Systematic Review of Public Health Data Lake Architectures Supporting Real-Time Analytics and Decision-Making

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Abstract
Public health decision-making increasingly relies on timely access to large, heterogeneous datasets, including electronic health records, laboratory results, syndromic surveillance, environmental monitoring, and social determinants of health. Traditional relational databases often struggle to handle the volume, velocity, and variety of modern public health data, limiting the ability to perform real-time analytics for outbreak detection, resource allocation, and policy planning. Data lakes have emerged as a scalable solution, providing centralized repositories capable of storing structured, semi-structured, and unstructured data while supporting advanced analytics and machine learning applications. This systematic review examines the current state of public health data lake architectures, focusing on their design, operational features, and capacity to support real-time analytics and evidence-based decision-making. A comprehensive literature search was conducted across scientific databases and grey literature to identify studies reporting on public health data lake implementations, integration frameworks, and analytic capabilities. Key dimensions analyzed include data ingestion mechanisms, storage models, interoperability standards, metadata management, governance frameworks, security and privacy measures, and analytic tools. Findings indicate that successful public health data lakes integrate multi-source datasets using standardized schemas and ontologies, enabling seamless data harmonization and real-time access. Advanced processing pipelines, including stream processing and event-driven architectures, facilitate continuous data updates and near real-time insights. Governance and security frameworks are critical for ensuring data quality, interoperability, and compliance with privacy regulations, particularly in sensitive domains such as patient-level health records. Additionally, the integration of machine learning and visualization tools enhances predictive modeling, anomaly detection, and operational decision support. This review highlights best practices in the design and deployment of public health data lakes, emphasizing the importance of scalability, flexibility, and governance. By consolidating diverse datasets into a unified, analyzable repository, public health data lakes enable timely, evidence-based decision-making, strengthen outbreak detection and response capabilities, and support resource optimization. The findings underscore the potential of data lake architectures as foundational infrastructure for modern, data-driven public health systems.

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Keywords: Public health, data lake architectures, real-time analytics, decision-making, big data, health informatics, data integration, interoperability, data governance, predictive modeling, disease surveillance, population health, electronic health records, data pipelines, streaming data, analytics platforms, data security, scalability, cloud computing

1. Introduction

The exponential growth of health data in recent years has transformed the landscape of public health management and decision-making. Hospitals, clinical laboratories, electronic health record (EHR) systems, wearable devices, mobile health applications, and national public health programs collectively generate vast volumes of heterogeneous data on a daily basis (Menson et al., 2018; Frempong et al., 2022). These datasets encompass structured information such as laboratory results and administrative records, semi-structured data like sensor feeds and log files, and unstructured content including clinical notes, imaging studies, and social media reports (Omolayo et al., 2022; Ojonugwa et al., 2022).

Harnessing this wealth of information is critical for enhancing population health outcomes, optimizing healthcare delivery, and supporting timely responses to emerging public health challenges (Oluyemi et al., 2021; Umana et al., 2022). A core requirement in this context is the ability to perform real-time analytics, enabling public health authorities to detect outbreaks, monitor disease trends, allocate resources efficiently, and implement evidence-based interventions. Traditional relational database management systems, however, often struggle to accommodate the volume, velocity, and variety of modern health data (Ajayi and Akanji, 2022; Oluoha et al., 2022). Fragmented storage across disparate systems, lack of interoperability standards, and the need for extensive pre-processing contribute to delays in analysis, undermining the capacity for timely decision-making. In the face of rapidly evolving health threats, such as infectious disease outbreaks or environmental hazards, these delays can result in suboptimal public health responses and increased morbidity and mortality (Chima et al., 2022; Akinboboye et al., 2022).

Data lakes have emerged as a promising solution for these challenges. A data lake is a centralized repository capable of storing raw data in its native format, whether structured, semi-structured, or unstructured (Aduwo et al., 2020; Sobowale et al., 2022). Unlike traditional databases that require predefined schemas, data lakes support flexible storage, schema-on-read architectures, and integration of multiple data sources. This flexibility enables the consolidation of diverse health datasets into a unified repository, facilitating real-time analytics, predictive modeling, and advanced machine learning applications (Oluyemi et al., 2020; Ajayi and Akanji, 2021). By enabling rapid access to harmonized data, data lakes offer the potential to improve public health decision-making, support evidence-based interventions, and enhance operational efficiency across healthcare systems (Akinboboye et al., 2021; Afrihyia et al., 2022).

Despite their promise, the design and implementation of public health data lakes remain heterogeneous. Variations exist in data ingestion pipelines, storage architectures, interoperability standards, metadata management, security protocols, and analytic tool integration. Moreover, systematic evaluations of their effectiveness in supporting real-time analytics and evidence-based decision-making are limited (Kufile et al., 2022; Oluoha et al., 2022). Without such assessments, public health authorities lack clear guidance on best practices for implementing scalable, secure, and operationally efficient data lakes capable of addressing contemporary health challenges (Aduwo et al., 2021; Ojonugwa et al., 2022).

