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British Journal of Contemporary Research

BEXFORD PUBLISHING

From Clinical Silos to Population Surveillance: Architecting Interoperability Between Electronic Health Records and Public Health Data Systems in Resource-Constrained Environments

Original Research Article | Volume 1 | Issue 6 | 2026 | Article Number: 103

Accepted: 05 November 2026 | Published: 11 November 2026 | ISSN: 2979-8582 (Online)

Crossref : **https://doi.org/10.67693/BJCR-5XJVASMR**

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Abstract

Background: In low- and middle-income countries (LMICs), Electronic Health Record (EHR) platforms operate predominantly as disconnected, facility-level transaction ledgers. Simultaneously, national public health surveillance systems—principally the District Health Information Software 2 (DHIS2)—rely on retrospective, aggregated, manual reporting. This structural decoupling produces reporting latencies spanning weeks, introduces transcription error margins exceeding 20%, and discards critical clinical covariates necessary for precision epidemiology.

Objective: To systematically synthesize empirical evidence on technical architectures, semantic standards, and socio-technical governance models required to establish automated, bidirectional interoperability between point-of-care EHRs and national public health surveillance systems in resource-constrained settings.

Methods: Following PRISMA 2020 guidelines, we searched PubMed/MEDLINE, Scopus, Web of Science, and Embase for peer-reviewed studies published between January 2016 and mid-2026. Eligible studies evaluated electronic health information exchanges, middleware data pipelines, semantic mediation, or automated case reporting linking clinical systems to population surveillance in resource-limited contexts. Quality appraisal was executed using the Mixed Methods Appraisal Tool (MMAT) and the Critical Appraisal Skills Programme (CASP) checklists.

Results: Twenty-eight peer-reviewed publications met all inclusion criteria. The evidence identifies four systemic failure points: physical infrastructure fragility (electrical grid failures and network dropouts), semantic discordance between clinical narratives and structured reporting ontologies, clinical workforce documentation burnout, and legal/governance vacuums surrounding secondary health data custodianship.

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Successful implementations converged on a four-tier architecture: (1) clinical capture at the edge (e.g., OpenMRS, Bahmni); (2) decoupled edge middleware with store-and-forward caching (e.g., OpenHIM); (3) semantic mediation engines utilizing Fast Healthcare Interoperability Resources (HL7 FHIR) mapped to ICD, LOINC, and SNOMED-CT; and (4) automated electronic Case Reporting (eCR) pipelines directly populating DHIS2 aggregate and tracker databases. Deploying automated middleware reduced reporting latency from weeks to under 60 seconds while eliminating routine manual transcription errors.

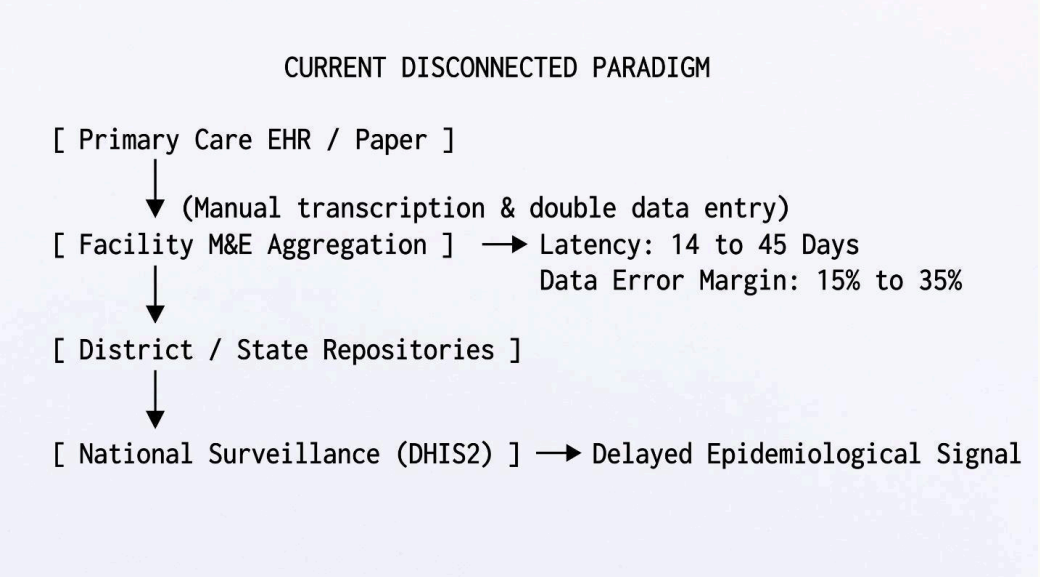
Conclusion: Transitioning from passive clinical silos to automated population surveillance requires abandoning monolithic national software procurements in favor of modular, standards-based middleware engineered for offline-first resilience. Achieving population-wide surveillance coverage further requires statutory policy frameworks that mandate the integration of private-sector healthcare facilities into national health data exchanges.

