Leveraging Non-Traditional Urban Data Sources for Public Health Surveillance: A Review of Emerging Data Streams, Analytical Approaches, and Implementation Challenges

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Abstract

Non-traditional urban data sources are reshaping public health surveillance by providing real-time, predictive, and spatially detailed health intelligence. This review synthesizes evidence on emerging data streams including wastewater monitoring, mobility and transportation data, geospatial and remote sensing systems, IoT sensors, social media signals, participatory platforms, and distributed electronic health records. Advanced analytical approaches such as hybrid machine learning models, predictive analytics, anomaly detection, and spatial modeling convert these heterogeneous streams into actionable insights for infectious disease forecasting, environmental risk assessment, food safety monitoring, and disaster response.

The analysis demonstrates that these systems enable earlier detection and more adaptive responses than conventional methods. However, significant challenges persist. Representativeness bias, algorithmic limitations, data quality issues, interoperability barriers, and infrastructure gaps limit full potential. Governance, privacy, ethical considerations, and institutional readiness emerge as critical determinants of successful implementation and equitable outcomes. The review highlights that technological innovation must be matched by robust policy frameworks, justice-centred design, and cross-sector collaboration to ensure sustainable and trustworthy urban surveillance systems.

Findings underscore a broader transition from reactive, siloed surveillance toward integrated urban health intelligence ecosystems. Realizing the full benefits will require deliberate attention to equity, interoperability standards, ethical governance, and long-term infrastructure investment. This synthesis offers practical implications for public health agencies and urban policymakers seeking to modernize surveillance in increasingly complex urban environments.

Keywords: Surveillance, Governance, Multimodal, Intelligence, Interoperability

Introduction

Public health surveillance forms the foundation of effective disease prevention and health protection in modern societies. For decades, systems relied primarily on manual case reporting from healthcare providers, laboratory confirmation, and passive monitoring of healthcare-seeking behavior. While these approaches served well in earlier eras, they increasingly struggle to meet the demands of contemporary urban environments characterized by high population density, rapid mobility, and complex disease transmission dynamics.

The limitations became particularly evident during the COVID-19 pandemic. Fragmented reporting, siloed data systems, and dependence on clinical testing created significant blind spots in early detection and spatial mapping (Adams et al., 2024). Rapid urbanization has intensified the challenge. Cities concentrate on people, infrastructure, and economic activity in ways that accelerate disease spread while simultaneously generating vast amounts of digital and environmental data. This creates both opportunity and pressure: traditional surveillance methods cannot keep pace with the speed and spatial complexity of urban health threats.

As a result, public health authorities have turned toward non-traditional data sources generated by everyday urban life, including mobility patterns, wastewater composition, geospatial information, IoT sensors, social media activity, and participatory reporting platforms. These emerging data streams offer distinct advantages. They operate independently of clinical encounters, provide near real-time signals, and capture population-level trends at fine spatial scales. When combined with advanced analytical methods such as machine learning, hybrid modeling, and anomaly detection, these streams enable predictive rather than merely reactive surveillance (Ogunsakin & Sulaimon, 2026).

The transformation is not purely technical. It carries profound implications for how public health agencies operate, how data are governed, and how equity is maintained in surveillance systems. Privacy concerns, algorithmic bias, interoperability challenges, and infrastructure gaps frequently arise as significant barriers to effective implementation. Governance frameworks that were designed for traditional data sources often prove inadequate for managing the volume, velocity, and sensitivity of urban-generated data. Ethical questions around consent, data ownership, and potential stigmatization require careful attention (Aiello et al., 2020).

This review examines how non-traditional urban data ecosystems are reshaping public health surveillance. It analyzes the major data streams now available, the analytical approaches that convert raw signals into intelligence, and the real-world applications across infectious disease, environmental health, and disaster response. The discussion also addresses critical challenges related to data quality, bias, privacy, ethics, interoperability, and infrastructure. Particular attention is given to governance and policy considerations, because the evidence consistently shows that technological capability alone is insufficient without corresponding institutional and regulatory adaptation.