The objectives of this study are twofold. First, it seeks to systematically review the architectures of public health data lakes, highlighting key design features, integration strategies, and governance frameworks. Second, it aims to assess their capabilities in supporting real-time analytics and evidence-based decision-making, including predictive modeling, outbreak detection, and operational resource planning. By synthesizing existing knowledge, this review provides insights into the current state of public health data lake architectures, identifies gaps in implementation, and informs strategies for optimizing the use of big data in modern health systems.

Integrating heterogeneous health datasets through well-designed data lakes offers a transformative approach to population health management (Adeshina, 2022; Okoli et al., 2022). Understanding their architectures and analytic capabilities is essential for enabling timely, evidence-based decision-making and enhancing public health preparedness and response.

2. Methodology

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology was applied to conduct a systematic review of public health data lake architectures supporting real-time analytics and decision-making. A comprehensive literature search was performed across multiple electronic databases, including PubMed, Scopus, Web of Science, Embase, and IEEE Xplore, covering publications from 2010 to 2025. Grey literature, including technical reports from the World Health Organization, national public health agencies, health informatics consortia, and industry white papers, was also reviewed. Search terms included combinations of “public health,” “data lake,” “real-time analytics,” “health information systems,” “big data,” and “decision support,” using Boolean operators and controlled vocabularies such as MeSH and Emtree to maximize search sensitivity. Reference lists of included studies were screened to identify additional relevant publications.

Eligibility criteria encompassed studies and reports that described the design, implementation, or evaluation of data lake architectures used in public health settings with an emphasis on supporting real-time analytics or decision-making processes. Both qualitative and quantitative studies, including case studies, system evaluations, and implementation research, were included. Exclusion criteria comprised studies focused solely on traditional data warehouses without real-time analytic capabilities, publications outside of the health domain, or those not available in English.

The study selection process was conducted in two stages. Initially, titles and abstracts were independently screened by two reviewers to identify potentially relevant studies. Subsequently, full-text articles of shortlisted studies were reviewed for eligibility. Discrepancies between reviewers were resolved through discussion or consultation with a third reviewer. The PRISMA flow diagram was employed to document the identification, screening, eligibility, and inclusion of studies, ensuring transparency and reproducibility.

Data extraction was conducted using a standardized form capturing study characteristics, including data lake architecture components, technologies employed (e.g., cloud computing, distributed storage, ETL pipelines), integration with electronic health records, analytics capabilities, real-time decision support features, scalability, and governance mechanisms. Key findings regarding operational performance, data quality, interoperability, and user adoption were also recorded.

Quality assessment was performed using design-appropriate tools such as the Critical Appraisal Skills Programme (CASP) checklist for qualitative studies, the Mixed Methods Appraisal Tool (MMAT) for mixed-methods studies, and structured evaluation criteria for technical reports and system case studies. Risk of bias was assessed at both study and outcome levels, considering factors such as reporting transparency, system evaluation rigor, and generalizability of findings.

Synthesis of findings was conducted through narrative and thematic analysis due to the heterogeneous nature of the literature. Key themes included data ingestion and integration strategies, storage and processing technologies, real-time analytics capabilities, governance and security protocols, and practical considerations for deployment in public health settings. Comparative analyses were used to identify common enablers, barriers, and best practices across different implementations and contexts.

This PRISMA-guided methodology ensures a rigorous, transparent, and reproducible approach to consolidating evidence on public health data lake architectures, providing insights for researchers, policymakers, and health informatics professionals seeking to leverage big data for real-time analytics and evidence-based decision-making.

2.1. Conceptual Framework

Understanding the role of data lake architectures in public health requires a clear conceptual framework that integrates definitions of key concepts, theoretical underpinnings, and the guiding principles of big data analytics (Awe, 2017; Halliday, 2021). A structured conceptualization helps elucidate how centralized data repositories, real-time analytics, and decision-making mechanisms converge to support evidence-based public health interventions and policy-making.

A public health data lake is a centralized repository designed to store vast quantities of health-related data in both raw and structured or unstructured formats. Unlike traditional databases that require a predefined schema for data storage, a data lake allows ingestion of heterogeneous datasets without prior transformation, supporting flexible schema-on-read approaches. These datasets may include electronic health records (EHRs), laboratory results, syndromic surveillance data, environmental monitoring outputs, wearable device metrics, mobile health applications, and social determinants of health. By consolidating these diverse data streams, a public health data lake enables comprehensive analytics that captures both clinical and population-level health trends (Taiwo et al., 2021; Isa, 2022).

Real-time analytics refers to the ability to process, analyze, and generate insights from data as it is produced, rather than relying on batch processing or delayed analysis. In the public health context, real-time analytics is critical for rapid outbreak detection, early warning of adverse health events, monitoring disease trends, and evaluating the immediate impact of interventions (Aduwo et al., 2021; Oluoha et al., 2022). This capability depends on high-throughput data ingestion pipelines, stream processing frameworks, and efficient computational infrastructures capable of handling high-velocity data from multiple sources.