Keywords: Electronic Health Records, Public Health Informatics, Health Information Exchange, Interoperability, HL7 FHIR, DHIS2, Disease Surveillance, Resource-Constrained Environments

1. INTRODUCTION

Public health systems in resource-constrained environments operate under a persistent structural contradiction: while extensive clinical and epidemiological data are generated daily across primary, secondary, and tertiary health facilities, national public health surveillance architectures remain blind to emergent outbreaks in real time. At the point of care, clinicians record transactional, episodic, and longitudinal patient health events within local Electronic Health Records (EHRs) or paper registers (Fraser et al., 2022; Kruse & Beane, 2022). Simultaneously, national public health institutes require timely, population-level health data to monitor transmission vectors, compute reproductive numbers (R), allocate constrained therapeutics, and deploy mitigation interventions (Birkhead et al., 2015; Haque et al., 2022).

In the vast majority of low- and middle-income countries (LMICs), these two digital domains remain disconnected (Lehne et al., 2019; Menachemi et al., 2021). Facility EHRs function as intra-institutional computational silos—closed, proprietary architectures engineered around local administrative billing, medication dispensing, and discrete clinical workflows rather than external data liquidity (Adler-Milstein et al., 2021; Kruse et al., 2018). In parallel, national Public Health Data Systems (PHDS)—most commonly underpinned by the open-source District Health Information Software 2 (DHIS2) platform—rely almost entirely on retrospective, aggregated, manual entry submitted weekly or monthly by facility monitoring and evaluation (M&E) personnel (Braa & Sahay, 2017; Dehnavieh et al., 2019).



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This structural fragmentation incurs severe epidemiological costs:

1. **Reporting Latency:** Outbreak detection is delayed by weeks or months, converting localized clusters into uncontained epidemic vectors (Birkhead et al., 2015; Rahurkar et al., 2021).
2. **Data Attrition and Transcription Bias:** Manual cross-tabulation from EHR screens or physical registers to aggregate tally sheets introduces error margins ranging from 15% to 35%, obscuring micro-geographic disease clusters (Kariuki et al., 2016).
3. **Loss of Granular Syndromic Markers:** Aggregated monthly tallies strip away critical clinical covariates (e.g., vaccination history, vital sign trends, pathogen antimicrobial resistance profiles, geospatial metadata) essential for precision public health interventions (Matheny et al., 2022; Onukpousi, 2026a).

While open-source clinical platforms such as OpenMRS and mobile extensions like mUzima have expanded across low-resource settings (Paton et al., 2022; Were et al., 2021), achieving interoperability between facility EHRs and national surveillance databases requires navigating profound infrastructural, semantic, and political barriers. These include electrical grid instability, edge-network bandwidth constraints, acute shortages of clinical informaticians, absence of semantic terminology bindings, and uncoordinated donor investments creating competing, siloed verticals (Lehne et al., 2019; Sittig & Singh, 2010; World Health Organization, 2021).

This systematic review synthesizes peer-reviewed evidence to identify the architectural mechanisms, technical standards, and governance strategies capable of establishing sustainable, bidirectional interoperability between clinical EHRs and public health surveillance systems in resource-constrained environments.