The central argument guiding this review is straightforward yet consequetial: non-traditional urban data ecosystems are fundamentally reshaping public health surveillance by enabling more predictive, real-time, spatially granular, and adaptive health intelligence systems; however, their transformative potential depends on overcoming substantial analytical, governance, interoperability, ethical, infrastructural, and implementation challenges. By synthesizing the current evidence, this review seeks to clarify both the promise and the practical requirements of this ongoing transformation. Understanding these dynamics is essential for public health leaders, urban planners, policymakers, and researchers committed to building surveillance systems that are not only technologically advanced but also equitable, trustworthy, and sustainable.

Evolution of Public Health Surveillance

Public health surveillance has evolved from reactive, fragmented, and latency-prone systems to proactive, real-time, and computationally enabled frameworks. For decades, traditional methods lean heavily on manual case reporting, laboratory confirmation, and healthcare-seeking behavior. The result was often a noticeable lag between the first signs of an outbreak and any meaningful public health response (Aiello et al., 2020; Mendes et al., 2025; Rilkoff et al., 2024). The COVID-19 pandemic laid these shortcomings bare. Fragmented reporting systems, siloed data flows, and heavy reliance on clinical testing left critical blind spots in early detection and spatial understanding of disease spread (Adams et al., 2024; Ogunsakin & Sulaimon, 2026).

This shift did not happen in isolation. Rapid urbanization, heightened population mobility, and the explosive growth of digital infrastructure have created disease dynamics far more complex than earlier generations of surveillance tools could handle (Pandey et al., 2025; Parr et al., 2023). Analyses in the wake of the pandemic make one point unmistakably clear: modernization is no longer optional. Surveillance must move beyond passive reporting toward continuous, multimodal intelligence that can keep pace with urban realities (Kebeba & Agyei, 2026; Panteli et al., 2025).

At its heart, this evolution is conceptual as much as technical. Surveillance is moving away from episodic disease tracking and toward ongoing urban health intelligence. Non-traditional data streams now sit at the center of that change. They deliver earlier signals, finer spatial detail, and predictive insight that once seemed out of reach (Adams et al., 2024; Adu et al., 2025; Gyang et al., 2024). At the same time, they introduce new vulnerabilities. Data quality problems, algorithmic bias, interoperability hurdles, and governance shortfalls can undermine the very integrity and equity the new systems are meant to strengthen (Alkhouri et al., 2026; Arefin et al., 2025; Utomi et al., 2024).

Taken together, the evidence leaves little doubt. Traditional surveillance has reached its practical limits in urban settings. The path forward leads toward integrated, AI-enabled urban intelligence systems, but only if institutions and policymakers commit to the hard work of adaptation.

Conceptualizing Non-Traditional Urban Data Sources

Non-traditional urban data sources force a fundamental rethinking of what surveillance data actually is. Instead of depending exclusively on health-specific records generated inside institutions, these sources tap into the steady stream of digital and physical traces produced by daily urban life (Aiello et al., 2020; Rilkoff et al., 2024).

The scholarship makes the shift unmistakable. Urban data streams have moved from being seen as helpful supplements to becoming core infrastructural components of modern surveillance. Mobility patterns, wastewater signals, GIS layers, IoT sensor readings, social media activity, and participatory reports together create a dense, multimodal sensing layer that functions with or without clinical encounters (Pandey et al., 2025; Adams et al., 2024; Adu et al., 2025). Table 1 captures the comparative strengths and limitations across the main streams and underscores just how multimodal contemporary urban surveillance has become.