Decision-making support involves the use of actionable, data-driven insights derived from integrated analytics to inform public health policies, outbreak responses, resource allocation, and preventive strategies. Decision support in this context extends beyond mere data visualization; it encompasses predictive modeling, scenario analysis, and operational guidance that help policymakers and health practitioners implement timely, evidence-based actions to improve population health outcomes (Oloruntoba and Omolayo, 2022; Isa, 2022).

The conceptual framework for public health data lakes draws upon data-to-decision frameworks within the field of public health informatics. These frameworks outline the sequential flow from raw data acquisition to actionable insights, emphasizing the transformation of heterogeneous data into meaningful knowledge that guides decision-making. Key stages include data ingestion, integration, cleaning, standardization, analysis, visualization, and interpretation. The framework highlights feedback loops where real-time insights inform policy and interventions, which in turn generate new data for ongoing monitoring and evaluation (Scholten et al., 2018; Aduwo et al., 2019). By embedding these processes into data lake architectures, public health systems can operationalize continuous learning and adaptive decision-making.

Additionally, the framework is grounded in the principles of big data analytics, commonly described by the four Vs: volume, velocity, variety, and veracity. Volume pertains to the massive scale of data generated from multiple health sources, necessitating scalable storage and processing capabilities. Velocity refers to the speed at which new data is produced and must be processed to enable timely interventions. Variety emphasizes the heterogeneity of health data, including structured EHRs, semi-structured sensor data, and unstructured social media or clinical notes. Veracity relates to the reliability, accuracy, and quality of data, ensuring that analytics yield trustworthy insights for decision-making. Incorporating these principles into the design and operation of public health data lakes enhances their utility in real-time monitoring, predictive modeling, and policy support.

The conceptual framework integrates these key concepts and theoretical principles into a cohesive model where public health data lakes serve as the foundation for real-time analytics and decision-making. Data ingestion pipelines capture heterogeneous health data, which is then harmonized and processed through analytic engines capable of real-time computation. Predictive and descriptive analyses generate insights that inform targeted interventions, policy formulation, outbreak response, and resource distribution. Feedback loops enable continuous refinement of analytic models, integration of new data sources, and adaptive decision-making (Eneogu et al., 2020; Osabuohien et al., 2021). This framework underscores the interplay between technological infrastructure, analytic methodologies, and public health objectives, demonstrating how data lakes can transform raw information into actionable knowledge.

The conceptual framework positions public health data lakes as a central enabler of real-time analytics and evidence-based decision-making. By integrating heterogeneous datasets, leveraging big data principles, and embedding data-to-decision pathways, the framework supports timely, scalable, and effective public health interventions. It provides a structured basis for evaluating the design, functionality, and impact of data lake architectures in strengthening health system responsiveness, optimizing resource allocation, and improving population health outcomes.

2.2. Public Health Data Lake Architectures

Public health data lake architectures have emerged as a transformative solution for managing the growing volume, variety, and velocity of health data, enabling real-time analytics and evidence-based decision-making as shown in figure 1. Unlike traditional data warehouses, data lakes provide a scalable and flexible environment capable of storing structured, semi-structured, and unstructured data, while supporting diverse analytical workflows. The architecture of a public health data lake encompasses several core components, mechanisms for integrating heterogeneous data, and advanced analytics and visualization layers, all of which collectively enhance public health surveillance, planning, and intervention (Ajayi and Akanji, 2022; Oluyemi et al., 2022).

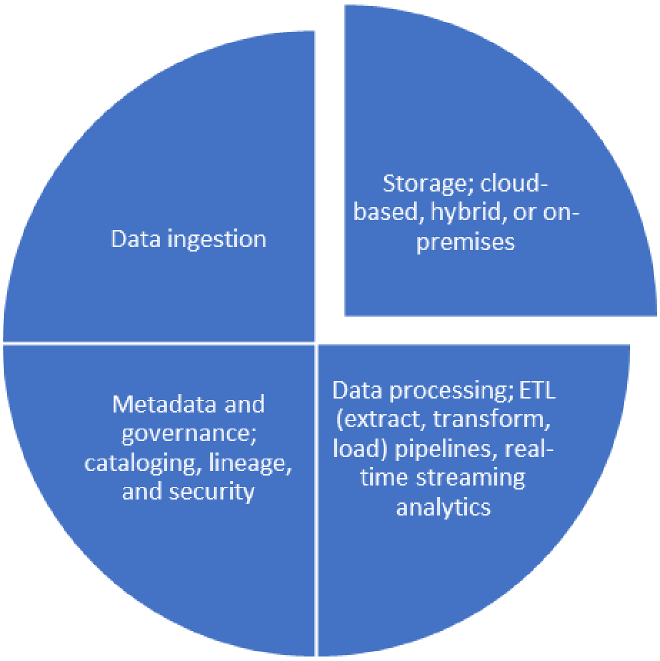

Fig 1: Core Components of Public Health Data Lake Architectures

At the foundation of data lake architecture is the data ingestion layer, responsible for collecting and importing data from multiple sources. In public health applications, this may involve batch ingestion, where large volumes of data are periodically transferred, or streaming ingestion, which allows real-time processing of incoming data from sources such as electronic health records (EHRs), laboratory information systems, wearable devices, and syndromic surveillance platforms. Streaming ingestion is particularly valuable for outbreak detection and rapid response, as it enables near-instantaneous analysis of health indicators and trends. Effective ingestion strategies must also include data validation and standardization processes to ensure data integrity and facilitate downstream analytics.

