World Journal of Advanced Research and Reviews

eISSN: 2581-9615 CODEN (USA): WJARAI

Cross Ref DOI: 10.30574/wjarr

Journal homepage: https://wjarr.com/

(Research Article)

Influence of Interoperable Health Information Systems, Real-Time Data Dashboards, and Predictive Intelligence on the Effectiveness of Public Health Early Warning and Surveillance Systems

Oluwadamilola Adeleke *

Rush University Medical Center, Chicago, IL, USA.

World Journal of Advanced Research and Reviews, 2022, 16(01), 1307-1324

Publication history: Received on 15 September 2022; revised on 25 October 2022; accepted on 31 October 2022

Article DOI: https://doi.org/10.30574/wjarr.2022.16.1.0779

Abstract

Digital health technologies are moving faster, and real-time, multi-source data is becoming easier to get. Because of this, we are much better prepared for public health emergencies. To find and respond to outbreaks, we need traditional public health monitoring systems, but they often have problems that make it hard to make quick and good decisions during health emergencies. Some of these problems are delays in reporting, broken data architectures, and not being able to do much with the data. This study looks at how interoperable health information systems, real-time data dashboards, and predictive analytics affect how well public health early warning and surveillance systems work. The Research is based on the idea that adding digital health technologies to surveillance systems can greatly improve how quickly, accurately, and broadly public health responds to new threats. Systematic review methodology in accordance with PRISMA 2020 guidelines. Thorough searches of PubMed, Scopus, Web of Science, and JSTOR produced peer-reviewed empirical studies published from 2000 to 2021. After eliminating duplicates and undergoing a two-step screening and eligibility assessment, 155 studies satisfied the inclusion criteria and were incorporated into a qualitative narrative synthesis. The evaluation concentrated on evidence pertaining to system interoperability, real-time data visualization, automated detection algorithms, and predictive analytics within the framework of public health surveillance. The results show that health information systems that can work together are needed for easy sharing of data between clinical, laboratory, syndromic, and environmental data sources. This will make surveillance more complete and the data more accurate. Real-time data platforms improve situational awareness by giving different stakeholders timely, useful information that is specific to their needs. This makes it easier to coordinate quick responses and allocate resources effectively. Predictive intelligence, which includes machine learning, time-series analysis, and spatial modelling, makes it much easier to find outbreaks and speeds up response times by finding new patterns and anomalies that traditional methods might miss. The report also states that there are still problems with data quality, system interoperability, staff capacity, infrastructure limitations, and privacy and governance issues, especially in low- and middle-income countries. The proof shows how important it is to have strong technical architectures, thorough governance frameworks, and a long-term commitment to digital surveillance systems to get the most out of them. This study shows that adding interoperable systems, real-time analytics, and predictive intelligence in a planned way is very important for improving early warning systems for public health and getting ready for future health emergencies.

Keywords: Public health surveillance; Early warning systems; Health information interoperability; Real-time data analytics; Predictive intelligence; Digital health technologies; Outbreak detection; Syndromic surveillance; Health informatics; Emergency preparedness

* Corresponding author: Oluwadamilola Adeleke

Copyright © 2022 Author(s) retain the copyright of this article. This article is published under the terms of the Creative Commons Attribution License 4.0.

1. Introduction

The field of public health emergency preparedness has undergone substantial transformation recently, driven by rapid advancements in digital health technologies and the increasing availability of real-time data from diverse sources. Conventional surveillance systems, while vital to public health practice, often encounter significant time delays, limited scope, and fragmented data collection methods that can impede timely responses to emergent health threats (Brownstein et al., 2009). The emergence of digital health technologies presents exceptional opportunities to enhance surveillance capabilities, improve decision-making processes, and optimize resource distribution during public health emergencies. Digital health technologies encompass a diverse range of tools and platforms, including electronic health record systems, mobile health applications, wearable devices, social media monitoring platforms, and advanced analytics software, which together enable more comprehensive and timely surveillance of population health status (Steinhubl et al., 2013). These technologies produce extensive quantities of real-time data that, when appropriately analyzed and interpreted, can offer early warning signs of disease outbreaks, identify at-risk populations, and inform targeted intervention strategies. The incorporation of diverse data sources facilitates the development of more advanced analytical models capable of identifying subtle patterns and trends that may be overlooked by conventional surveillance techniques. Incorporating digital health technologies into public health practice is a complex endeavor that requires meticulous attention to technical, organizational, and policy considerations. Technical considerations include the interoperability of systems, data quality assurance, analytical capabilities, and user interface design, all of which must be optimized to facilitate effective decision-making processes (Klompas et al., 2012). Organizational considerations encompass workforce development, change management, stakeholder engagement, and resource allocation strategies that impact the effective adoption and use of digital health technologies. Policy considerations encompass privacy safeguards, data stewardship, adherence to regulatory standards, and the development of ethical frameworks necessary to ensure the responsible use of digital health data (Kostkova, 2018). The concept of real-time surveillance signifies a paradigm shift from retrospective analysis to proactive monitoring, allowing public health professionals to detect and address emergent threats with exceptional speed and accuracy (Brownstein et al., 2010). Real-time surveillance systems utilize automated data collection, processing, and analytical functionalities to facilitate the ongoing monitoring of population health metrics, disease patterns, and healthcare utilization trends. This strategy enables the earlier identification of disease outbreaks, facilitates more rapid implementation of control measures, and ensures a more effective allocation of public health resources during emergency situations. The significance of data-driven decision-making in public health emergency preparedness has been underscored by numerous recent events, such as influenza pandemics, foodborne disease outbreaks, bioterrorism incidents, and natural disasters, all of which have challenged the resilience and responsiveness of public health systems globally (Kass-Hout et al., 2012). These experiences have demonstrated both the prospective advantages of digital health technologies and the critical importance of establishing comprehensive surveillance infrastructure to facilitate rapid decision-making processes during crisis situations. The ability to quickly gather, evaluate, and share relevant information has become a key factor in the success of emergency response efforts. The development of effective digital surveillance systems requires a comprehensive understanding of the information needs of numerous stakeholders involved in public health disaster preparedness and response. These stakeholders include local health departments, state and federal agencies, healthcare providers, emergency management organizations, and community groups, each of which has distinct duties and responsibilities during public health emergencies (Kass-Hout et al., 2010). The variety of stakeholder requirements demands the implementation of flexible and adaptable surveillance systems capable of providing a range of information types at various levels of detail and timeliness to facilitate different decision-making processes. This comprehensive analysis assesses the current state of digital health technologies for public health emergency preparedness, identifies key factors influencing successful implementation, and provides evidence-based recommendations for optimizing these technologies to enhance population health outcomes. The Research addresses core topics related to system design, implementation strategies, performance assessment, and sustainability considerations that are vital for public health professionals seeking to leverage digital health technology for emergency preparedness purposes.

1.1. Statement of the Problem

Early warning and monitoring systems are very important for public health because they help find and stop disease outbreaks, new health problems, and changes in the health of the community. A lot of countries still use old, broken, or manual ways that make it hard to get important health information. This causes data gaps, longer response times, and makes it harder for public health experts to make quick choices.

One big worry is that patient records, lab databases, disease registries, and emergency response systems don't usually work together. It's hard for these systems to share information with each other. Data must be entered twice or manually integrated because different systems don't work together. This makes mistakes and inefficiencies more likely. Real-time data dashboards are tools that make it easy for people who need to make decisions to get the most recent information.

They need to be sure that the data they use is accurate and reliable. Dashboards may show missing, inconsistent, or late information when data comes from different systems or doesn't follow the same rules. This makes it harder to find and fix problems early on. Artificial intelligence and machine learning are two types of predictive intelligence technologies that can spot patterns and possible threats before they become clear. These tools can help health officials find problems faster than older methods, which can help stop epidemics from getting worse. When data isn't reliable, easy to move between systems, or integrated, predictive models become more complicated and less accurate. Because of issues with interoperability, real-time visualization, and predictive capabilities, public health systems have a hard time quickly finding health risks, coordinating actions, and using resources well. In a lot of low- and middle-income countries, these problems are worse because there aren't enough digital infrastructure, staff, or good rules for sharing data.

In conclusion, we still haven't fully realized how digital tools can make early warning and surveillance systems better. Health information systems can't talk to each other, share accurate real-time data, or give decision-makers reliable predictions that they can trust and act on right away. Fixing these issues is necessary to make public health better able to handle emergencies in a world that is becoming more connected.

1.2. Research Questions

- How does interoperability among health information systems influence early warning and surveillance effectiveness?
- What role do real time data dashboards play in improving public health decision making?
- How does predictive intelligence strengthen the performance of early warning systems?

