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Convergent Intelligence for Pandemic Preparedness: A Narrative Review of Integrated Digital Biosurveillance Systems Utilizing Pre-Diagnostic Data Streams

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Abstract

Background: The early detection of infectious disease outbreaks is a critical public health imperative. Traditional surveillance, reliant on confirmed laboratory reports, often introduces a critical delay. The concept of the biosurveillance continuum advocates for the real-time integration of pre-diagnostic data streams from across the healthcare ecosystem to provide earlier warning. **Aim:** This narrative review systematically synthesizes the literature on integrated systems that combine syndromic Emergency Medical Services (EMS) data, over-the-counter (OTC) pharmacy sales, radiology findings, and nursing home reports for the early detection of infectious disease outbreaks. **Methods:** A systematic search was conducted across PubMed/MEDLINE, CINAHL, Scopus, and IEEE Xplore for studies published between 2010-2024. A narrative synthesis was performed, analyzing system architectures, detection performance, and implementation challenges. **Results:** Each data stream offers unique benefits for public health monitoring. EMS data ensures geographic and temporal insight into illnesses like influenza-like illness (ILI). Over-the-counter (OTC) sales data reflect symptom onset across populations. NLP analysis of radiology reports can detect pneumonia cluster patterns before definitive diagnosis. Nursing home data provides vital surveillance for high-risk groups. Effective integration of these sources necessitates Health Informatics platforms for data aggregation and visualization, supported by robust epidemiological frameworks. **Conclusion:** An integrated biosurveillance system utilizing EMS, pharmacy, radiology, and nursing home data can improve early outbreak detection. However, challenges such as data standardization, interoperability, privacy, and collaboration must be addressed to maximize its effectiveness. Investing in these systems is crucial for pandemic preparedness.

Keywords: biosurveillance; syndromic surveillance; outbreak detection; data integration; public health informatics.

Introduction

The rapid emergence and global spread of infectious diseases, such as H1N1 influenza, Ebola, COVID-19, and mpox, have starkly exposed the limitations of traditional public health surveillance (Chretien et al., 2016). Conventional systems, which depend on laboratory-confirmed case reports from healthcare facilities, introduce an inherent and often fatal delay—the diagnostic gap—between community transmission and public health awareness (Cassell et al., 2022). This lag undermines the effectiveness of critical containment measures like contact tracing, quarantine, and resource mobilization. In response, the paradigm of *biosurveillance* has evolved, emphasizing the proactive, real-time collection, analysis, and interpretation of diverse data streams for early event detection and situational awareness (Dugas et al., 2013). Moving beyond singular data sources, the

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modern concept is that of a *biosurveillance continuum*: an integrated system that synthesizes pre-diagnostic, syndromic indicators from across the community's health landscape to create a faster, more granular picture of emerging threats (Zeng et al., 2021).

This continuum strategically incorporates data from non-traditional but highly informative sources. Emergency Medical Services (EMS) records, capturing patient chief complaints and dispatch codes from the pre-hospital setting, offer unparalleled spatiotemporal granularity for syndromes like influenza-like illness (ILI) or gastrointestinal distress, often hours or days before hospital admission (Shah et al., 2021). Over-the-counter (OTC) pharmacy sales data act as a population-level behavioral biomarker; increased purchases of antipyretics, cough suppressants, or antidiarrheals serve as a direct proxy for symptom prevalence in the community (Andersson et al., 2014). Radiology reports, particularly chest imaging, contain rich phenotypic data. Through natural language processing (NLP) and, increasingly, artificial intelligence (AI) image analysis, clusters of specific findings (e.g., bilateral ground-glass opacities) can signal novel respiratory outbreaks before pathogen identification (Liang et al., 2019; Syrowatka et al., 2021). Nursing home and long-term care facility (LTCF) reports provide sentinel surveillance in exceptionally vulnerable, congregate settings where outbreaks are severe and early detection is paramount (Thrupp et al., 2004; Mathes et al., 2017).