The storage layer forms the backbone of the data lake, providing scalable and cost-effective solutions for managing massive datasets. Cloud-based storage platforms offer flexibility and elasticity, allowing storage capacity to expand dynamically as data volumes grow. Hybrid architectures combine cloud resources with on-premises storage, which can enhance data security, compliance, and latency for sensitive health information. On-premises solutions remain relevant in contexts with stringent regulatory requirements or limited internet connectivity. Storage design must also incorporate redundancy and fault tolerance to ensure high availability and disaster recovery capabilities, which are critical for maintaining continuous public health monitoring (Anyebe et al., 2018; Mitchell et al., 2022).

Data processing capabilities are integral to transforming raw data into actionable insights. Extract, transform, load (ETL) pipelines are used to clean, normalize, and structure data for analysis. Advanced pipelines support real-time streaming analytics, enabling immediate identification of anomalies, emerging trends, or high-risk events. Integration of workflow orchestration tools facilitates automated data movement, transformation, and quality control, reducing manual intervention and enhancing operational efficiency. Metadata management and governance play a pivotal role in ensuring the usability, security, and compliance of the data lake. Comprehensive metadata catalogs document data lineage, provenance, and schema definitions, while governance frameworks enforce access controls, encryption protocols, and compliance with privacy regulations such as HIPAA or GDPR.

A defining feature of public health data lakes is their capacity to integrate heterogeneous data types. Structured data, such as patient demographics, laboratory results, and EHR entries, are easily ingested into relational or columnar storage formats. Semi-structured data, including JSON or XML files from health surveys, biosensors, or immunization registries, can be processed using schema-on-read approaches. Unstructured data, such as clinical notes, imaging data, or social media feeds, require specialized processing pipelines for natural language processing (NLP), image recognition, or text mining. By accommodating diverse data types, data lakes enable holistic public health analyses that capture clinical, behavioral, environmental, and social determinants of health.

The analytics and visualization layer translates raw data into actionable knowledge for public health decision-making. Interactive dashboards allow real-time monitoring of disease incidence, vaccination coverage, hospital utilization, and other key metrics. Predictive modeling and machine learning applications leverage historical and real-time data to forecast disease outbreaks, assess risk factors, and optimize resource allocation. AI and ML algorithms are particularly valuable for early warning systems, anomaly detection, and syndromic surveillance, providing public health authorities with advanced tools to anticipate and respond to emerging threats (Aduwo et al., 2019; Ojonugwa et al., 2022). Furthermore, visual analytics facilitates communication of complex trends to policymakers, clinicians, and community stakeholders, enhancing transparency and evidence-based planning.

Public health data lake architectures integrate multiple layers of technology and governance to manage complex and diverse datasets effectively. Core components such as data ingestion, storage, processing pipelines, and metadata management provide the foundation for reliable and scalable data infrastructure. The ability to integrate structured, semi-structured, and unstructured data ensures a comprehensive view of population health, while analytics and visualization layers, enhanced by AI and machine learning, enable predictive insights and real-time decision-making. By providing a flexible, scalable, and intelligent platform, data lakes support timely public health interventions, outbreak prediction, and strategic planning, making them indispensable tools for modern health systems confronting the challenges of big data and rapidly evolving health threats.

2.3. Support for Real-Time Decision-Making

Public health systems increasingly depend on timely, accurate, and actionable data to respond to evolving health challenges. Data lakes, with their capacity to integrate heterogeneous datasets and support advanced analytics, are positioned as critical infrastructure for real-time decision-making in population health management (Umekwe and Oyedele, 2021; OLAJIDE et al., 2021). This explores how public health data lakes enable rapid insights, examines relevant performance metrics, and highlights key challenges in their operationalization.

One of the most prominent applications of real-time analytics via data lakes is epidemic monitoring and outbreak response. Data lakes consolidate inputs from hospital admissions, laboratory test results, syndromic surveillance, wearable devices, and social media signals, enabling continuous monitoring of disease incidence and trends. Real-time detection of anomalies in health indicators facilitates rapid identification of outbreaks, triggering alerts and guiding targeted interventions such as vaccination campaigns, quarantine measures, or public advisories. For example, during influenza seasons or emerging infectious disease events, public health agencies can leverage near-real-time data to track transmission hotspots, predict outbreak trajectories, and allocate resources proactively.

Resource allocation and hospital capacity planning constitute another critical use case. Integrated data on patient load, bed occupancy, staffing levels, and supply chains can be processed in real time to forecast demand for hospital services. Predictive models built on longitudinal and streaming data allow administrators to optimize allocation of intensive care units, ventilators, medications, and personnel, reducing bottlenecks and improving patient outcomes. In regions with limited healthcare infrastructure, such capabilities are particularly valuable for minimizing avoidable morbidity and mortality during public health emergencies.