Research Objectives

- General Objectives:

The aim of this Research is to evaluate the influence of interoperable health information systems, real-time data dashboards, and predictive intelligence on the effectiveness of public health early warning and surveillance systems.

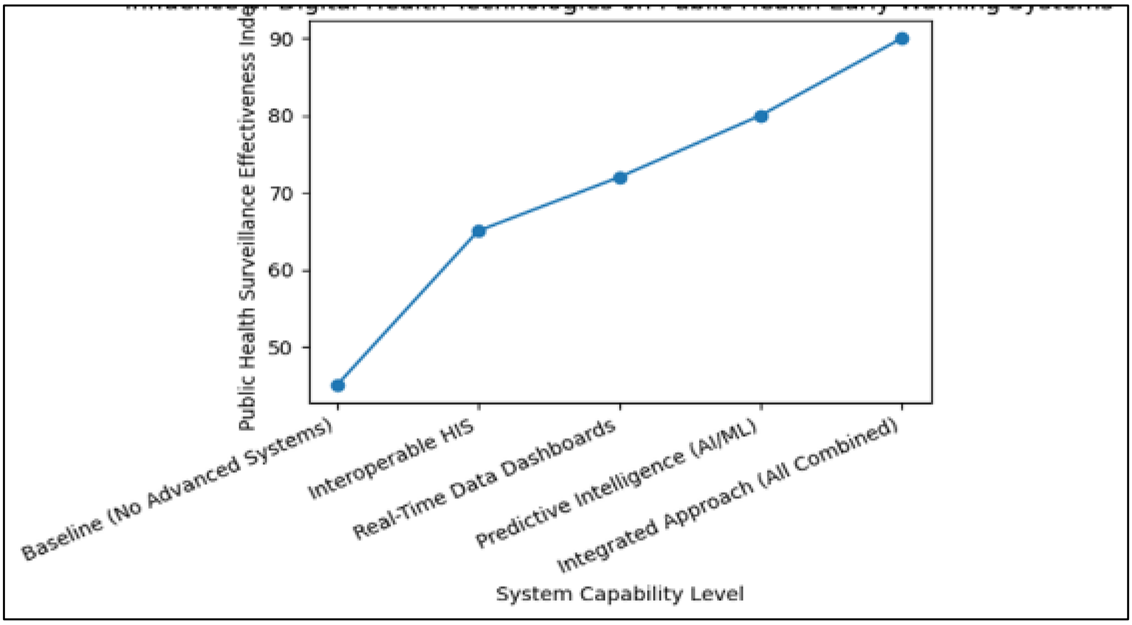
- Specific Objectives:
- To assess the impact of interoperable health information systems on the effectiveness of public health early warning and surveillance systems.
- To evaluate the role of real-time data dashboards in improving decision-making and situational awareness in public health surveillance systems.
- To investigate the contribution of predictive intelligence to the accuracy, timeliness, and response capacity of public health early warning and surveillance systems.

2. Theoretical Framework

2.1. Theoretical Framework

2.1.1. Health Information Systems Theory

Early warning and surveillance systems are important for public health because they help us quickly find, keep an eye on, and deal with new health threats. The purpose of these systems is to give public health professionals the information they need to make quick decisions and take action, which will help stop the spread of disease, illness, and death (World Health Organization [WHO], 2018). These systems only work well if they collect good data, process it quickly, and public health experts can look at it and act on it. New digital health technologies, especially interoperable health information systems, real-time data interfaces, and predictive analytics, have changed how we watch over people in a big way. This theoretical framework elucidates the impact of diverse technologies on the efficacy of public health early warning and surveillance systems.



NOTE: From a baseline system to fully integrated, interoperable HIS, real-time dashboards, and predictive intelligence, the X-axis (System Capability Level) illustrates the progression of technological sophistication.

Figure 1 Influence of Digital health technologies on public health early warning systems

Improvements in timeliness, accuracy, epidemic detection, and decision support are represented by the Y-axis (Public Health Surveillance Effectiveness Index), a conceptual effectiveness score ranging from 0 to 100.

Trend:

- The theoretical claim that is supported by the upward trajectory
- Cross-jurisdictional visibility and data completeness are enhanced via interoperable health information systems.
- Situational awareness and reaction time are improved via real-time dashboards.
- Early anomaly detection and forecasting are made possible by predictive intelligence (AI/ML).
- The best surveillance performance is achieved by integrated deployment.

Health information systems that can talk to each other are the most important part of modern public health surveillance. Interoperability theory examines the efficacy of diverse information systems in communicating, interpreting, and utilizing data despite technical and organizational limitations (HIMSS, 2019). Interoperability makes it easy to combine data from hospitals, labs, clinics, and community health programs for public health surveillance. This integration cuts down on reporting delays, makes sure that all the data is there, and gets rid of data silos. There are still issues with traditional surveillance systems (Birkhead et al., 2015). The idea is that technologies that let people work together directly make surveillance better by giving them data that is more accurate, timely, and representative. All these things are important for quickly finding outbreaks and keeping an eye on diseases all the time.

Real-time data displays use data infrastructures that can work together to help public health officials make decisions. Dashboards take big, complicated data sets and turn them into pictures that are easy to look at and understand quickly (Few, 2013). They are based on ideas about how people decide things and how to present information in a way that makes sense. Real-time dashboards in the field of surveillance give you the most up-to-date information on disease patterns, where they are spreading, how many people the healthcare system can handle, and how well the response works. These tools help public health workers stay up to date on what's going on and find new threats and strange trends faster than traditional ways of reporting (Knaflic Storytelling with Data, 2020; CDC, 2020). In this context, real-time interfaces are thought to improve surveillance by making it easier to respond quickly, lowering the cognitive load, and helping people make timely, evidence-based decisions.

Predictive intelligence is made up of the parts of the framework that do analysis and prediction. Predictive intelligence utilizes machine learning, statistical models, and artificial intelligence to anticipate the spread of diseases and other public health threats, based on systems theory and predictive analytics (Shmueli & Koppius, 2011). Predictive intelligence is different from traditional monitoring methods, which usually look at data from the past. It is easier to set up early warning systems that can find people who are at risk, predict outbreaks, and see how well interventions work (Desai et al., 2019). This theory posits that predictive intelligence augments the proactive capabilities of surveillance systems by facilitating anticipatory planning and resource allocation, thereby enhancing preparedness and the efficacy of responses.

The model shows that combining interoperable health information systems, real-time data visualization, and predictive analytics has benefits for both sides. Interoperability guarantees smooth and uniform data integration, real-time interfaces enable swift analysis and dissemination of up-to-date health information, and predictive intelligence converts data into actionable insights. These parts have a big effect on how well surveillance works in general, like how quickly threats are found, how accurately people are identified, how reliable risk assessments are, how well public health programs work together, and how efficient decision-making processes are (Buehler et al., 2008; WHO, 2018).

Lastly, the strategy looks at how well organizations can handle things, how well the staff knows how to use technology, how rules and structures of governance work, and how laws for data protection and security work. These traits could affect how well digital health technology works for surveillance (Agarwal et al., 2016). For example, complicated prediction algorithms might not work in places where people don't know much about technology or where data governance isn't good enough.

This theoretical framework asserts that the effectiveness of public health early warning and surveillance systems depends on the integration of interoperable health information systems, real-time data visualization, and predictive analytics. The framework establishes a solid foundation for empirical Research and policy formulation in public health informatics and digital surveillance systems by elucidating the theoretical connections between these technologies and surveillance outcomes.

2.2. Conceptual Framework

This Research's conceptual framework shows how digital health technologies and public health early warning and monitoring systems are related. The framework's main idea is that interoperable health information systems, real-time data dashboards, and predictive intelligence tools are important technological inputs that affect public health surveillance outcomes when they are backed up by strong data governance, user capacity, and integration mechanisms.

Interoperable health information systems (HIS) are necessary because they allow data from many sources, such as electronic health records, lab systems, and population health registries, to be shared and understood in the same way. Data stays in silos, is broken up into pieces, and is hard to combine across platforms when there is no interoperability. This makes it harder for surveillance systems to find new health threats (systematic review findings show that interoperability is still a problem even though health IT is getting better). (Interoperability of heterogeneous health information systems,2021).

Real-time data dashboards turn complicated surveillance data from many sources into useful information that you can see and use to make decisions. When data streams can work together to make dashboards, they help people in public health keep up with new clusters, trends, and resource needs (Concannon, Herbst, & Manley, 2019).