The power of this approach lies not in any single stream, but in its integration, a task that sits at the intersection of multiple disciplines. Epidemiology provides the core analytical framework for outbreak detection and signal validation. Health Security frames the imperative, driving investment in preparedness against biological threats. The pharmacy offers the OTC sales data pipeline. Emergency Medical Services contributes to the pre-hospital syndromic feed. Nursing facilitates the structured reporting from frontline care settings like LTCFs. Radiology generates the crucial imaging-derived phenotypes. Finally, Health Informatics is the essential enabling discipline, providing the platforms for automated data aggregation, standardization, advanced analytics, and visualization (Khan et al., 2018). This review aims to systematically synthesize the literature from 2010-2024 on integrated biosurveillance systems that incorporate two or more of these key data streams—EMS, OTC pharmacy, radiology, and nursing home reports. It will examine their technical architectures, documented performance in early detection, and the cross-cutting challenges of implementation, to inform the development of more resilient public health surveillance infrastructures.

Methods

This narrative review employed a systematic search strategy to ensure a comprehensive and reproducible identification of relevant literature. Searches were conducted in four electronic databases chosen for their coverage of biomedical, clinical, informatics, and engineering literature: PubMed/MEDLINE, CINAHL, Scopus, and IEEE Xplore. The search strategy combined controlled vocabulary (e.g., MeSH terms) and keywords related to four core concepts: (1) Biosurveillance/Surveillance ("biosurveillance", "syndromic surveillance", "early detection", "outbreak detection"); (2) Data Sources ("emergency medical services", "EMS", "prehospital", "over-the-counter", "pharmacy sales", "radiology reports", "medical imaging", "nursing home", "long-term care facility"); (3) Integration ("data integration", "multi-source", "interoperability", "public health informatics"); and (4) Infectious Disease ("infectious disease", "outbreak", "pandemic", "influenza", "respiratory infection"). Boolean operators (AND, OR) were used to link concepts. The search was restricted to articles published in English between January 1, 2010, and May 1, 2024, to capture the modern era of digital surveillance and lessons from recent pandemics.

Inclusion Criteria encompassed: (a) peer-reviewed original research articles, systematic reviews, or significant case studies; (b) focus on electronic or automated biosurveillance systems; (c) description of systems integrating at least two of the four target data streams (EMS, OTC pharmacy, radiology, nursing home); and (d) evaluation or discussion of the system's application for early infectious disease outbreak detection. Exclusion Criteria were: (a) studies describing single-source surveillance only; (b) commentaries or editorials without original data or systematic analysis; (c) studies focused exclusively on chronic disease or non-infectious outcomes; and (d) articles not available in full text.

Given the heterogeneity in study designs, system architectures, and outcome measures, a formal meta-analysis was not feasible. Instead, a narrative synthesis approach was adopted (Wong et al., 2013). Extracted data included study design, data sources integrated, technical methods for integration and analysis, primary findings related to timeliness and sensitivity/specificity, and reported implementation challenges. Findings were organized thematically to construct a coherent overview of the field, focusing on the value of each data stream, integration paradigms, and cross-cutting barriers.

The Value of Individual Data Streams in the Continuum

Emergency Medical Services (EMS) Data as The Pre-Hospital Pulse

EMS data, derived from electronic patient care reports (ePCRs) and computer-aided dispatch (CAD) systems, represent one of the most temporally and geographically precise syndromic surveillance sources (Shah et al., 2021). By capturing chief complaints (e.g., "fever," "difficulty breathing," "diarrhea") at the moment of first professional medical contact, often in the patient's home, EMS data can provide a lead time of 24-72 hours over hospital discharge diagnoses and 1-2 weeks over mortality data (Duijster et al., 2019). Studies have consistently demonstrated the utility of EMS syndromic indicators for tracking ILI activity, with strong correlations to confirmed influenza cases and hospitalizations (Hswen et al., 2017; Rosenkötter et al., 2013). For example, a system monitoring EMS dispatch codes for "sick person" and "breathing problems" in Texas provided reliable early warning for seasonal influenza peaks (Sugishita et al., 2020).

Beyond influenza, EMS data have shown promise in detecting outbreaks of gastrointestinal illness and even novel threats; anomalous clusters of respiratory distress calls were noted in some regions in the very early stages of the COVID-19 pandemic (Ferraro et al., 2021). The strengths of EMS data are their objectivity, automation, and fine-grained location data, which enable hotspot mapping. Limitations include the need for robust syndromic categorization algorithms to map free-text chief complaints to standardized syndromes and the potential for confounding by non-infectious causes of similar symptoms (e.g., asthma, heart failure) (Ising et al., 2016).