Data lakes also support policy evaluation and intervention assessment by enabling continuous monitoring of health outcomes and program effectiveness. For instance, the impact of a public health campaign, vaccination drive, or nutritional intervention can be assessed in near-real time through metrics such as disease incidence reduction, adherence rates, or changes in population behavior. Rapid feedback loops allow policymakers to refine strategies, reallocate resources, and make evidence-based decisions without waiting for delayed periodic reports (Okenwa et al., 2019; Ezeilo et al., 2022).

The effectiveness of data lakes in supporting real-time decision-making can be assessed using multiple performance metrics. Data latency—the delay between data generation and its availability for analysis—is critical; low-latency systems ensure timely detection of trends and rapid response. Throughput, or the volume of data processed per unit time, determines the system's capacity to handle high-velocity inputs, particularly during health crises. Data accuracy and quality are fundamental to trust in analytics outputs; erroneous or inconsistent data can lead to misguided decisions. Finally, predictive validity—the ability of analytic models to reliably forecast health events or resource needs—serves as a benchmark for assessing the practical utility of real-time decision support (Ojonugwa et al., 2021; Oluoha et al., 2021). High-performing systems balance speed, volume, and accuracy to deliver actionable insights to health authorities.

Despite their potential, operationalizing data lakes for real-time decision-making poses several challenges. Data privacy and compliance represent a primary concern. Public health data often contain sensitive patient information, necessitating adherence to regulations such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States or the General Data Protection Regulation (GDPR) in the European Union. Ensuring that data lakes implement robust encryption, access control, and anonymization protocols is essential for legal compliance and public trust.

Interoperability and standardization also remain significant hurdles. Data lakes must integrate heterogeneous sources that use disparate coding systems, terminologies, and formats. Standardizing these inputs—through ontologies, common data models, or mapping frameworks—is necessary to ensure consistency, comparability, and meaningful analytics (Balogun et al., 2020; Ozobu et al., 2022).

Finally, scalability and cost constraints, especially in low-resource settings, can limit the deployment of high-performance data lakes. The infrastructure required to store, process, and analyze large-scale, high-velocity datasets demands substantial computational resources, software platforms, and skilled personnel. Addressing these constraints may involve cloud-based solutions, open-source technologies, and regional collaborations to optimize cost-effectiveness and sustainability.

Public health data lakes provide a powerful foundation for real-time decision-making, enhancing epidemic monitoring, outbreak response, resource allocation, hospital capacity planning, and policy evaluation. By integrating diverse datasets and enabling advanced analytics, data lakes facilitate timely, evidence-based interventions that improve population health outcomes. Key performance metrics, including data latency, throughput, accuracy, and predictive validity, serve as benchmarks for evaluating system effectiveness. However, challenges related to data privacy, interoperability, and resource limitations must be addressed to fully realize their potential, particularly in low-resource environments. When implemented effectively, data lakes represent a transformative tool for modern public health systems, bridging the gap between data generation and actionable insights (Olajide et al., 2021; Komi et al., 2022).

2.4. Comparative Analysis of Architectures

The evolution of public health data infrastructure has led to the emergence of diverse data lake architectures, each designed to address specific operational, analytical, and strategic requirements. Comparative analysis of these architectures provides valuable insights into the trade-offs associated with technology selection, deployment, scalability, and integration with decision support systems (Kufile et al., 2022; Osabuohien, 2022). Key dimensions for comparison include cloud-based versus on-premises solutions, batch-oriented versus stream-oriented systems, open-source versus proprietary platforms, and their capacity for integration with decision support systems (DSS).

Cloud-based versus on-premises solutions represent a primary consideration in public health data lake design. Cloud-based architectures offer significant advantages in terms of scalability, flexibility, and cost-effectiveness. They allow dynamic allocation of storage and processing resources to accommodate fluctuating data volumes, reducing the need for upfront capital investment in infrastructure. Cloud solutions also facilitate remote access and collaboration across geographically dispersed public health agencies, enabling real-time analytics and shared insights. However, challenges remain regarding data privacy, regulatory compliance, and internet connectivity dependency. On-premises solutions, by contrast, provide greater control over data security and compliance, particularly in jurisdictions with strict data protection regulations or for sensitive patient-level datasets (Ojonugwa et al., 2022; Merotiwon et al., 2022). They offer low-latency access to local networks and can integrate with legacy systems more easily, yet require substantial capital expenditure, ongoing maintenance, and dedicated technical expertise to scale efficiently. The choice between cloud-based and on-premises deployments often hinges on a balance between scalability, regulatory requirements, and resource availability.

Batch-oriented versus stream-oriented systems reflect different approaches to data ingestion and processing. Batch-oriented systems aggregate large datasets at predefined intervals, transforming and loading them for downstream analysis. This approach is efficient for historical data analysis, periodic reporting, and retrospective epidemiological studies, but it lacks the immediacy required for real-time surveillance. Stream-oriented systems, in contrast, process data in near real-time as it is generated, enabling immediate detection of anomalies, rapid outbreak identification, and timely response interventions. Stream-oriented architectures are particularly valuable for syndromic surveillance, remote monitoring of chronic disease indicators, and emergency response scenarios. However, they demand more sophisticated infrastructure, low-latency networks, and advanced stream-processing frameworks, increasing operational complexity. Optimal public health data lake implementations often employ hybrid approaches, combining batch processing for historical datasets with streaming analytics for real-time monitoring.