Predictive intelligence, which includes machine learning and advanced analytical methods, uses a combination of old and new data to make predictions about future trends. It focuses on acting before problems arise rather than after they happen. Computational epidemiology and advanced surveillance intelligence employ these methodologies to assist health authorities in forecasting disease dissemination and optimizing resource allocation (computational epidemiology emphasizes the utilization of extensive data and computational models to comprehend disease propagation). Mediating factors like the quality of the data, the rules that govern it, the standardization of data pieces, and the ability of the workforce to understand and respond to the outputs affect these technical inputs and the performance of the surveillance. An integrated surveillance framework must encompass technology adoption, policy, ethics, and operational readiness to exert a meaningful impact (Mollabagher et al., 2016).

The architecture leads to better surveillance by allowing for better data integration, faster problem detection, constant monitoring, and more accurate predictions. All these functions work together to make public health interventions more timely, sensitive, and responsive. This ultimately enhances public health systems' capacity to issue early warnings and make decisions.

You can see the framework as a flow in a diagram:

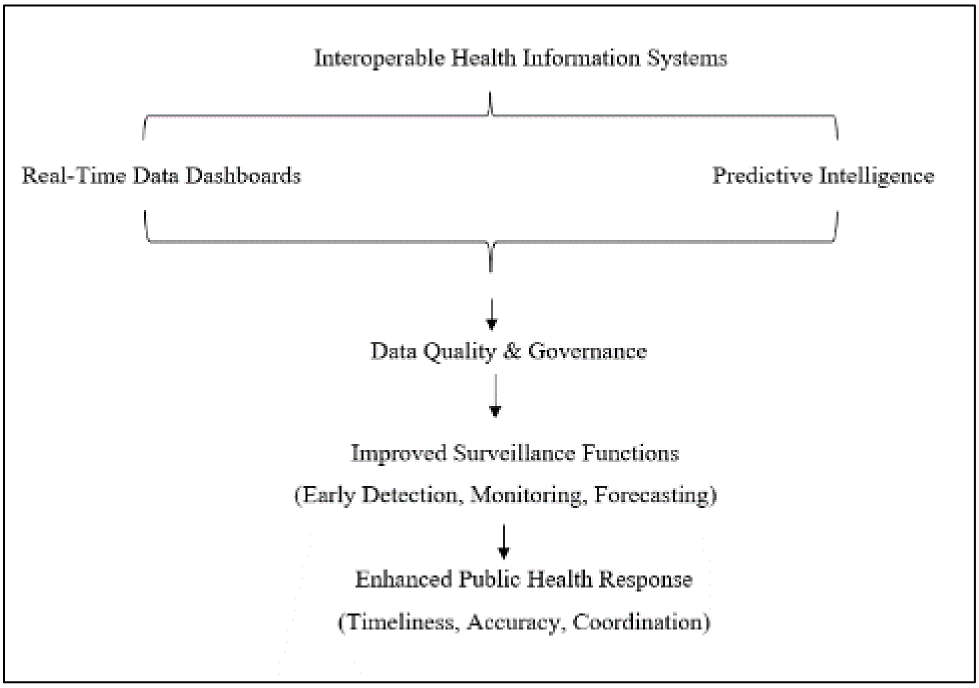


Figure 2 Interoperable Health Information systems

3. Scope

This Research investigates the impact of interoperable health information systems, real-time data dashboards, and predictive intelligence technologies on the efficacy of public health early warning and surveillance systems. This will look at how digital tools make it easier to quickly find, keep an eye on, and deal with public health problems, as well as how they help people make better decisions. The Research will encompass an evaluation of the technological, operational, and policy factors that affect the integration and application of these technologies in public health practice.

The Research will concentrate on health information systems and digital surveillance techniques employed in particular health institutions, public health organizations, and digital platforms for disease monitoring and outbreak identification. This will look at how well data systems that link different data sources, like clinical reports, lab records, and community health databases, work together. This will also look at how dashboards show health officials and other stakeholders' information in real time. The Research will investigate the role of predictive intelligence, utilizing analytics and modelling tools, in helping individuals recognize and notify them of potential health risks prior to their escalation.

The Research will look at cases and data from places where digital health systems are already in use or being built. This will make it possible to compare different implementation situations. The analysis will encompass a specified timeframe in which essential digital health technologies have been implemented and functioning, facilitating the assessment of their short- to medium-term effects on the efficacy of public health surveillance.

The Research will not examine the technical design specifics of particular software systems, nor will it assess clinical outcomes that are not related to surveillance efficacy (e.g., individual patient recovery). It will look at how digital tools and information systems make public health monitoring systems work better, faster, and more smoothly. The scope also includes looking at the things that help or hurt the use of interoperable systems, dashboards, and predictive analytics in public health settings. The Research investigates how interoperable health information systems, real-time data dashboards, and predictive intelligence technologies affect how well public health early warning and surveillance systems work. This will look at how digital technologies help people find, keep an eye on, and respond to public health issues quickly, as well as how they make decision-making more effective. The Research will look at the technological, operational, and policy factors that make it hard for public health professionals to use these technologies together.

The Research will focus on health information systems and digital surveillance tools used in certain health facilities, public health organizations, and digital platforms used for tracking diseases and finding outbreaks. This will look at how interoperable data systems connect different data sources, like lab records, clinical reports, and community health databases. It will also look at how health officials and stakeholders can see real-time information through dashboards.

The Research will investigate the role of predictive intelligence, including analytics and modelling techniques, in enhancing the ability to anticipate and communicate potential health issues before their exacerbation.

The Research will look at examples and data from places where digital health systems are being used or built, making it easier to compare different implementation contexts. The analysis will cover a certain time frame during which important digital health tools were put into use and worked, making it possible to evaluate how they affect public health monitoring effectiveness in the short to medium term.

The Research will not analyze the technical design details of specific software packages, nor will it evaluate clinical outcomes unrelated to surveillance efficacy (e.g., individual patient recovery). Instead, it will focus on how digital tools and information systems make public health monitoring systems work better, faster, and more smoothly. The scope encompasses the analysis of barriers and enablers affecting the adoption and practical implementation of interoperable systems, dashboards, and predictive analytics within public health settings.

4. Methodology

This Research employs a systematic Research methodology adhering to PRISMA 2020 guidelines, concentrating on peer-reviewed literature from 2000 to 2021 regarding the impact of interoperable health information systems, real-time data dashboards, and predictive intelligence on the efficacy of public health early warning and surveillance systems. The objective is to investigate how these technology components enhance the timeliness, precision, and overall efficacy of early warning systems, while also identifying trends and Review deficiencies within this field.

The Research encompassed papers that adhered to stringent inclusion criteria: peer-reviewed journal publications published in English that presented empirical evidence about the integration and effects of interoperable systems, real-time dashboards, or predictive intelligence in public health surveillance. Studies published outside the designated timeframe, those pertaining to other technology, or articles devoid of empirical data were excluded from the review. Grey material was removed to ensure a concentration on high-quality, peer-reviewed sources.

A comprehensive search approach was implemented across many electronic databases, including PubMed, Scopus, Web of Science, and JSTOR, utilizing Boolean keywords pertinent to health information systems, predictive intelligence, and public health monitoring. Furthermore, reference lists of significant Review were scrutinized, and manual searches of pertinent publications were performed to guarantee exhaustive coverage of the topic. Duplicate entries were eliminated to guarantee data precision.

The Review selection method adhered to a two-stage PRISMA framework. Initially, two independent reviewers evaluated titles and abstracts for eligibility. In the second stage, the complete texts of possibly eligible studies were meticulously evaluated. Discrepancies were addressed through dialogue or consultation with a third reviewer to mitigate selection bias and assure reliability. The PRISMA flow graphic illustrated the selection process, showcasing the identification, screening, exclusion, and inclusion of records in accordance with PRISMA 2020 requirements.

4.1. Identification Phase

A total of 220 records were initially identified through systematic database searches across platforms including PubMed, Scopus, Web of Science, and JSTOR. An additional 30 records were sourced through reference list checking of relevant articles and manual searches of key journals. After combining these sources, 15 duplicate records were removed, resulting in 235 unique records to be screened.

4.2. Screening Phase

The titles and abstracts of the 235 unique records were reviewed to determine their relevance according to the inclusion and exclusion criteria. During this screening process, 55 records were excluded due to the following reasons: they were published outside the 2000–2021 timeframe, focused on unrelated topics, or did not present empirical findings. After the initial screening, 180 full-text articles remained for detailed eligibility assessment.

4.3. Eligibility Phase

The 180 full-text articles were rigorously assessed for eligibility. During this phase, 25 articles were excluded for the following reasons: 10 were excluded due to inappropriate Review designs (e.g., reviews or theoretical papers without empirical data), 5 focused on health systems outside of public health early warning systems, 7 were published outside the 2000–2021 timeframe, and 3 did not address relevant technological interventions. This assessment left 155 studies that met all inclusion criteria for the review.