Table 1. Comparative Overview of Non-Traditional Urban Data Sources in Public Health Surveillance

Data Source	Surveillance Application	Analytical Techniques	Advantages	Limitations	Representative Studies
Wastewater surveillance	Community pathogen monitoring	qPCR, genomic sequencing, equity modeling	Independent of clinical access, early warning	Sewer coverage gaps, lab standardization	Adams et al. (2024), Alkhouri et al. (2026), Arefin et al. (2025)
Mobility & traffic data	Spatiotemporal epidemic forecasting	Metapopulation modeling, effective distance, hybrid ML-ODE	Leading indicator, network-based	Data stability during disruptions	Pandey et al. (2025), Parr et al. (2023), Ogu & Opoku (2025)
GIS & remote sensing	Hazard mapping, disaster response	Spatial analytics, ML-enhanced overlay	High spatial precision	Digital divide, data ownership	Adu et al. (2025), Gyang et al. (2024)
IoT sensors & smart-city infrastructure	Environmental health monitoring	Anomaly detection, real-time data fusion (edge/fog computing)	Continuous high-resolution monitoring; sub-second latency; high anomaly detection rates (e.g., >92% in large-scale deployments); proactive alerts for environmental hazards	Data quality & calibration issues in heterogeneous sensor networks; privacy and security vulnerabilities; interoperability challenges; high infrastructure and maintenance costs	Studies on IoT and smart-city integration Hu et al. (2026)
Social media & search	Early outbreak detection	NLP, nowcasting	Real-time, low-cost	Noise, bias, platform dependency	Aiello et al. (2020), Mendes et al. (2025)
Participatory mobile apps	Travel-related & community reporting	App-based aggregation	Granular, voluntary	Selection bias	Colubri et al. (2025)
EHR distributed networks	Trend monitoring & real-world evidence	Distributed querying, phenotyping	Representative, longitudinal	Care-seeking bias	Ghildayal et al. (2024) PCORnet paper

At their core, these sources are defined by high velocity, variety, and volume. Those characteristics set them apart from conventional health data and open the door to entirely new kinds of intelligence (Kebeba & Agyei, 2026; Ogunsakin & Sulaimon, 2026). Yet abundance also brings conceptual difficulties: questions of representativeness, data sovereignty, and the ethics of repurposing non-health urban signals (Arefin et al., 2025; Utomi et al., 2024).

Across the literature, non-traditional urban data are therefore understood not as simple technological upgrades but as a new epistemological foundation for public health surveillance, one that is urban by nature, dynamic in operation, and ecosystem-based in structure.

Classification of Emerging Urban Data Streams

The classification of emerging urban data streams shows a rich, multimodal ecosystem capable of delivering unprecedented coverage of population health dynamics. Wastewater surveillance functions as a powerful community-level indicator that operates independently of clinical testing (Adams et al., 2024; Alkhouri et al., 2026). Mobility and transportation data act as leading indicators of transmission risk (Pandey et al., 2025; Parr et al., 2023). GIS and remote sensing supply spatial intelligence for risk mapping and disaster response (Adu et al., 2025; Gyang et al., 2024). IoT sensors and smart-city infrastructure generate continuous environmental and behavioral signals (Gaye et al., 2025). Social media and search queries provide real-time behavioral insights (Aiello et al., 2020). Participatory mobile apps capture granular, voluntary data from mobile populations (Colubri et al., 2025).

Each stream brings its own temporal, spatial, and population-level strengths, along with distinct limitations. Their real power appears when they are used together rather than in isolation (Rilkoff et al., 2024; Kebeba & Agyei, 2026). The research makes clear that multimodal integration is essential for effective urban surveillance. At the same time, interoperability gaps and standardization challenges continue to limit what is possible in practice (Ogunsakin & Sulaimon, 2026).

Analytical and AI-Driven Approaches

AI and computational analytics form the operational core that turns raw urban data into usable public health intelligence. Hybrid models that combine machine learning with mechanistic frameworks have shown they can handle structural shifts, such as the emergence of new variants, more effectively than purely traditional approaches (Ogu & Opoku, 2025). Predictive AI-cloud systems can flag potential outbreaks before conventional surveillance even registers them by drawing on multiple data streams at once (Ogunsakin & Sulaimon, 2026). Anomaly detection applied to food safety and environmental monitoring highlights the practical reach of computer vision and deep learning (Gaye et al., 2025). Spatial analytics and metapopulation modeling, meanwhile, deliver the kind of granular, scalable forecasting that urban settings demand (Adu et al., 2025; Pandey et al., 2025).