Open-source versus proprietary platforms further define the landscape of data lake architectures. Open-source platforms, such as Apache Hadoop, Spark, and Kafka, provide flexibility, customization, and community-driven innovation. They allow organizations to tailor processing pipelines, analytics workflows, and data governance mechanisms to specific public health needs. Open-source solutions also reduce licensing costs, which can be critical in resource-constrained settings. Proprietary platforms, however, offer integrated solutions with vendor support, preconfigured security features, optimized performance, and simplified deployment, reducing the burden on internal technical teams (Isa et al., 2021; Komi et al., 2022). Proprietary tools often include advanced analytics, machine learning libraries, and dashboarding capabilities that facilitate rapid implementation of decision support systems. The trade-off involves balancing customization and cost with ease of deployment, reliability, and vendor-provided support.

Integration with decision support systems is a defining factor in the utility of public health data lakes. Effective integration allows analytical outputs—such as predictive models, anomaly detection alerts, and population health dashboards—to inform policy decisions, resource allocation, and intervention strategies. Cloud-based and stream-oriented architectures typically enhance integration capabilities, providing APIs, real-time data feeds, and interoperability with electronic health records, laboratory systems, and emergency response platforms. Open-source frameworks can be highly adaptable for custom DSS integration, while proprietary solutions often offer plug-and-play compatibility with commercial decision support software. Successful integration ensures that insights derived from heterogeneous data sources are translated into actionable decisions, enhancing the responsiveness, precision, and effectiveness of public health interventions.

Comparative analysis of public health data lake architectures highlights the trade-offs and complementary strengths across deployment models, processing paradigms, and platform types. Cloud-based architectures provide scalability and collaborative advantages, while on-premises solutions ensure regulatory compliance and low-latency access. Batch-oriented systems excel in historical data analysis, whereas stream-oriented systems enable real-time monitoring and rapid response. Open-source platforms offer customization and cost efficiency, while proprietary solutions provide integrated features and vendor support. Across all architectures, the ability to integrate with decision support systems remains critical for translating data into actionable insights (Ikponmwoba et al., 2020; Kufile et al., 2022). Optimal public health data lake design often involves hybrid approaches that combine these elements strategically to meet technical, operational, and public health objectives, ensuring that real-time analytics and decision-making capabilities are fully leveraged to improve population health outcomes.

2.5. Gaps and Limitations

Despite the promising potential of public health data lakes to support real-time analytics and evidence-based decision-making, several gaps and limitations hinder their widespread implementation and effectiveness. These constraints relate to limited empirical evidence, performance evaluation challenges, security and privacy concerns, and the complexity of integrating diverse health and social datasets as shown in figure 2 (Evans-Uzosike et al., 2021; Uddoh et al., 2021). Understanding these limitations is critical for guiding future research, improving system design, and optimizing the utility of data lakes in population health management.

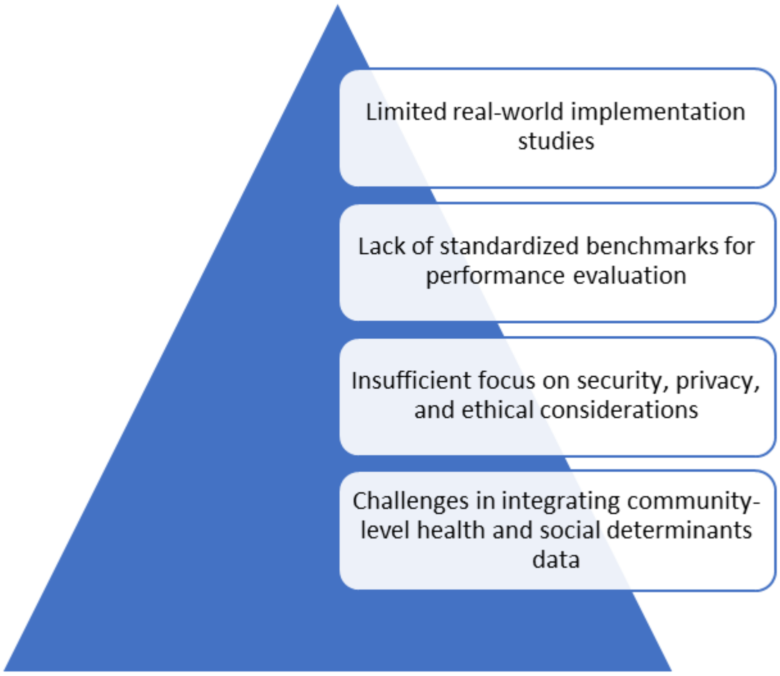

Fig 2: Gaps and Limitations

A major gap in the literature is the scarcity of documented real-world implementations of public health data lakes. While conceptual frameworks and pilot projects exist, there are few large-scale, systematically evaluated deployments that demonstrate sustained use in operational public health settings. Most studies focus on technical feasibility, data integration strategies, or proof-of-concept models rather than long-term impact on decision-making, outbreak response, or health outcomes. This lack of empirical evidence limits the ability of policymakers and health administrators to assess the practical benefits, cost-effectiveness, and scalability of data lakes. Without rigorous implementation studies, best practices remain largely theoretical, reducing confidence in adopting these systems across diverse health contexts.