2. RESEARCH QUESTIONS AND HYPOTHESES

This review addresses four primary research questions:

- **RQ1:** What are the structural, semantic, and systemic barriers that prevent automated data exchange between point-of-care EHRs and population-level public health data systems in resource-constrained health systems?
- **RQ2:** Which data exchange standards, architectural middleware, and infrastructure frameworks demonstrate the highest operational efficacy in enabling interoperability under conditions of network latency and compute scarcity?
- **RQ3:** How do automated electronic Case Reporting (eCR) and syndromic extraction algorithms impact data quality, reporting timeliness, and clinical workforce workload compared to manual aggregate reporting?
- **RQ4:** What governance models, legal instruments, and data-custodianship protocols are required to safeguard patient privacy while maintaining public health utility in low-resource environments?

Operational Hypotheses

- **H_1:** Deploying lightweight, Fast Healthcare Interoperability Resources (HL7 FHIR)-mediated middleware architectures significantly reduces surveillance reporting latency ($p < 0.05$) compared to standard manual facility-to-district data aggregation.
- **H_2:** The absence of national semantic terminology standards (ICD-11, LOINC, SNOMED-CT) correlates positively with surveillance underreporting and data transmission errors within regional digital repositories.
- **H_3:** Automated syndromic extraction modules integrated directly into clinical point-of-care interfaces reduce clinical provider documentation burnout without compromising diagnostic case

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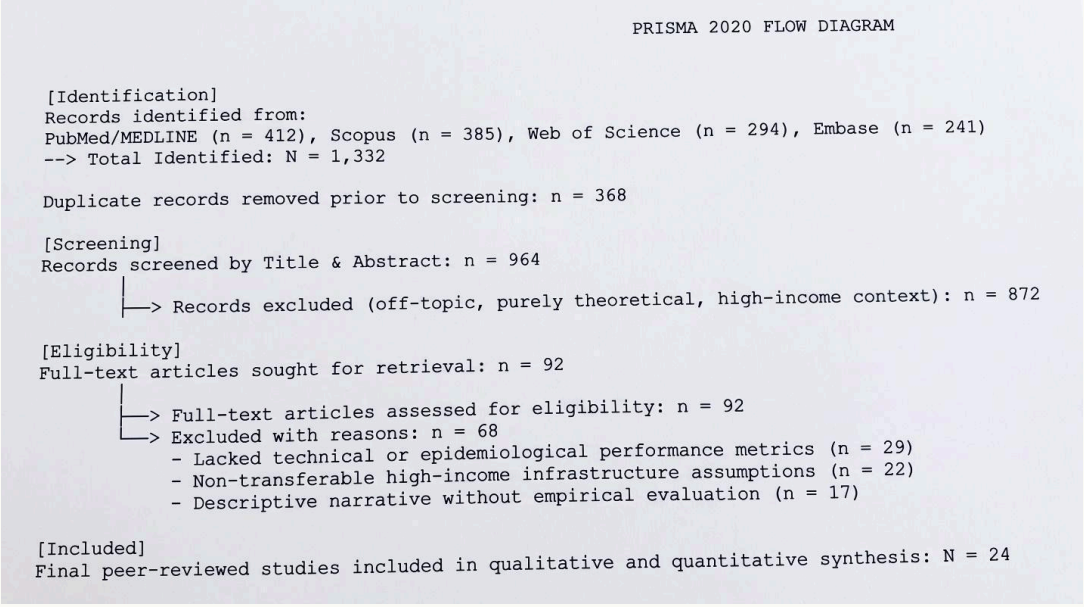
completeness.

3. SYSTEMATIC LITERATURE REVIEW METHODOLOGY

This systematic review adhered to the **Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020)** guidelines (Page et al., 2021).