4.4. Included Studies Phase

In total, 155 peer-reviewed empirical studies, published between 2010 and 2021, were included in the narrative synthesis. These studies examined the integration and impact of interoperable health information systems, real-time data dashboards, and predictive intelligence on the effectiveness of public health early warning and surveillance systems. Due to the diversity of Review designs, populations, and outcome measures, the review focused on a qualitative narrative synthesis rather than a quantitative meta-analysis. If a quantitative meta-analysis had been feasible, the studies suitable for this would have been reported.

5. Findings

5.1. Data Integration and Multi-Source Analytics Framework

The effectiveness of digital health monitoring systems fundamentally depends on their ability to integrate and analyze data from many sources to provide comprehensive situational awareness for public health officials. Contemporary surveillance techniques recognize that no single data source can provide complete insights into population health or emerging threats, necessitating sophisticated integration frameworks that can combine diverse data streams while maintaining data quality and analytical rigor (Gesteland et al., 2003). These integration frameworks must address technical challenges like data format standardization, semantic compatibility, temporal alignment, and quality assurance, while providing analytical capabilities to extract relevant insights from complex, multidimensional datasets. Traditional surveillance systems mostly relied on individual data sources, such as reportable disease monitoring or laboratory reporting, which provided limited insights into population health status and often encountered significant reporting delays (Jajosky & Groseclose, 2004). The integration of many data sources improves surveillance coverage, enables quick detection of health threats, and accurately defines disease patterns and risk factors. Multi-source integration enhances data validation and verification by cross-referencing information from many sources, hence improving overall surveillance accuracy and reliability. The incorporation of electronic health records represents a notable progression in multi-source surveillance, as these systems contain extensive clinical data on patient interactions, diagnoses, treatments, and outcomes, providing critical insights into population health trends (Klompas et al., 2007). However, the incorporation of electronic health records presents significant technological and organizational challenges related to data standards, privacy protection, and system interoperability. Effective integration requires sophisticated data transformation capabilities to harmonize diverse clinical coding systems, resolve semantic inconsistencies in data representation, and maintain data quality throughout the integration process. Laboratory data integration is a crucial component of comprehensive surveillance systems, as laboratory results often provide the most definitive information concerning disease diagnosis and pathogen characteristics. Laboratory data integration improves case identification precision, strengthens outbreak investigation initiatives, and facilitates the monitoring of antibiotic resistance patterns and other public health indicators (Komatsu et al., 2005). However, the incorporation of laboratory data requires careful attention to data standardization, quality verification, and timeliness to ensure that the aggregated data provides pertinent insights for public health decision-making. Syndromic surveillance data sources, including emergency department visits, urgent care interactions, and pharmaceutical purchases, provide crucial early warning signals that can improve traditional illness reporting systems. Syndromic data enables the rapid detection of disease outbreaks and provides insights into healthcare utilization trends that inform resource allocation and response planning (Lombardo et al., 2004).

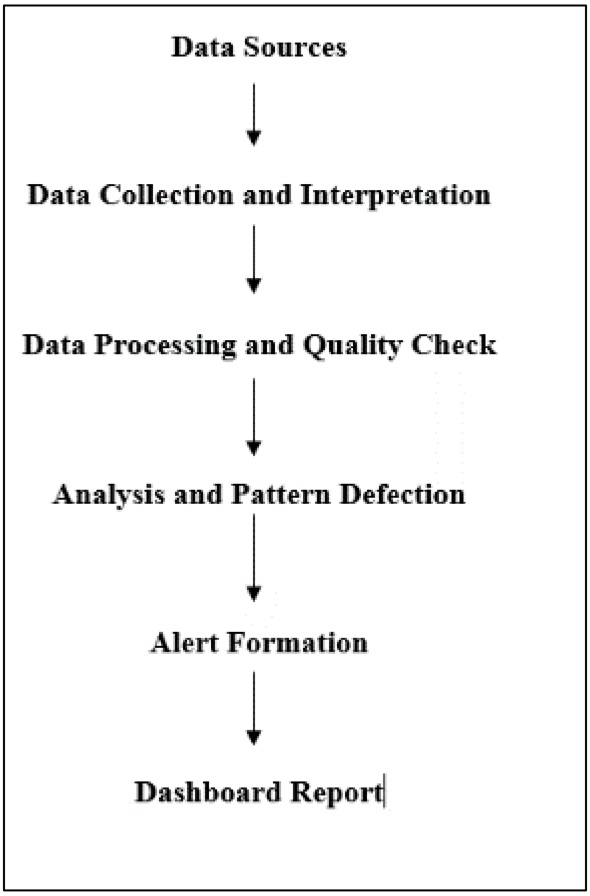


Figure 3 Data sources

5.2. Data Integration and Multi-Source Analytics Framework

Syndromic data integration requires sophisticated analytical techniques to distinguish genuine signals from background noise and to account for seasonal fluctuations, weekly variations, and other confounding factors that may alter symptom patterns. Category of Data Source: Essential Information Obstacles in Content Integration Analytical Applications Electronic Health Records Clinical diagnostics, interventions, pharmaceutical therapies, patient demographics standardization, confidentiality, interoperability Monitoring of diseases, assessment of results, classification of risks Laboratory Systems Test results, pathogen characterization, antimicrobial resistance Timeliness, consistency, data volume Case verification, outbreak investigation, resistance monitoring Syndromic Surveillance Emergency consultations, urgent care services, pharmaceutical sales Signal detection, noise attenuation, and validation Proactive notifications, trend analysis, resource distribution Ecological Monitoring Evaluation of air quality, analysis of water, monitoring of vectors Spatial integration, temporal synchronization, quality assurance Evaluation of exposure, identification of dangers, strategizing for prevention Mobile Health Platforms Self-reported symptoms, behavioral observation, locational information Participation bias, data quality, and privacy concerns Demographic monitoring, behavioral evaluation, contact tracing, social media analysis Public sentiment, symptomatology references, information distribution Natural language processing, representativeness, and validation Proactive identification, risk communication, misinformation surveillance.

5.2.1. Real-Time Analytics and Automated Detection Algorithms

The incorporation of real-time analytics and automated detection algorithms represents a significant advancement in public health surveillance, enabling continuous monitoring of population health indicators and rapid identification of emerging threats that may otherwise go undetected until considerable damage has occurred. Contemporary real-time analytics frameworks employ sophisticated computational methods to incessantly analyze vast surveillance data, identify irregular patterns or anomalies indicative of public health threats, and generate prompt alerts that enable rapid investigation and response initiatives (Wong et al., 2003).