Another limitation is the absence of standardized benchmarks to assess the performance of data lake architectures in public health. Metrics such as data latency, throughput, predictive accuracy, and real-time responsiveness vary widely across studies, and evaluation methodologies are often inconsistent. The lack of uniform performance standards makes it challenging to compare systems, identify optimal architectures, or establish minimum operational requirements. Furthermore, few studies systematically evaluate the end-to-end effectiveness of data lakes, from data ingestion and harmonization to predictive analytics and actionable decision support. Developing standardized evaluation frameworks is essential for guiding design improvements, validating system efficacy, and ensuring reproducibility across different health jurisdictions.

Data security, privacy, and ethical compliance represent critical but often underexplored aspects of public health data lake design. Health datasets frequently contain sensitive personal information, necessitating adherence to legal frameworks such as HIPAA, GDPR, or national data protection laws. However, many existing architectures prioritize technical integration and analytic capacity over robust privacy-preserving measures. Insufficient attention to data encryption, access control, anonymization, and auditability can expose systems to breaches or Kingsley et al., 2020; Akinrinoye et al., 2021misuse, undermining public trust and limiting adoption (v). Ethical considerations, including equitable access to insights, potential biases in predictive models, and implications for vulnerable populations, are also inadequately addressed in current literature, representing a significant gap in responsible deployment of data lakes.

Integrating community-level health indicators and social determinants of health into data lakes remains a persistent challenge. While hospital and laboratory data are often structured and readily available, community-level metrics—such as socioeconomic status, education, environmental exposures, or neighborhood-level health behaviors—are frequently unstructured, incomplete, or collected at varying spatial and temporal resolutions. Harmonizing these datasets with clinical and administrative records requires advanced data engineering, robust ontologies, and consistent metadata standards. Failure to integrate these dimensions limits the capacity of data lakes to support comprehensive public health analytics, potentially overlooking critical drivers of health inequities and population-level disease patterns.

The utility of public health data lakes for real-time analytics is constrained by several key gaps and limitations. Limited empirical evidence from large-scale implementations restricts understanding of practical benefits, scalability, and cost-effectiveness. The absence of standardized performance benchmarks complicates evaluation and comparison of system designs. Security, privacy, and ethical considerations remain underdeveloped, threatening compliance and public trust. Finally, difficulties in integrating community-level and social determinants data reduce the comprehensiveness of insights and limit the capacity to inform equitable, population-centered interventions. Addressing these gaps through rigorous implementation studies, development of evaluation frameworks, strengthened privacy protocols, and enhanced integration of diverse data sources is essential to maximize the potential of data lakes as foundational infrastructure for modern, data-driven public health systems (Osabuohien, 2017; Oyeyemi, 2022).

2.6. Future Directions

The rapid growth of health data, driven by electronic health records, wearable devices, environmental sensors, and social media, presents both opportunities and challenges for public health systems as shown in figure 3. Public health data lake architectures are evolving to meet these demands, and future directions emphasize hybrid and edge computing, AI-driven automation, standardized interoperability frameworks, and the integration of multidimensional data sources to support holistic decision-making (Aduwo and Nwachukwu, 2019; Oluyemi et al., 2020).