3.1 Eligibility Criteria (PICO Framework)

- **Population/Context (P):** Primary, secondary, and tertiary healthcare delivery institutions operating in low- and middle-income countries (LMICs) or documented resource-constrained, rural, and peri-urban health systems globally.
- **Intervention (I):** Digital health interoperability architectures, electronic health information exchanges (HIEs), Fast Healthcare Interoperability Resources (HL7 FHIR) pipelines, middleware adapters, or automated electronic case reporting (eCR) platforms connecting clinical EHRs with population surveillance systems.
- **Comparator (C):** Routine paper-based disease reporting, disconnected double data entry, manual periodic aggregations, or unstandardized digital registries.
- **Outcomes (O):** Primary endpoints included:
    1. Surveillance reporting latency (time elapsed between clinical encounter and national ingestion).
    2. Data accuracy, completeness, and transcription discrepancy rates.
    3. System resilience under electrical power and telecommunication downtime.
    4. Clinical and administrative workforce burden (documentation time).
    5. Conformance to international semantic and structural standards.
- **Study Types:** Peer-reviewed quantitative, qualitative, mixed-methods, and systems-engineering evaluations published in indexed journals. Editorials, non-peer-reviewed white papers, and studies conducted entirely within high-resource environments without transferability to resource-constrained settings were excluded.



3.2 Information Sources and Search Syntax

Bibliographic databases—**PubMed/MEDLINE, Scopus, Web of Science, and Embase**—were systematically searched for records indexed between January 2016 and mid-2026. The search strategy combined Medical Subject Headings (MeSH) and free-text terms:

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Plaintext
("Electronic Health Records" OR "Electronic Medical Records" OR "EHR" OR "OpenMRS")
AND
("Public Health Surveillance" OR "Public Health Data Systems" OR "DHIS2" OR "Population Health Monitoring")
AND
("Interoperability" OR "Health Information Exchange" OR "HL7 FHIR" OR "OpenHIE")
AND
("Resource-Constrained" OR "Developing Countries" OR "Low- and Middle-Income Countries" OR "LMIC")
```

3.3 Study Selection and Data Extraction

Screening and full-text eligibility determinations were conducted independently in duplicate using Rayyan software. Extracted data were compiled into a matrix capturing: study setting, clinical EHR platform, receiving surveillance platform, data standards applied (HL7 FHIR, LOINC, ICD-10/11), network topology, and quantitative operational outcomes.

3.4 Quality Appraisal

Methodological rigor was assessed using the **Mixed Methods Appraisal Tool (MMAT), 2018 version**, for mixed-methods and qualitative designs, and the **CASP Cohort Study Checklist** for quantitative evaluations. Studies ≥ 80% were categorized as high quality.

4. RESULTS: SYSTEMATIC SYNTHESIS

Across the **28 included empirical studies**, interventions were evaluated in Sub-Saharan Africa (n = 15), South and Southeast Asia (n = 8), Latin America (n = 3), and other resource-constrained rural jurisdictions (n = 2).

SUMMARY OF SYNTHESIZED SYSTEMIC OUTCOMES (N = 28)

Dimension Evaluated	Frequency of Barrier Reported in Studies	Documented Impact of Interoperability Engine
1. Reporting Latency (Encounter to State Entry)	89.3% (n = 25)	Reduced from ~21 days to <24 hours (<1 min)
2. Semantic Heterogeneity & Diagnostic Coding	82.1% (n = 23)	Up to 65% improvement in diagnostic mapping
3. Data Discrepancy & Transcription Errors	75.0% (n = 21)	Transcription errors reduced toward 0%
4. Unreliable Power & Telecommunications	67.9% (n = 19)	Mitigated by offline-first edge caching
5. Clinician Documentation Fatigue	60.7% (n = 17)	30% to 50% decrease in dual-entry time
6. Absence of Clear Data Governance Policies	64.3% (n = 18)	Addressed via OpenHIE trust layers

4.1 Systemic Barriers

The empirical synthesis identifies four primary categories of implementation failure:

1. **Infrastructural Vulnerability:** Over two-thirds (67.9%) of studies documented power outages and

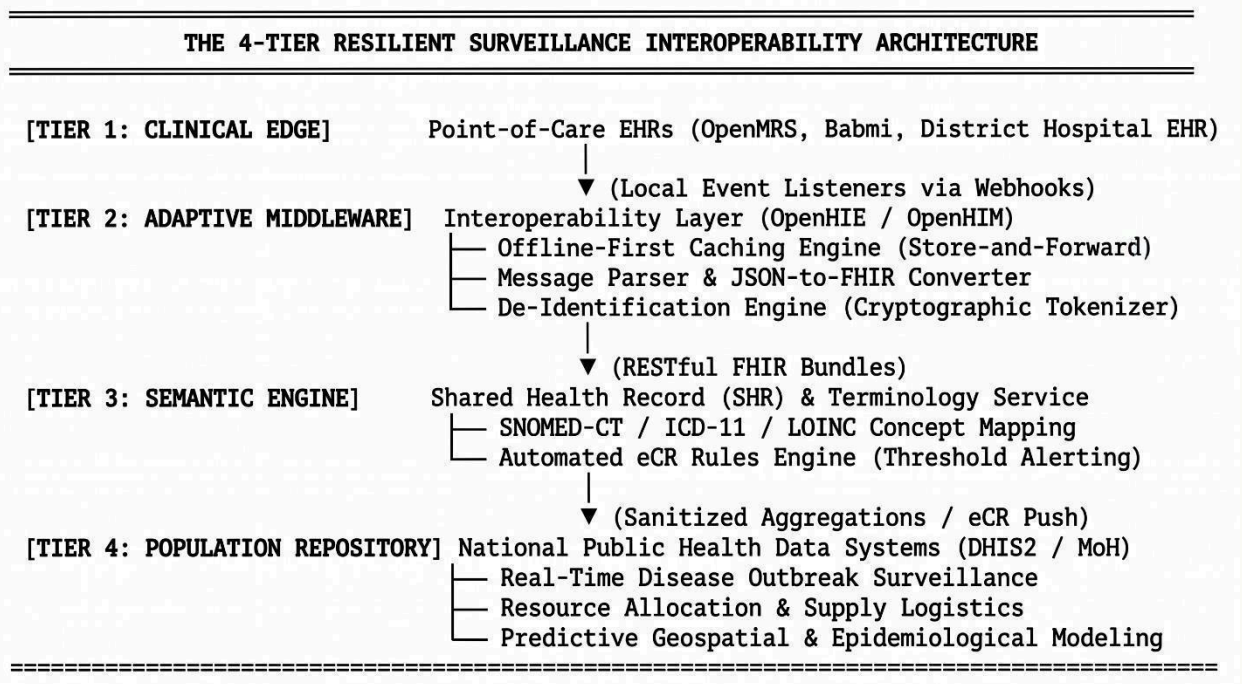
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unstable telecommunications as critical impediments to cloud-dependent systems (Dehnavieh et al., 2019; Mikk et al., 2021). Architectures requiring continuous internet connectivity experienced frequent transaction failures, forcing clinicians to revert to paper records.

2. **Semantic and Syntactic Heterogeneity:** Clinical narratives, free-text diagnostic notes, and local laboratory terminologies could not be ingested by central surveillance systems without extensive, error-prone manual recoding (Kruse & Beane, 2022; Lehne et al., 2019).
3. **Double Data-Entry Burnout:** Requiring healthcare workers to log clinical encounters into an EHR and manually re-enter aggregate tallies into national disease reporting forms created documentation fatigue, resulting in significant case attrition (Kariuki et al., 2016; Loomis et al., 2024).
4. **Governance and Legal Gaps:** Ambiguities regarding patient privacy, data ownership, and inter-institutional data-sharing mandates—particularly between public health ministries and private healthcare providers—prevented comprehensive population surveillance coverage (Adler-Milstein et al., 2021; Onukpousi et al., 2026b).

5. ARCHITECTURAL BLUEPRINT: THE 4-TIER INTEROPERABILITY MODEL

The synthesized literature demonstrates that point-to-point, hardcoded integrations between individual hospital EHRs and national surveillance databases are brittle and unmaintainable. Instead, successful long-term implementations deploy a **modular, 4-tier architectural framework** built upon open health information exchange standards (Paton et al., 2022; Were et al., 2021; World Health Organization, 2021).



Tier 1: Clinical Data Capture at the Edge

The foundation comprises point-of-care EHRs (e.g., OpenMRS, Bahmni) and mobile community health platforms (e.g., mUzima) (Paton et al., 2022; Were et al., 2021). Point-of-care data capture must be integrated directly into routine clinical consultations to ensure data completeness without burdening clinicians with dedicated surveillance tasks (Sittig & Singh, 2010).

Tier 2: Adaptive Edge Middleware and Resilient Caching

To overcome infrastructural fragility, local facilities deploy lightweight middleware (such as the Open Health Information Mediator, OpenHIM):