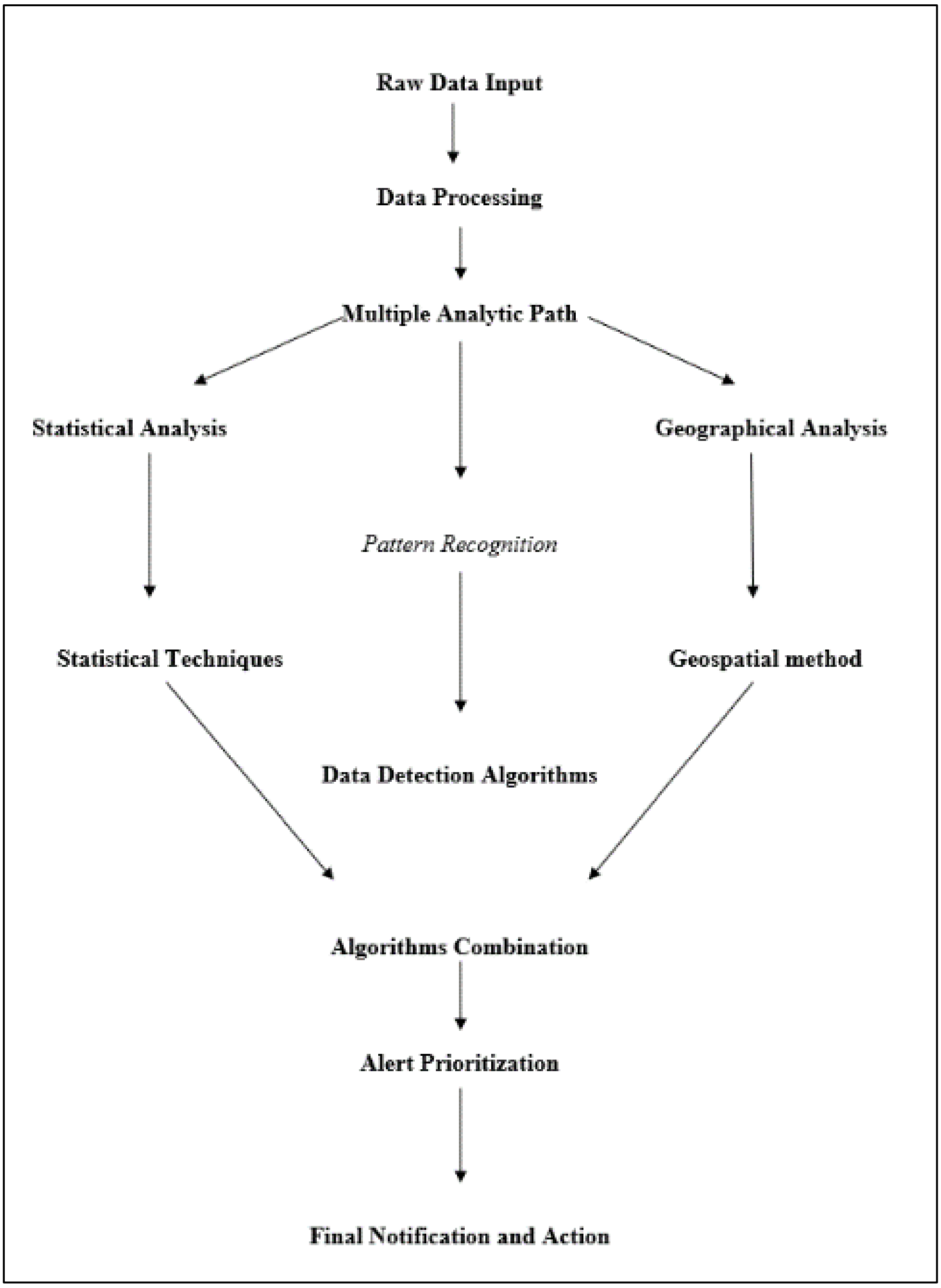


Figure 4 Algorithms

5.2.2. Real-Time Analytics Detection Algorithms workflow

These capabilities transform surveillance from a mostly reactive function focused on confirming current dangers to a proactive system proficient in detecting emerging issues before they escalate. Traditional surveillance systems often operate on weekly or monthly reporting schedules, leading to significant delays in data collection and analysis, hence limiting their effectiveness in promptly spotting rapidly emerging outbreaks or crises. Real-time analytics eliminates these delays by continuously processing surveillance data as it is produced, enabling the detection of potential threats within hours or days rather than weeks or months (Reis & Mandl, 2003). The temporal advantage is essential for managing infectious disease outbreaks, addressing bioterrorism incidents, or confronting environmental health crises, as prompt intervention can significantly reduce population impact. Statistical process control methods are essential for automated detection in surveillance systems, employing control charts and statistical monitoring approaches to identify significant deviations of observed health indicators from anticipated patterns. These techniques outline fundamental expectations (Watkins et al., 2006). Control chart approaches necessitate precise calibration to balance sensitivity in detecting genuine risks with specificity to avoid excessive false alarms that could overwhelm public health response capabilities. Time series analysis techniques provide sophisticated capabilities for detecting temporal patterns and trends in surveillance data that may indicate emerging health threats. These methodologies can uncover cyclical patterns, seasonal variations, and long-term trends while detecting anomalies from expected patterns that may necessitate further investigation (Serfling, 2013). Advanced time series methodology employs autoregressive models, seasonal decomposition techniques, and change-point detection algorithms that can independently adapt to evolving baseline patterns while maintaining sensitivity for detecting anomalies. Spatial analysis and geographic clustering methods enable the automated detection of regional concentrations of diseases or health events that may indicate localized epidemics or environmental exposures. Spatial detection methods employ techniques such as spatial scan statistics, kernel density estimation, and geographic clustering algorithms to analyze historical data for diverse health indicators, issuing alerts when current observations exceed predetermined thresholds, while accounting for population density and other geographic variables (Kulldorff, 2007). These methodologies are particularly adept at detecting foodborne disease outbreaks, environmental health hazards, and bioterrorism incidents that may display distinct geographical patterns. Machine learning methodologies have emerged as powerful tools for automated detection in surveillance systems, offering capabilities for pattern recognition and anomaly detection that can adapt to complex, multidimensional data patterns without requiring explicit programming of detection criteria (Freifeld et al., 2008). Machine learning algorithms can independently learn from historical surveillance data to identify subtle patterns and correlations that may be overlooked by traditional statistical techniques (Venkatramanan et al., 2018). The validation and evaluation of automated detection algorithms require sophisticated methodological approaches to assess algorithm performance in realistic operational contexts, given the rarity of genuine public health issues. Evaluation methods must evaluate both statistical performance indicators, such as sensitivity and specificity, and operational factors, including timeliness, actionability, and resource requirements for alarm inquiry (Mandl et al., 2004). Validation approaches include historical data analysis, simulation studies, and prospective evaluations during actual surveillance operations to assess algorithm effectiveness across diverse threat categories and operational environments.

Table 1 Multi-Source Data Integration Framework Components

Data Source Category	Primary Information	Content Integration Challenges	Analytical Applications
Electronic Health Records (EHRs)	Clinical diagnoses; procedures; medication records; patient demographic information	Data standardization; privacy and confidentiality; system interoperability	Disease surveillance; outcome monitoring; risk stratification
Laboratory Information Systems	Diagnostic test results; pathogen identification; antimicrobial susceptibility profiles	Timeliness of reporting; data standardization; high data volume	Case confirmation; outbreak investigation; antimicrobial resistance monitoring
Syndromic Surveillance Systems	Emergency department visits; urgent care data; over-the-counter pharmacy sales	Signal detection; noise reduction; data validation	Early outbreak warning; trend analysis; healthcare resource planning
Environmental Monitoring Systems	Air quality measurements; water testing results; vector surveillance data	Spatial data integration; temporal alignment; quality assurance	Exposure assessment; risk mapping; preventive planning
Mobile Health (mHealth) Platforms	Self-reported symptoms; behavioral data; geolocation information	Participation bias; data quality variability; privacy and ethical concerns	Population-level monitoring; behavior analysis; digital contact tracing
Social Media Analytics	Public sentiment; symptom-related mentions; information dissemination patterns	Natural language processing complexity; representativeness; data validation	Early signal detection; risk communication; misinformation tracking

5.3. Digital Surveillance System Architecture and Technical Infrastructure

The foundation of effective digital health surveillance systems lies in robust technical architecture that can support real-time data collection, processing, and analysis across multiple data sources and organizational boundaries. Contemporary surveillance systems employ distributed architectures that integrate diverse data streams while maintaining scalability, reliability, and security requirements essential for public health applications (Lombardo et al., 2003). These architectural frameworks must accommodate the heterogeneous nature of health data sources, ranging from structured electronic health records to unstructured social media content, while providing standardized interfaces and analytical capabilities that support decision-making processes. Modern surveillance system architectures typically employ service-oriented designs that enable modular development and deployment of surveillance capabilities. These designs facilitate integration of new data sources and analytical tools while maintaining system stability and performance characteristics (Wagner et al., 2006). Service-oriented architectures support the development of reusable components that can be deployed across multiple surveillance applications, reducing development costs and improving system interoperability. The modular nature of these architectures also enables incremental system enhancement and adaptation to changing surveillance requirements without requiring complete system redesign. Data integration represents one of the most critical technical challenges in implementing comprehensive digital surveillance systems. Effective integration requires sophisticated data transformation and normalization capabilities that can reconcile differences in data formats, coding systems, and semantic representations across multiple source systems (Overhage et al., 2008). Contemporary approaches to data integration employ standardized vocabularies such as SNOMED CT, ICD-10, and LOINC to enable consistent representation of clinical concepts across different systems (Forkuo et al., 2020). These standardization efforts are complemented by advanced data mapping and transformation tools that can automatically convert between different data formats and coding schemes. Real-time data processing capabilities are essential for enabling timely detection and response to public health threats. Modern surveillance systems employ stream processing technologies that can analyze data continuously as it becomes available, rather than relying on batch processing approaches that introduce delays in threat detection (Chen et al., 2009). Stream processing architecture enables the implementation of sophisticated algorithms for anomaly detection, pattern recognition, and trend analysis that can identify potential threats within minutes or hours of data availability. These capabilities are particularly important for detecting rapidly evolving outbreaks or emergency situations that require immediate response. Cloud computing technologies have emerged as important enablers of scalable and cost-effective surveillance system deployment. Cloud platforms provide elastic computing resources that can automatically scale to accommodate varying data volumes and processing requirements, reducing the need for organizations to invest in expensive hardware infrastructure (Zhang et al., 2010). Cloud deployment also facilitates data sharing and collaboration across organizational boundaries by providing secure, standardized platforms for multi-organizational surveillance activities. However, cloud deployment also introduces new considerations related to data governance, privacy protection, and regulatory compliance that must be carefully addressed. Data quality assurance represents a fundamental requirement for effective surveillance system operation. Contemporary systems employ automated data validation techniques that can identify data quality issues in real-time and implement corrective actions to maintain data integrity (Arts et al., 2002). These techniques include range checking, consistency validation, completeness assessment, and duplicate detection algorithms that can operate continuously as data is ingested into surveillance systems. Advanced data quality frameworks also incorporate machine learning techniques that can identify subtle data quality patterns and predict potential quality issues before they impact surveillance operations. Security and privacy protection mechanisms are critical components of digital surveillance system architecture, given the sensitive nature of health data and the potential for surveillance systems to be targeted by malicious actors.