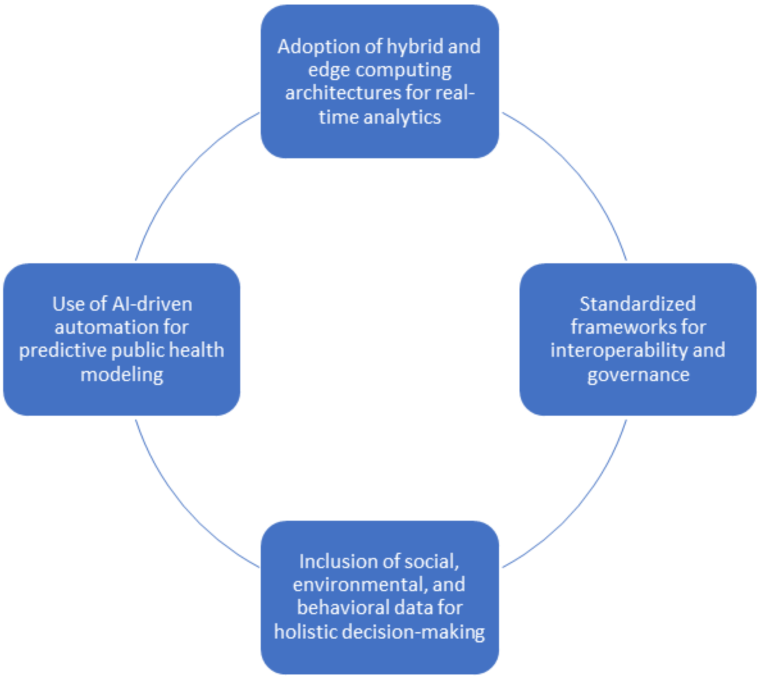

Fig 3: Future Directions

Adoption of hybrid and edge computing architectures represents a key innovation in enhancing real-time analytics capabilities. Hybrid architectures combine cloud-based storage and processing with on-premises resources, allowing public health agencies to balance scalability, data security, and latency requirements. Edge computing, in which data processing occurs closer to the data source, reduces delays associated with transmitting large datasets to centralized servers. This is particularly valuable for real-time monitoring of infectious disease outbreaks, chronic disease indicators, or environmental health hazards in geographically dispersed regions. By processing data at the edge, health authorities can generate immediate alerts and actionable insights, improving responsiveness and reducing the risk of delayed interventions.

AI-driven automation is poised to transform predictive public health modeling. Machine learning algorithms and artificial intelligence tools can analyze complex, high-dimensional datasets to forecast disease outbreaks, identify at-risk populations, and optimize resource allocation. Automation reduces the time and manual effort required for data cleaning, integration, and analysis, allowing public health teams to focus on interpretation and intervention. Predictive models can be continuously updated with streaming data, improving accuracy and enabling proactive rather than reactive decision-making. The integration of AI also supports anomaly detection, early warning systems, and scenario modeling, providing public health authorities with sophisticated tools to anticipate and mitigate emerging threats.

Standardized frameworks for interoperability and governance are critical for the effective scaling of public health data lakes. Interoperability standards facilitate seamless integration of heterogeneous datasets from electronic health records, laboratory information systems, mobile health platforms, and environmental monitoring networks. Governance frameworks ensure data privacy, security, quality, and ethical use, while enabling responsible data sharing across local, national, and global public health networks. Standardization also supports reproducibility and comparability of analyses, which is essential for evidence-based policy formulation and international collaboration in outbreak management and chronic disease surveillance (Oluyemi et al., 2020; Akinrinoye et al., 2020).

The inclusion of social, environmental, and behavioral data expands the analytical horizon of public health data lakes. Beyond clinical and laboratory metrics, incorporating data on socioeconomic status, population mobility, dietary patterns, air quality, climate factors, and social determinants of health allows for a more comprehensive understanding of health outcomes. Holistic datasets support multidimensional modeling of disease risk and health inequities, enabling interventions that address both biological and contextual drivers of health. Integrating these diverse data sources facilitates precision public health, where interventions can be tailored to the needs of specific populations and communities.

The future of public health data lake architectures is characterized by enhanced computational strategies, intelligent automation, standardized interoperability, and comprehensive data integration. Hybrid and edge computing will enable timely real-time analytics, while AI-driven predictive modeling provides actionable insights for proactive intervention. Standardized frameworks ensure secure, interoperable, and ethically governed data ecosystems, and the inclusion of social, environmental, and behavioral determinants allows for holistic decision-making. By embracing these directions, public health systems can leverage the full potential of big data to improve population health, enhance outbreak preparedness, and implement targeted, evidence-based interventions that address both clinical and societal determinants of health (Ikponmwoba et al., 2022; Chima et al., 2022).

3. Conclusion

Public health data lakes represent a transformative infrastructure for enhancing the capacity of health systems to perform real-time analytics and support evidence-based decision-making. By consolidating heterogeneous datasets—including electronic health records, laboratory results, syndromic surveillance, wearable device metrics, and social determinants of health—data lakes enable near-immediate access to comprehensive information. This integration allows public health authorities to detect emerging disease outbreaks, monitor population health trends, optimize resource allocation, and evaluate the effectiveness of interventions with unprecedented speed and precision. The systematic review of public health data lake architectures highlights their potential to bridge fragmented data silos, improve operational efficiency, and facilitate predictive modeling that informs timely and strategic decision-making.

The strategic implications of these findings are significant. Investment in scalable, secure, and interoperable data lake architectures is essential to realize their full potential. Scalable infrastructures allow health systems to handle the increasing volume and velocity of health data, while robust security and privacy measures ensure compliance with regulations and maintain public trust. Interoperability, facilitated by standardized ontologies, metadata frameworks, and integration protocols, ensures that diverse datasets can be harmonized and analyzed effectively. Collectively, these investments strengthen the capacity of public health agencies to respond rapidly to health emergencies, monitor population-level outcomes, and implement evidence-driven interventions.

A clear call to action emerges from this review. Policymakers, health agencies, informaticians, and technical stakeholders should prioritize the adoption and integration of data lakes within public health systems. This includes supporting infrastructure development, establishing governance frameworks, addressing ethical and privacy concerns, and promoting workforce training in big data analytics. By doing so, health systems can transform raw health data into actionable knowledge, improving responsiveness, efficiency, and equity in public health practice. Ultimately, the deployment of well-designed public health data lakes is a critical step toward more timely, data-driven, and effective public health decision-making, enhancing preparedness, resilience, and population health outcomes globally.

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