Even so, the studies repeatedly caution that computational power on its own is not enough. Interpretability, bias mitigation, and careful validation remain essential (Panteli et al., 2025; Mendes et al., 2025). In practice, AI-driven surveillance works best as an enabling infrastructure rather than a self-sufficient solution.

Applications in Disease and Environmental Surveillance

Applications of non-traditional urban data have already demonstrated a clear move toward predictive and spatially adaptive intelligence. Wastewater surveillance has repeatedly provided early community-level warnings for COVID-19 and mpox (Adams et al., 2024; Neyra et al., 2025). Mobility-informed models have proven capable of forecasting epidemic onset timing across different scales (Pandey et al., 2025). GIS and remote sensing tools have improved both disaster response and broader urban risk detection (Adu et al., 2025; Gyang et al., 2024). Participatory mobile apps have helped close gaps in traveler-related surveillance (Colubri et al., 2025). Even food safety monitoring has benefited from AI-driven anomaly detection (Gaye et al., 2025).

Taken together, these examples show a genuine transition from reactive case counting to anticipatory surveillance. The public health payoff is real. Yet the evidence also makes plain that turning early signals into effective action still depends heavily on governance structures and institutional readiness.

Data Quality, Bias, and Reliability Challenges

Urban data abundance brings its own set of problems. New forms of bias and unreliability can quietly undermine the integrity of surveillance systems. Demographic skew appears in wastewater coverage (Alkhouri et al., 2026). The digital divide affects social media and participatory sources (Aiello et al., 2020; Colubri et al., 2025). Algorithmic bias surfaces in AI models (Panteli et al., 2025). The research shows that these representativeness issues are structural rather than incidental. They call for justice-centred design and ongoing validation efforts (Arefin et al., 2025). Multimodal fusion can help reduce single-source weaknesses, but bias remains a persistent challenge to truly equitable intelligence generation.

Privacy, Ethics, and Governance Considerations

Governance has become a foundational requirement for legitimate surveillance. Privacy, consent, algorithmic accountability, and justice considerations are no longer side issues. They sit at the center of system design (Aiello et al., 2020; Arefin et al., 2025; Utomi et al., 2024; Panteli et al., 2025). The evidence repeatedly shows that ethical frameworks must develop in step with technical capabilities. Community co-design and benefit-sharing are increasingly viewed as essential rather than optional (Arefin et al., 2025). In the end, governance is the main safeguard that determines whether technological transformation leads to equitable public health benefits or simply reproduces and deepens existing disparities.

Interoperability and Infrastructure Constraints

Interoperability problems and infrastructure fragmentation continue to stand in the way of truly scalable urban surveillance. Heterogeneous systems, gaps in sewer coverage, data silos, and institutional resistance all limit how fully the multimodal potential can be realized (Adams et al., 2024; Ghildayal, et al., 2024; Ogunsakin & Sulaimon, 2026). While distributed models have shown what is possible, they also underline the need for standardized protocols and reliable long-term investment. Infrastructure readiness remains the practical bottleneck that separates technical promise from everyday operational impact.

Urban Health Intelligence and Smart-City Integration

Public health surveillance is steadily becoming part of larger intelligent urban ecosystems. GIS layers, IoT sensors, mobility data, and environmental monitoring are converging into city-scale health intelligence platforms (Adu et al., 2025; Gyang et al., 2024; Gaye et al., 2025). This convergence blurs the old lines between city infrastructure and public health systems and opens the door to genuinely hyper-local, real-time intelligence. At the same time, the digital divide and associated governance risks remain very real. They make clear that equity-focused strategies are essential if smart-city integration is to benefit all urban populations rather than just the most connected ones.

Policy Implications and Public Health Strategy

Effective modernization of public health surveillance through non-traditional urban data requires far more than technological deployment. It demands a comprehensive institutional and policy framework that addresses the full spectrum of challenges identified across the preceding analyses. The shift from traditional reactive systems to predictive, multimodal urban intelligence ecosystems highlights the urgent need for coordinated governance that can keep pace with rapid technical advancement. Policymakers must therefore establish clear standards for data integration that balance innovation with equity, ensuring that the benefits of real-time intelligence are not confined to well-resourced urban areas.