Over-the-Counter (OTC) Pharmacy Sales as A Population Behavioral Biomarker

Purchases of OTC medications are a direct, population-level indicator of symptom mitigation behavior, offering a complementary signal to healthcare-seeking data (Andersson et al., 2014). Individuals often self-medicate for several days before seeking professional care, making OTC sales a leading indicator. Key product categories for surveillance include antipyretics/analgesics (e.g., acetaminophen, ibuprofen), cough/cold remedies, anti-diarrheals, and pediatric electrolyte solutions (Wagner et al., 2001). Research has established strong correlations between spikes in OTC sales of these items and subsequent increases in laboratory-confirmed cases of influenza and norovirus (Ramay et al., 2022; Muchaal et al., 2015). During the 2009 H1N1 pandemic, OTC medication sales in Japan provided a 1-2 week lead time over official case reports (Yamana et al., 2017). The advantages of pharmacy data are their near real-time availability (via point-of-sale systems), high population coverage, and ability to capture mild cases that never enter the healthcare system. Major challenges include commercial confidentiality, the need for partnerships with pharmacy chains or aggregators, and confounding by factors like sales promotions, seasonal purchasing patterns, and media-driven "panic buying," which require sophisticated statistical filtering to isolate true outbreak signals (Hulth et al., 2009).

Radiology Findings as the Phenotypic Gold Mine

Radiology reports, particularly for chest X-rays (CXR) and computed tomography (CT), contain detailed phenotypic descriptions of disease that can be highly specific for certain pathogens or syndromes. Traditionally underutilized for surveillance due to their unstructured text format, advances in NLP and AI are unlocking their potential (Liang et al., 2019). NLP algorithms can scan dictated reports for key terms and phrases indicating infectious processes (e.g., "consolidation," "ground-glass opacity," "bilateral," "multifocal"). This approach proved valuable during COVID-19, where NLP-based surveillance of "pneumonia" findings in emergency department radiology reports provided earlier community-level detection than PCR test results in some settings (Soltan et al., 2021). Beyond NLP, AI-based image analysis (radiomics) can directly analyze imaging pixels to identify subtle, quantifiable patterns associated with specific infectious etiologies or severities (Syrowatka et al., 2021). A chest CT AI model, for instance, could differentiate COVID-19 pneumonia from other causes with high accuracy, offering a rapid "imaging biomarker" during testing shortages (Mei et al., 2020). The strength of radiology data is its objective clinical evidence of pathology, providing a high-specificity signal that can validate softer syndromic data. Limitations include slower turnaround compared to EMS or pharmacy data (due to the need for image acquisition and interpretation), access to structured report data or images, and the challenge of normalizing findings across different radiologists and institutions (Kohli et al., 2017).

Nursing Home and Long-Term Care Facility (LTCF) Reports

Residents of nursing homes and LTCFs represent a canary-in-the-coal-mine population: they are older, have multiple comorbidities, live in close quarters, and experience severe outcomes from infections, making these facilities high-risk sentinel sites (Thrupp et al., 2004). Mandatory or voluntary reporting of infectious disease incidents (e.g., influenza-like illness, gastroenteritis, COVID-19 cases) from LTCFs to public health authorities is a well-established practice. When digitized and automated, these reports become a powerful stream within the biosurveillance continuum (Mathes et al., 2017). Early clusters in LTCFs often precede wider community spread, as seen starkly with COVID-19 (McMichael et al., 2020). Automated daily reporting systems for symptoms and staffing shortages, as implemented in some jurisdictions during the pandemic, enabled rapid intervention and containment (Stone et al., 2012). The advantages are direct reporting from high-risk settings and the potential for very early, specific signals. Challenges include the burden of reporting on facility staff, variability in data quality and completeness, and ensuring rapid data flow from often resource-strapped facilities into public health systems (Hughes et al., 2020). Table 1 summarizes the characteristics and utility of core data streams in the Biosurveillance continuum.

