diagnostics. *Diagnostics.*, 14(13):23, December 2025. URL https://www.mdpi.com/2075-4418/14/23/2675.

[34] J. Yang, N. T. Dung, P. N. Thach, N. T. Phong, V. D. Phu, and K. D. Phu. Generalizability assessment of AI models across hospitals in a low-middle and high income country. *Nat Commun*, 15:8270, September 2024.

[35] C. Mennella, U. Maniscalco, G. De Pietro, and M. Esposito. Ethical and regulatory challenges of AI technologies in healthcare: A narrative review. *Heliyon*, 10(4):e26297, February 2024.

[36] S. M. Williamson, V. Prybutok, S. M. Williamson, and V. Prybutok. Balancing Privacy and Progress: A Review of Privacy Challenges, Systemic Oversight, and Patient Perceptions in AI-Driven Healthcare. *Applied Sciences.*, 2024(2):5, December 2024. URL https://www.mdpi.com/2076-3417/14/2/675.

[37] P. Radanliev. Privacy, ethics, transparency, and accountability in AI systems for wearable devices. *Front Digit Health*, 7:1431246, June 2025.

[38] J. Rad. Health inequities: a persistent global challenge from past to future. *Int J Equity Health*, 24:148, May 2025.

[39] O. Adepoju, P. Dang, H. Nguyen, and J. Mertz. Equity in Digital Health: Assessing Access and Utilization of Remote Patient Monitoring, Medical Apps, and Wearables in Underserved Communities. *Inquiry*, 61:00469580241271137, September 2024.

[40] Oliveira N. C. de, P. B. Júnior, and C. Júnior A. T. da. Bento E de S, Tonholo J, Aquino T, et al. Environmental Planning and Non-Communicable Diseases: A Systematic Review on the Role of the Metabolomic Profile. *International Journal of Environmental Research and Public Health.*, 20(14):23, December 2023. URL https://www.mdpi.com/1660-4601/20/14/6433.

[41] O. P. Lawal, D. U. Okeh, P. C. Ezeamii, A. K. Olowookere, I. Muhammed, C. V. Ugwu, et al. Reimagining Mathematical Modeling for a Responsive and Integrated Future in Infectious Disease Epidemiology. *Global Journal of Epidemiology and Infectious Disease*, pages 43–53, December 2025.

[42] M. Spek, R. P. Venekamp, Hond A. A. de, Groot E de, Geersing GJ, and et al. Dobbe AS. Development and internal validation of a diagnostic prediction model for life-threatening events in callers with shortness of breath: a cross-sectional study in out-of-hours primary care. *Br J Gen Pract*, 75(756):e500–8, July 2025.

[43] S. Abdulrahman and M. Trengove. Mitigated deployment strategy for ethical AI in clinical settings. *BMJ Health Care Inform.*, 32(1): e101363, July 2025.

[44] Q. Abbas, W. Jeong, and S. W. Lee. Explainable AI in Clinical Decision Support Systems: A Meta-Analysis of Methods, Applications, and Usability Challenges. *Healthcare (Basel)*, 2025.

[45] de Winton Cummings PJ, Baker KK, Appell L, Rios MD, Diekema DJ, and Kitzmann T et al. Equity in epidemic response: an action-oriented framework for guiding public health in equitable responses to major infectious disease emergencies. *Int J Equity Health*, 24:69, March 2025.

[46] V. I. S. Mendes, B. M. F. Mendes, R. P. Moura, I. M. Lourenço, M. F. A. Oliveira, K. L. Ng, et al. Harnessing artificial intelligence for enhanced public health surveillance: a narrative review. *Front Public Health*, 13, July 2025. Article 1601151.

[47] T. Wauu. WAUU Journal. 3(1):2023–2, April 2023.

[48] U. Fischer-Abaigar, C. Kern, N. Barda, and F. Kreuter. Bridging the gap: Towards an expanded toolkit for AI-driven decision-making in the public sector. *Government Information Quarterly*, 41(4):101976, December 2024.

[49] H. Rilkoff, S. Struck, C. Ziegler, L. Faye, D. Paquette, and D. Buckeridge. Innovations in public health surveillance: An overview of novel use of data and analytic methods. *Can Commun Dis Rep*, 50(3-4):93–101.