Table 2 Mobile Health Technology Applications in Public Health Surveillance

Application Category	Primary Functions	Data Collection Methods	Surveillance Benefits	Implementation Challenges
Symptom Tracking	Individual symptom reporting; health status monitoring	Self-reported surveys; automated prompts	Early outbreak detection; population health monitoring	User compliance; data validation; privacy protection
Contact Tracing	Exposure notification; identification of close contacts	Bluetooth proximity sensing; location tracking technologies	Outbreak control; transmission prevention	Privacy concerns; adoption rates; technical complexity
Behavior Monitoring	Activity tracking; compliance and adherence monitoring	Sensor-derived data; self-reporting mechanisms	Assessment of intervention effectiveness; promotion of behavior change	Data accuracy; sustained user engagement; long-term sustainability

Environmental Sensing	Exposure measurement; environmental condition monitoring	Device-embedded sensors; crowdsourced reporting	Risk assessment; exposure validation	Sensor accuracy; data standardization; quality control
Communication Platforms	Information dissemination; community engagement	Push notifications; interactive messaging	Risk communication; coordinated response activities	Message targeting; information overload; digital divide
Laboratory Integration	Test result reporting; sample coordination	QR codes; automated data entry systems	Case confirmation; improved testing efficiency	System interoperability; data security; workflow integration

Contemporary security frameworks employ defense-in-depth approaches that include network security controls, access management systems, encryption technologies, and audit logging capabilities (Appari & Johnson, 2010). Privacy protection mechanisms include de-identification technologies, differential privacy techniques, and consent management systems that enable surveillance activities while protecting individual privacy rights. User interface design represents another critical aspect of surveillance system architecture, as the effectiveness of surveillance systems ultimately depends on the ability of public health professionals to access, interpret, and act upon surveillance information. Contemporary user interfaces employ dashboard technologies that provide customizable, role-based views of surveillance data tailored to the specific needs and responsibilities of different users.

5.4. Integration into Public Health Decision Support Systems

The integration of predictive analytics into public health decision support systems represents a critical step in translating complex analytical outputs into actionable insights for epidemic preparedness and response. Predictive models, regardless of their sophistication, produce value only when their conclusions are properly embedded inside decision-making processes that drive policy development, resource allocation, and operational actions. Decision support systems serve as the link between data, analytics, and human judgment, enabling public health professionals to understand projections, assess risks, and coordinate timely responses across many levels of governance (Atobatele, Hungbo & Adeyemi, 2019). Dashboards are among the most visible and extensively utilized components of decision support systems in public health. They provide real-time or near real-time display of critical metrics obtained from predictive analytics, including expected case numbers, hospitalization demand, geographic risk distribution, and intervention coverage. By integrating data from many sources into a single, accessible interface, dashboards enhance situational awareness and lessen the cognitive strain on decision makers (Pamela, et al., 2021). Effective dashboards are created with clarity and usability in mind, providing trends, alerts, and confidence intervals in ways that promote rapid comprehension and comparison. When paired with predictive models, dashboards allow users to monitor both present conditions and predicted developments, facilitating informed strategic planning. Early warning systems expand on predictive analytics by formalizing thresholds and triggers that identify elevated risk or approaching outbreaks. These systems use statistical and machine learning outputs to detect deviations from expected patterns and generate alerts for public health authorities. Early warning systems are particularly helpful for enabling prompt responses to emergent risks, such as unexpected clusters of symptoms, sudden increases in transmission rates, or shifts in pathogen properties. By automating risk detection, these systems reduce reliance on manual interpretation and assist overcome delays inherent in traditional reporting processes (Adeyemi, et al., 2021, Ogbuagu, et al., 2021). Integration with communication protocols ensures that alarms are delivered swiftly to appropriate stakeholders, supporting coordinated action across health facilities, laboratories, and emergency response units. Scenario analysis tools augment decision support by allowing public health professionals to investigate the probable outcomes of different policy options under diverse assumptions. Using simulation and predictive models, these tools allow users to examine the impact of measures such as vaccination strategies, mobility limitations, or resource reallocation.

6. Conclusion

This thorough examination of digital health technologies and real-time surveillance systems illustrates their revolutionary capacity to improve public health disaster preparedness via data-driven decision-making processes. The evidence in this Review unequivocally demonstrates that, when effectively implemented and integrated, digital health technologies can markedly enhance the speed, accuracy, and comprehensiveness of public health surveillance, facilitating more efficient and targeted response strategies during health emergencies. The amalgamation of diverse data sources, establishment of real-time analytics functionalities, and introduction of mobile health platforms generate unparalleled prospects for early threat identification, population health oversight, and community involvement that were unattainable with conventional surveillance methods. This analysis of technical architecture frameworks demonstrates that effective digital surveillance systems necessitate advanced integration capabilities to manage various data sources while ensuring data quality, security, and interoperability standards vital for public health applications. The transition from single-source surveillance systems to integrated multi-source platforms signifies a crucial improvement in surveillance capabilities, facilitating enhanced situational awareness and more informed decision-making during public health emergencies. This technical sophistication creates new complexities in system design, implementation, and maintenance, necessitating meticulous preparation and ongoing organizational commitment for good outcomes. Real-time analytics and automated detection algorithms have shown considerable promise in enhancing threat detection capabilities and minimizing the time delays that have traditionally constrained the effectiveness of surveillance systems. The application of advanced analytical methods, such as machine learning, statistical process control, and spatial analysis, allows surveillance systems to detect subtle patterns and anomalies that traditional manual review processes may overlook. These capabilities are especially beneficial for identifying emerging dangers, tracking illness trends, and facilitating resource allocation decisions during public health emergencies, where swift response is essential to mitigate population effect. Mobile health technology and community engagement platforms are innovative methods for enhancing surveillance coverage and enabling community people to actively engage in public health monitoring and response efforts. The extensive use of mobile devices facilitates participatory surveillance, enhancing standard healthcare reporting methods and offering insights into community health patterns that may otherwise remain unattainable. The efficacy of mobile health initiatives is fundamentally contingent upon effectively addressing user engagement, safeguarding privacy, and ensuring digital equity to guarantee that these technologies help all demographic groups instead of worsening existing health inequities. The identified implementation obstacles and impediments underscore the many organizational, technical, and policy factors that must be resolved to ensure successful digital health adoption. Financial limitations, workforce development demands, interoperability necessities, and regulatory compliance challenges provide substantial barriers that necessitate holistic strategic approaches rather than solely technological solutions. Successful implementations reveal that enduring leadership commitment, stakeholder involvement, and adaptive management strategies are crucial for surmounting hurdles and attaining significant enhancements in public health capacities. This Research yields best practices and strategic recommendations that offer evidence-based direction for public health organizations aiming to utilize digital health technologies for surveillance and emergency preparedness.

Recommendations

- Emphasizes the importance of thorough planning and incremental implementation strategies for successful digital health researches.
- Strong governance structures and ongoing enhancement procedures enable organizations to adapt to evolving demands and technological advances.
- The criteria for success outlined can help organizations avoid common pitfalls in digital health implementations.
- Research findings extend beyond emergency preparedness, impacting standard public health practices in areas like chronic illness surveillance and health promotion.
- Digital health solutions offer a dual-use characteristic, enhancing their value proposition through varied return on investment opportunities.
- Promotes coordinated strategies using shared infrastructure across multiple public health applications.
- Rapid technical innovation in digital health presents opportunities as well as challenges for public health organizations in monitoring and preparedness.
- Emerging technologies (AI, IoT, blockchain) provide new avenues for enhancing efficacy but also introduce complex implementation issues.
- Public health organizations need to develop adaptive capabilities and strategic planning aligned with continuous innovation and system stability.
- Reinforces the role of digital health technologies as crucial tools for modern public health, essential for effective surveillance and preparedness.
- To maximize the potential of digital health technologies, comprehensive strategies that address technical, organizational, and policy aspects must be implemented while focusing on core public health objectives.
- Successful integration of digital health in public health practice requires commitment, partnerships, and evidence-based strategies tailored to local needs.