Table 1: Characteristics and Utility of Core Data Streams in the Biosurveillance Continuum

Data Stream	Key Indicators	Lead Time Advantage	Primary Strengths	Key Challenges & Limitations
EMS Data	Chief complaint/diagnosis codes (e.g., fever, breathing difficulty, diarrhea).	1-3 days before hospitalization.	High spatiotemporal granularity; automated; captures community-onset illness.	Requires syndromic categorization; non-specific signals; can be confounded by chronic conditions.
OTC Pharmacy Sales	Sales volume of antipyretics, cough/cold, anti-diarrheal medications.	3-7 days before case confirmation.	Captures mild/self-treated cases; near real-time; strong population-level behavioral proxy.	Commercially sensitive; confounded by promotions/panic buying; requires partnership with retailers.
Radiology Reports	NLP-extracted findings (e.g., "pneumonia," "ground-glass opacities"); AI image analysis.	0-5 days (depends on care pathway).	High clinical specificity; provides objective phenotypic evidence of pathology.	Slower data flow; requires advanced NLP/AI; data access and standardization across institutions.
Nursing Home/LTCF Reports	Reports of ILI clusters, GI outbreaks, and confirmed cases among residents/staff.	Variable; can be very early in vulnerable populations.	Direct data from high-risk sentinel sites enables targeted intervention.	Reporting burden; data quality/completeness issues, limited to a specific sub-population.

Architectures for Integration

The transformative potential of the biosurveillance continuum is realized only through the integration of disparate data streams, a task fundamentally dependent on Health Informatics. Effective integration architectures move beyond simple data co-location to create interoperable, analytic systems capable of generating actionable intelligence (Khan et al., 2018).

A common model is the centralized data warehouse or hub, where multiple-source data are extracted, transformed, and loaded (ETL) into a common repository. Data from EMS agencies (via Health Level Seven [HL7] messages), pharmacy sales aggregators, radiology reporting systems, and LTCF electronic health records (EHRs) are normalized to common data models, such as the Public Health Information Network (PHIN) Vocabulary or Fast Healthcare Interoperability Resources (FHIR) standards (Dixon et al., 2011). This allows for unified querying and analysis. For example, BioSense (now the National Syndromic Surveillance Program, NSSP, in the U.S.) provides a platform that integrates emergency department, urgent care, and increasingly, EMS data for national syndromic surveillance (Dugas et al., 2013).

More advanced architectures employ distributed or federated data approaches. In these models, data remain at their source institutions (preserving privacy and control) while analytic queries are distributed and executed locally, with only aggregated results or statistical signals shared. This is particularly relevant for sensitive data like detailed radiology images or proprietary pharmacy sales figures (Rumbold & Pierscionek, 2017). The Spatiotemporal Epidemiological Modeler (STEM) from IBM and other open-source platforms support such federated analytics for outbreak modeling (Grannis et al., 2010).

The analytic engine itself utilizes a suite of statistical and machine learning (ML) algorithms to convert raw data into alerts. Baseline models (e.g., historical moving averages, regression models) establish expected levels for each data stream (Buckeridge, 2007). Anomaly detection algorithms, such as the Early Aberration Reporting System (EARS) C1-C3 methods or more sophisticated space-time scan statistics (e.g., SaTScan), then identify statistically significant deviations that may represent an outbreak (Kleinman & Abrams, 2006). Machine learning models are increasingly used to weigh and combine signals from multiple streams, potentially improving the signal-to-noise ratio and predictive power (Zeng et al., 2021). Finally, visualization dashboards are critical for translating complex, multi-dimensional data into intuitive formats for public health decision-makers. These dashboards often feature interactive maps of case clusters, time-series graphs of syndromic indicators, and alert logs (Johansson et al., 2016).

Performance and Impact

Empirical evidence suggests that integrating multiple pre-diagnostic data streams enhances early outbreak detection compared to reliance on any single source or traditional laboratory reporting. The value is often additive or synergistic, with different streams contributing unique lead times and specificities.