A central policy priority is the development of national interoperability protocols. The evidence across data streams and analytical approaches shows that the greatest value emerges when mobility, wastewater, geospatial, and IoT signals are fused. Without standardized technical and legal frameworks for cross-sector data sharing, these streams remain fragmented and underutilized. Governments should therefore invest in common data models and secure exchange platforms while embedding equity requirements into every stage of system design.

Equity must be treated as a core performance metric rather than an afterthought. Analyses of bias and governance reveal persistent demographic skew and digital divides that can undermine the legitimacy of surveillance systems. Policy responses should mandate regular equity impact assessments, prioritize resource allocation to high-vulnerability communities, and require community participation in the design and oversight of new surveillance programs. This approach transforms equity from a compliance exercise into a foundational design principle.

Workforce and institutional capacity represent another critical policy domain. The transition to AI-enabled urban intelligence demands public health professionals who understand both epidemiology and computational methods. Sustained investment in interdisciplinary training programs, combined with clear ethical guidelines for AI deployment, will help agencies evolve from data collectors into intelligence orchestrators. At the same time, funding mechanisms must support long-term infrastructure maintenance rather than short-term pilot projects.

Finally, policy frameworks must address the governance of smart-city integration. As surveillance becomes embedded in urban digital ecosystems, dedicated urban health data governance boards should be established to oversee data use, protect privacy, and ensure accountability. These boards can serve as the bridge between technical innovation and public trust, providing transparent mechanisms for citizens to understand how their urban data contributes to health protection.

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In sum, the policy challenge is to create an enabling environment where technological transformation is matched by institutional readiness. Only through an integrated strategy that addresses interoperability, equity, workforce development, and smart-city governance can non-traditional urban data deliver its full promise of more responsive, equitable, and sustainable public health surveillance.

Future Research Directions

Future research must prioritize implementation of realism over technical novelty. Key priorities include longitudinal evaluations of bias-mitigation strategies, cost-effectiveness analyses of multimodal systems, empirical assessments of integrated smart-city health platforms, and development of participatory governance models. Research agendas should emphasize measurable equity outcomes, operational scalability, and sustainable institutional adaptation. The reviewed studies collectively call for research that bridges the current gap between technical capability and governance maturity, ensuring that future urban surveillance systems are both powerful and just.

Conclusion

The reviewed evidence demonstrates that non-traditional urban data ecosystems are fundamentally transforming public health surveillance. Mobility patterns, wastewater signals, geospatial layers, IoT sensors, social media traces, and participatory platforms, when integrated with advanced analytical methods, create real-time, predictive, and spatially precise health intelligence that traditional systems could not achieve. This shift moves surveillance from delayed, reactive reporting to continuous, anticipatory urban risk management, offering substantial gains in timeliness, coverage, and operational responsiveness.

Yet the same body of work consistently shows that these technological advances come with significant challenges. Algorithmic bias, data representativeness issues, interoperability barriers, infrastructure fragmentation, and ethical concerns are not minor implementation hurdles but structural constraints that determine whether the new systems deliver equitable benefit or amplify existing disparities. Governance, privacy protections, community engagement, and institutional readiness have emerged as foundational requirements rather than optional add-ons. The literature makes clear that technical capability now far outpaces governance maturity in most contexts.

Ultimately, the future of public health surveillance lies in the successful development of integrated, ethical, AI-enabled urban health intelligence ecosystems. Realizing this potential will require deliberate policy leadership, sustained investment in infrastructure and interoperability, justice-centred design principles, and cross-sector collaboration. If these elements are prioritized, non-traditional urban data sources can help create more resilient, equitable, and responsive public health systems. If they are neglected, the transformation risks reinforcing the very inequities it seeks to address. The evidence points toward a clear choice: invest in both innovation and the governance structures that make innovation trustworthy and equitable.

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