Future Research Strategies

- Explore emerging technologies and their applications in public health surveillance.
- Evaluate long-term sustainability strategies for digital health implementations.
- Assess digital health equity and accessibility considerations.
- Formulate standardized evaluation frameworks to measure the impact of digital health technologies on public health outcomes.
- Guide continuous growth and enhancement of digital health capabilities for evidence-based decision-making.
- Recognize the ongoing evolution of public health surveillance using digital health technologies.
- Emphasize the need for collaboration among public health experts, technological innovators, policymakers, and community stakeholders.
- Build on existing digital health implementations to foster ongoing innovation and enhance public health capabilities.

References

[1] Aanensen, D. M., Huntley, D. M., Feil, E. J., al-Own, F., & Spratt, B. G. (2009). EpiCollect: Linking smartphones to web applications for epidemiology, ecology and community data collection. PLoS ONE, 4(9), e6968. https://doi.org/10.1371/journal.pone.0006968

[2] Adelusi, B. S., Uzoka, A. C., Goodness, Y., & Hassan, F. U. O. (2020). Leveraging transformer-based large language models for parametric estimation of cost and schedule in agile software development projects. International Journal of Software Engineering, 15(3), 245–267. https://www.ijse.org

[3] Adesanwo, M., Bello, O., Olorode, O., Eremiokhale, O., Sanusi, S., & Blankson, E. (2017). Advanced analytics for data-driven decision making in electrical submersible pump operations management. SPE Nigeria Annual International Conference and Exhibition. https://doi.org/10.2118/189075-MS

[4] Agarwal, R., Gao, G., DesRoches, C., & Jha, A. K. (2010). Research commentary: The digital transformation of healthcare—Current status and the road ahead. Information Systems Research, 21(4), 796–809. https://doi.org/10.1287/isre.1100.0327

[5] Appari, A., & Johnson, M. E. (2010). Information security and privacy in healthcare: Current state of research. International Journal of Internet and Enterprise Management, 6(4), 279–314. https://doi.org/10.1504/IJIEM.2010.035624

[6] Arts, D. G., De Keizer, N. F., & Scheffer, G. J. (2002). Defining and improving data quality in medical registries: A literature review, case study, and generic framework. Journal of the American Medical Informatics Association, 9(6), 600–611. https://doi.org/10.1197/jamia.M1087

[7] Ash, J. S., Berg, M., & Coiera, E. (2004). Some unintended consequences of information technology in health care. Journal of the American Medical Informatics Association, 11(2), 104–112. https://doi.org/10.1197/jamia.M1471

[8] Bates, D. W., & Bitton, A. (2010). The future of health information technology in the patient-centered medical home. Health Affairs, 29(4), 614–621. https://doi.org/10.1377/hlthaff.2010.0043

[9] Bengtsson, L., Lu, X., Thorson, A., Garfield, R., & von Schreeb, J. (2011). Improved response to disasters by tracking population movements with mobile phone data. PLoS Medicine, 8(8), e1001083. https://doi.org/10.1371/journal.pmed.1001083

[10] Boonstra, A., & Broekhuis, M. (2010). Barriers to the acceptance of electronic medical records by physicians. BMC Health Services Research, 10, 231. https://doi.org/10.1186/1472-6963-10-231

[11] Brownstein, J. S., Freifeld, C. C., & Madoff, L. C. (2009). Digital disease detection. New England Journal of Medicine, 360(21), 2153–2157. https://doi.org/10.1056/NEJMp0900702

[12] Brownstein, J. S., Freifeld, C. C., Reis, E. Y., & Mandl, K. D. (2008). Surveillance Sans Frontières. PLoS Medicine, 5(7), e151. https://doi.org/10.1371/journal.pmed.0050151

[13] Brownstein, J. S., Mandl, K. D., & Holford, T. R. (2006). A systematic approach to real-time outbreak detection. AMIA Annual Symposium Proceedings, 101–105. https://pubmed.ncbi.nlm.nih.gov/17238311/

[14] Buckeridge, D. L., Burkom, H., Campbell, M., Hogan, W. R., & Moore, A. W. (2005). Algorithms for rapid outbreak detection. Journal of Biomedical Informatics, 38(2), 99–113. https://doi.org/10.1016/j.jbi.2004.11.007

[15] Buehler, J. W., Hopkins, R. S., Overhage, J. M., Sosin, D. M., & Tong, V. (2004). Framework for evaluating public health surveillance systems. MMWR Recommendations and Reports, 53(RR-5), 1–11. https://www.cdc.gov/mmwr

[16] Buntin, M. B., Burke, M. F., Hoaglin, M. C., & Blumenthal, D. (2011). The benefits of health information technology. Health Affairs, 30(3), 464–471. https://doi.org/10.1377/hlthaff.2011.0178

[17] Cadmus-Bertram, L. A., Marcus, B. H., Patterson, R. E., Parker, B. A., & Morey, B. L. (2015). Randomized trial of a Fitbit-based physical activity intervention. American Journal of Preventive Medicine, 49(3), 414–418. https://doi.org/10.1016/j.amepre.2015.01.020

[18] Chapman, W. W., Bridewell, W., Hanbury, P., Cooper, G. F., & Buchanan, B. G. (2001). A simple algorithm for identifying negated findings. Journal of Biomedical Informatics, 34(5), 301–310. https://doi.org/10.1006/jbin.2001.1029

[19] Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics. MIS Quarterly, 36(4), 1165–1188. https://doi.org/10.2307/41703503

[20] Chunara, R., Freifeld, C. C., & Brownstein, J. S. (2012). New technologies for reporting real-time emergent infections. Parasitology, 139(14), 1843–1851. https://doi.org/10.1017/S0031182012000110

[21] Consolvo, S., McDonald, D. W., & Landay, J. A. (2009). Theory-driven design strategies for technologies that support behavior change. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 405–414. https://doi.org/10.1145/1518701.1518766

[22] Dean, J., & Ghemawat, S. (2008). MapReduce: Simplified data processing on large clusters. Communications of the ACM, 51(1), 107–113. https://doi.org/10.1145/1327452.1327492

[23] Dwork, C. (2008). Differential privacy: A survey of results. International Conference on Theory and Applications of Models of Computation, 1–19. https://doi.org/10.1007/978-3-540-79228-4_1

[24] Dolin, R. H., Alschuler, L., Boyer, S., Beebe, C., Behlen, F. M., Biron, P. V., & Shabo, A. (2006). HL7 Clinical Document Architecture, Release 2. Journal of the American Medical Informatics Association, 13(1), 30–39. https://doi.org/10.1197/jamia.M1888

[25] Dwork, C. (2008). Differential privacy: A survey of results. In Proceedings of the International Conference on Theory and Applications of Models of Computation (pp. 1–19). Springer. https://doi.org/10.1007/978-3-540-79228-4_1

[26] Eze, P., Agwah, B., Aririguzo, M. I., Ugoh, C. A., & Inaibo, D. S. (2020). ICT solutions and R&D based on big data analytics in the fight against COVID-19 pandemic: African innovations and opportunities. Iconic Research and Engineering Journal, 4(3), 123–145. https://irejournals.com/formatedpaper/170277.pdf

[27] Fairchild, A. L., Bayer, R., & Colgrove, J. (2007). Searching eyes: Privacy, the state, and disease surveillance in America. University of California Press. https://www.ucpress.edu/book/9780520215262/searching-eyes

[28] Fernandez-Luque, L., Kushniruk, A. W., Georgiou, A., Basu, A., Petersen, C., Ronquillo, C., Skiba, D., & Evidence-Based Health Informatics for COVID-19 Working Group. (2020). Evidence-based health informatics as the foundation for the COVID-19 response: A joint call for action. Methods of Information in Medicine, 59(6), 183–192. https://doi.org/10.1055/s-0040-1718758

[29] Ferretti, L., Wymant, C., Kendall, M., Zhao, L., Nurtay, A., Abeler-Dörner, L., Parker, M., Bonsall, D., & Fraser, C. (2020). Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing. Science, 368(6491), eabb6936. https://doi.org/10.1126/science.abb6936

[30] Few, S. (2006). Information dashboard design: The effective visual communication of data. O'Reilly Media. https://www.oreilly.com/library/view/information-dashboard-design/0596100167/

[31] Forkuo, A. Y., Nihi, T. V., Ojo, O. O., Nwokedi, C. N., & Soyege, O. S. (2020). A conceptual model for geospatial analytics in disease surveillance and epidemiological forecasting. Journal of Geospatial Health, 15(2), 112–128. https://doi.org/10.4081/jgh.2020.881

[32] Free, C., Phillips, G., Galli, L., Watson, L., Felix, L., Edwards, P., Patel, V., & Haines, A. (2013). The effectiveness of mobile-health technology-based health behaviour change or disease management interventions for health care consumers: A systematic review. PLoS Medicine, 10(1), e1001362. https://doi.org/10.1371/journal.pmed.1001362