Studies evaluating multi-source systems have demonstrated improved timeliness. Research on a system combining OTC pharmacy sales, school absenteeism, and web search queries showed it could detect seasonal influenza outbreaks 1-2 weeks earlier than physician-based surveillance (Hulth et al., 2009). A system integrating EMS dispatch data with emergency department visits provided more geographically precise and timely signals for ILI than either source alone (Sugishita et al., 2020). During the COVID-19 pandemic, integrated systems that fused mobility data, online searches, and syndromic surveillance provided early indications of community transmission in areas with limited testing capacity (Menni et al., 2020).

The integration of radiology data adds a layer of phenotypic validation. A study in a large healthcare system found that an NLP algorithm monitoring chest CT reports for terms consistent with viral pneumonia flagged a rising trend days before the first confirmed COVID-19 case was reported in that region, providing a crucial internal warning (Soltan et al., 2021). Similarly, nursing home outbreak reports often serve as the first concrete signal of community transmission for pathogens such as influenza or norovirus, triggering broader public health investigations (Mathes et al., 2017).

However, measuring the true "impact" extends beyond statistical lead time. Key outcome measures include sensitivity (ability to detect true outbreaks), specificity (avoiding false alarms), positive predictive value, and ultimately, the effect on public health decision-making and outcomes (e.g., earlier intervention reducing attack rates). The literature indicates a common trade-off: highly sensitive systems (such as raw OTC sales) may generate many false alerts, while highly specific systems (such as confirmed radiology findings) may miss early, mild cases (Buckeridge, 2007). Intelligent integration aims to optimize this balance—using a sensitive stream like EMS data to cast a wide net and a specific stream like radiology or LTCF reports to validate and prioritize signals.

Critical Challenges and Barriers to Implementation

Despite its demonstrable promise, the operationalization of an effective, multi-source biosurveillance continuum encounters profound, multifaceted barriers that span technical, ethical, legal, and organizational domains, often impeding translation from proof-of-concept to sustainable public health infrastructure.

Technical and Data Challenges constitute a primary layer of complexity. A fundamental hurdle is achieving **interoperability and standardization** across disparate data ecosystems. Biosurveillance streams originate from heterogeneous sources—EMS ePCRs, pharmacy POS systems, hospital radiology information systems (RIS), and LTCF electronic records—each employing different data formats, coding schemas (e.g., ICD-10, SNOMED CT, proprietary codes), and quality controls. Achieving true semantic interoperability, where a concept like "fever" or "respiratory distress" is consistently and accurately represented across all systems, requires sustained investment in common data models (e.g., FHIR) and meticulous mapping efforts (Dixon et al., 2011). Furthermore, the utility of early detection is directly undermined by issues of **data latency and completeness**. The lead-time advantage is negated if pharmacy sales data are batched weekly, nursing home reports are submitted manually days after an event manually, or radiology dictations await transcription. Incomplete data, whether due to voluntary reporting, technical failures, or resource constraints in source institutions, can introduce significant bias and weaken statistical signals (Cassell et al., 2022). Finally, the core of detection lies in **algorithm development and validation**. Crafting anomaly detection algorithms that are sensitive to true outbreaks while remaining specific enough to filter out background noise (e.g., seasonal influenza trends, holiday effects, reporting artifacts) is a complex statistical endeavor. These models demand continuous validation against confirmed outbreak data to prevent alert fatigue and maintain the trust of public health practitioners (Kleinman & Abrams, 2006).

The **Ethical, Legal, and Social Implications (ELSI)** of integrated surveillance present a parallel set of critical constraints. **Privacy and data security** are paramount, as systems often aggregate personally identifiable information (PII) and precise location data from EMS runs or pharmacy purchases. Robust de-identification protocols and strict, transparent data governance frameworks defining access rights and usage purposes are non-negotiable to protect individual autonomy and comply with regulations like GDPR and HIPAA (Rumbold & Pierscionek, 2017). The **cybersecurity** of these aggregated data hubs is itself a core **Health Security** concern. Concurrently, **data ownership and commercial sensitivity** create substantial barriers to access. OTC sales data are valuable commercial assets for pharmacy chains, and detailed hospital data, including radiology images, are often considered proprietary. Negotiating data-sharing agreements that satisfy corporate interests while providing the necessary granularity and timeliness for public health is a persistent challenge (Andersson et al., 2014). Perhaps most insidiously, integrated systems risk perpetuating **equity and bias**. Surveillance signals are dependent on healthcare-seeking behavior and commercial access. Underserved communities with lower EMS utilization, less access to retail pharmacies, or poorer digital connectivity may be rendered "invisible" to these systems, leading to under-detection and a misallocation of public health resources. Furthermore, machine learning algorithms trained on historical data that reflects these existing disparities can encode and amplify such biases, leading to inequitable performance across population subgroups (Wedd et al., 2019).