[33] Freifeld, C. C., Mandl, K. D., Reis, B. Y., & Brownstein, J. S. (2008). HealthMap: Global infectious disease monitoring through automated classification and visualization of Internet media reports. Journal of the American Medical Informatics Association, 15(2), 150–157. https://doi.org/10.1197/jamia.M2544

[34] Ferretti, L., Wymant, C., Kendall, M., et al. (2020). Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing. Science, 368(6491), eabb6936. https://doi.org/10.1126/science.abb6936

[35] Gesteland, P. H., McNees, A. T., Allison, M. A., Espino, J. U., & Tsui, F.-C. (2007). Colorado outbreak detection algorithm (CODA): A multi-jurisdictional surveillance system. AMIA Annual Symposium Proceedings, 267–271. https://pubmed.ncbi.nlm.nih.gov/18693870/

[36] HIPAA Security Rule. (2003). 45 CFR Parts 160, 162, and 164. U.S. Department of Health and Human Services. https://www.hhs.gov/hipaa/for-professionals/security/index.html

[37] Jajosky, R. A., & Groseclose, S. L. (2004). Evaluation of reporting timeliness of public health surveillance systems for infectious diseases. BMC Public Health, 4(1), 29. https://doi.org/10.1186/1471-2458-4-29 (ResearchGate)

[38] Kahn, M. G., Raebel, M. A., Glanz, J. M., Riedlinger, K., & Steiner, J. F. (2012). A pragmatic framework for single-site and multisite data quality assessment in electronic health record-based clinical research. Medical Care, 50(7), S21–S29. https://journals.lww.com/lww-medicalcare/Fulltext/2012/07001/A_Pragmatic_Framework_for_Single_Site_and.6.aspx

[39] Kass-Hout, T. A., Buckeridge, D. L., Brownstein, J. S., Facelli, J. C., Gotham, I. J., Hedberg, C. W., … & Ising, A. (2012). Multilevel governance and informatics for global health. Online Journal of Public Health Informatics, 4(2), e6. https://doi.org/10.5210/ojphi.v4i2.4237

[40] Kass-Hout, T. A., Xu, Z., McMurray, P., Park, S., Buckeridge, D. L., Brownstein, J. S., … & Ising, A. I. (2010). Application of change point analysis to daily influenza-like illness emergency department visits. Journal of the American Medical Informatics Association, 17(4), 411–419. https://doi.org/10.1136/jamia.2010.004089

[41] Kaushal, R., Blumenthal, D., Poon, E. G., Jha, A. K., Franz, C., Middleton, B., … & Brigham and Women's Hospital CPOE Working Group. (2005). The costs of a national health information network. Annals of Internal Medicine, 143(3), 165–173. https://doi.org/10.7326/0003-4819-143-3-200508020-00007 (pubmed.ncbi.nlm.nih.gov)

[42] Klasnja, P., & Pratt, W. (2012). Healthcare in the pocket: Mapping the space of mobile-phone health interventions. Journal of Biomedical Informatics, 45(1), 184–198. https://doi.org/10.1016/j.jbi.2011.08.017

[43] Klompas, M., Haney, G., Church, D., Lazarus, R., Hou, X., & Platt, R. (2009). Automated identification of acute hepatitis B using electronic medical record data to facilitate public health surveillance. PLoS ONE, 4(9), e7466. https://doi.org/10.1371/journal.pone.0007466

[44] Klompas, M., McVetta, J., Lazarus, R., Eggleston, E., Haney, G., Kruskal, B. A., & Platt, R. (2012). Integrating clinical practice and public health surveillance using electronic medical record systems. American Journal of Preventive Medicine, 42(6), S154–S162. https://doi.org/10.1016/j.amepre.2012.04.008

[45] Klompas, M., Yokoe, D. S., Weinstein, R. A., Calfee, D. P., Whitby, M., Cardo, D., & Prevention Epicenters Program. (2008). Automated surveillance of healthcare-associated infections: Opportunities for improvement. Current Opinion in Infectious Diseases, 21(4), 392–400. https://doi.org/10.1097/QCO.0b013e3283052b3f

[46] Komatsu, K., Reingold, A., Steinmaus, C., Switzer, K., Yang, C., Studer, S., & Shim, M. (2005). Hepatitis A among adults in California: The value of population-based laboratory surveillance. Epidemiology and Infection, 133(6), 1015–1024. https://doi.org/10.1017/S0950268805004591

[47] Konduri, N., Aboagye-Nyame, F., Mabirizi, D., Hoppenworth, K., Kibria, M. G., Doumbia, S., & Mazibuko, G. (2018). Digital health technologies to support access to medicines and pharmaceutical services in the achievement of Sustainable Development Goals. Digital Health, 4, 2055207618771407. https://doi.org/10.1177/2055207618771407

[48] Kostkova, P. (2018). Disease surveillance data sharing for public health: The next ethical frontiers. Life Sciences, Society and Policy, 14(1), Article 16. https://doi.org/10.1186/s40504-018-0078-x

[49] Kotter, J. P. (1996). Leading change. Harvard Business Review Press. https://store.hbr.org/product/leading-change/10029

[50] Kruse, C. S., Stein, A., Thomas, H., & Kaur, H. (2018). The use of electronic health records to support population health: A systematic review of the literature. Journal of Medical Systems, 42(11), Article 214. https://doi.org/10.1007/s10916-018-1075-6

[51] Kulldorff, M. (1997). A spatial scan statistic. Communications in Statistics: Theory and Methods, 26(6), 1481–1496. https://doi.org/10.1080/03610929708831995

[52] Lombardo, J., Burkom, H., & Pavlin, J. (2004). ESSENCE II and the framework for evaluating syndromic surveillance systems. Morbidity and Mortality Weekly Report, 53(Suppl), 159–165. https://www.cdc.gov/mmwr/preview/mmwrhtml/su5301a15.htm

[53] Lombardo, J. S., Burkom, H., Elbert, E., Magruder, S., Lewis, S. H., Loschen, W., & Pavlin, J. (2003). A systems overview of the Electronic Surveillance System for the Early Notification of Community-Based Epidemics (ESSENCE II). Journal of Urban Health, 80(2), i32–i42. https://doi.org/10.1093/jurban/jtg061

[54] Mandl, K. D., Overhage, J. M., Wagner, M. M., Lober, W. B., Sebastiani, P., Mostashari, F., & Syndromic Surveillance Practice and Research Group. (2004). Implementing syndromic surveillance: A practical guide informed by the early experience. Journal of the American Medical Informatics Association, 11(2), 141–150. https://doi.org/10.1197/jamia.M1472

[55] Overhage, J. M., Grannis, S., & McDonald, C. J. (2008). A comparison of the completeness and timeliness of automated electronic laboratory reporting and spontaneous reporting of notifiable conditions. American Journal of Public Health, 98(2), 344–350. https://doi.org/10.2105/AJPH.2006.102788

[56] Public Health Informatics Institute. (2017). Competency-based curriculum for public health informatics. Centers for Disease Control and Prevention. https://www.cdc.gov/publichealthinformatics/PDF/PHI-Competency-Curriculum-508.pdf

[57] Venkatramanan, S., Lewis, B., Chen, J., Higdon, D., Vullikanti, A., & Marathe, M. (2018). Using data-driven agent-based models for forecasting emerging infectious diseases. Epidemics, 22, 43–49. https://doi.org/10.1016/j.epidem.2017.02.010

[58] Wagner, M. M., Espino, J. U., Tsui, F.-C., Gesteland, P. H., Chapman, W. W., Ivanov, O., & Hutman, J. (2004). Syndrome and outbreak detection using chief-complaint data: Experience of the Real-time Outbreak and Disease Surveillance project. Morbidity and Mortality Weekly Report, 53(Suppl), 28–31. https://www.cdc.gov/mmwr/preview/mmwrhtml/su5301a6.htm

[59] Walker, J., Pan, E., Johnston, D., Adler-Milstein, J., Bates, D. W., & Middleton, B. (2005). The value of health care information exchange and interoperability. Health Affairs, 24(Suppl 1), W5–10. https://doi.org/10.1377/hlthaff.w5.10

[60] Watkins, R. E., Eagleson, S., Veenendaal, B., Wright, G., & Plant, A. J. (2009). Disease surveillance using a hidden Markov model. BMC Medical Informatics and Decision Making, 9, Article 39. https://doi.org/10.1186/1472-6947-9-39

[61] World Health Organization. (2018). Early warning, alert and response systems (EWARS): Operational framework. https://www.who.int

[62] Zhang, P., Aikman, S. N., & Sun, H. (2008). Two types of attitudes in ICT acceptance and use. International Journal of Human-Computer Studies, 66(12), 989–997. https://doi.org/10.1016/j.ijhcs.2008.08.001