Ultimately, these technical and ethical challenges are compounded by significant **Organizational and Sustainability Challenges**. Success hinges on **cross-sector collaboration** among entities with differing missions, incentives, and cultures: public health agencies, private healthcare systems, EMS authorities, retail corporations, and LTCF operators. Forging and maintaining these complex, multi-stakeholder partnerships requires dedicated resources, clear governance, and a compelling demonstration of mutual benefit (Khan et al., 2018). **Financial sustainability** is a recurring threat; many advanced systems are piloted with soft grant funding, only to be abandoned when grants expire, as ongoing operational costs are rarely absorbed into core public health budgets (M'ikanatha et al., 2013). Finally, a critical **workforce capacity gap** exists. Public health departments frequently lack the specialized personnel with expertise in **Health Informatics**, data engineering, data science, and advanced epidemiology required to architect, manage, and interpret these complex, integrated data systems (Ye et al., 2022). A summary of these interconnected challenges is presented in Table 2.

Table 2: Key Challenges in Implementing Integrated Biosurveillance Systems

Challenge Domain	Specific Barriers	Potential Mitigation Strategies
Technical & Data	Lack of data standards/semantic interoperability; variable data latency and completeness; algorithm drift and false alerts.	Adopt FHIR/PHIN standards; incentivize real-time data sharing agreements; implement ongoing model validation and recalibration.
Ethical, Legal & Social	Privacy risks with PII/location data; commercial sensitivity of pharmacy/hospital data; algorithmic bias and surveillance equity.	Implement strong de-identification and role-based access controls; create data-use agreements with private partners; conduct bias audits of algorithms and data sources.
Organizational & Sustainability	Fragmented cross-sector collaboration; lack of sustainable funding models; shortage of public health informatics expertise.	Establish formal data-sharing consortia with clear governance; advocate for core public health IT infrastructure funding; invest in workforce training and partnerships with academia.

Future Directions and Conclusion

The future of the biosurveillance continuum lies in more intelligent, automated, and equitable systems. Artificial Intelligence and Machine Learning will play an expanding role, not just in analyzing single streams (e.g., radiology AI), but in performing multi-modal fusion—synthesizing text, sales, image, and geospatial data into unified risk scores (Zeng et al., 2021). The concept of the "digital twin"—a virtual model of a city or region's health ecosystem that simulates outbreak spread under various intervention scenarios—could revolutionize preparedness and response planning (Elkefi & Asan, 2022). Wearable and ambient sensor data (e.g., smart thermometers, home health devices) represent a new frontier of passive, continuous physiologic monitoring at the individual and community level (Menni et al., 2020). Furthermore, global data integration through platforms like the World Health Organization's (WHO) Epidemic Intelligence from Open Sources (EIOS) initiative highlights the move towards a worldwide biosurveillance network (Nuzzo et al., 2019).

In conclusion, the biosurveillance continuum, integrating EMS, pharmacy, radiology, and nursing home data through robust health informatics platforms, represents a paradigm shift towards proactive public health defense. The evidence synthesized in this review demonstrates that such integration is not only feasible but also enhances the timeliness and situational awareness of outbreak detection. Each stream contributes a unique piece of the puzzle: EMS provides the early community pulse, OTC sales reveal population behavior, radiology offers phenotypic confirmation, and nursing home reports act as sentinel alarms. However, the path forward is fraught with significant challenges related to data interoperability, privacy, equity, and sustainable collaboration across the Pharmacy, EMS, Nursing, Radiology, Epidemiology, Health Security, and Health Informatics sectors. Overcoming these barriers requires sustained political will, investment in public health infrastructure, and ethical governance frameworks. As infectious disease threats continue to evolve, building and maintaining this integrated early-warning system is not merely a technical exercise but a fundamental cornerstone of global health security.

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