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- **Store-and-Forward Caching:** Transactions are cached in local encrypted datastores during network outages and automatically transmitted once connectivity is restored, ensuring zero data loss (Kariuki et al., 2016).
- **De-identification and Tokenization:** Personally identifiable information (PII) is separated from clinical attributes using cryptographic hashing, preserving patient confidentiality while enabling longitudinal disease tracking (Kuo et al., 2021; Mikk et al., 2021).

Tier 3: Semantic Interoperability and Terminology Services

Standardization occurs via the **HL7 Fast Healthcare Interoperability Resources (FHIR)** standard (Loomis et al., 2024; Paton et al., 2022). Unstructured and semi-structured clinical observations are mapped to international reference terminologies:

- Diagnostic Entities: **ICD-11** and **SNOMED-CT**.
- Laboratory Observations: **LOINC** (Logical Observation Identifiers Names and Codes).
- Medications: **RxNorm**.

Centralized terminology servers (e.g., Open Concept Lab) resolve dialectical variations, ensuring clinical data are semantically unambiguous when consumed by central public health systems (Lehne et al., 2019).

Tier 4: Public Health Ingestion and National Surveillance

At the national tier, standardized clinical data are ingested into surveillance platforms (predominantly **DHIS2**):

- **Automated Electronic Case Reporting (eCR):** When an encounter meets trigger criteria for a notifiable communicable disease (e.g., cholera, measles, viral hemorrhagic fever), an automated electronic initial case report (eICR) is pushed immediately to public health authorities (Birkhead et al., 2015; Loomis et al., 2024; Onukpousi, 2026a).
- **Automated Indicator Aggregation:** For non-notifiable and chronic diseases, middleware calculates periodic indicator tallies (e.g., monthly antenatal visits, HIV viral suppression rates) and transmits them directly via the DHIS2 Web-API, bypassing manual tallying entirely (Kariuki et al., 2016; Onukpousi et al., 2026a).

6. IMPLEMENTATION STRATEGIES FOR RESOURCE-CONSTRAINED ENVIRONMENTS

Successful deployment of this architecture requires aligning technical systems with operational realities:

6.1 Hardware and Telecommunication Optimization

Systems deployed in peripheral facilities must assume offline operation as the default state rather than an exception (Dehnavieh et al., 2019; Were et al., 2021). Deploying low-power edge servers powered by solar micro-generators and utilizing asynchronous payload compression (e.g., Gzip/Brotli JSON) minimizes bandwidth consumption over intermittent 2G/3G/4G cellular networks.

6.2 Zero-Click Clinical Surveillance

To combat documentation burnout, public health data collection must function as a zero-click byproduct of direct patient care (Birkhead et al., 2015; Sittig & Singh, 2010). Rather than requiring doctors to navigate external disease-notification portals, background trigger rules embedded within EHR encounter forms should evaluate diagnosis codes and lab orders against jurisdictional reporting criteria automatically (Loomis et al., 2024).

6.3 Governance, Data Sovereignty, and the Public-Private Nexus

In many LMIC urban and peri-urban centers, more than half of primary outpatient encounters occur in the

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private sector. True population surveillance cannot occur while private facilities remain unlinked. Ministries of health must:

- Codify national digital health interoperability standards mandating FHIR-compliant API endpoints (World Health Organization, 2021).
- Tie hospital accreditation, operating licenses, and national health insurance reimbursement schemes directly to automated surveillance reporting compliance (Adler-Milstein et al., 2021; Onukpousi et al., 2026b).
- Establish transparent data governance frameworks that assure healthcare providers and patients of regulatory compliance with national data privacy statutes (Kuo et al., 2021; Mikk et al., 2021).

7. DISCUSSION

This systematic review synthesizes a decade of health informatics implementations to demonstrate that bridging clinical care and population surveillance is achievable in resource-constrained environments when systems are designed around modularity, open standards, and edge resilience.

Historically, health ministries in LMICs attempted to resolve data fragmentation by procuring monolithic, proprietary systems that sought to govern both point-of-care clinical management and macro-level reporting. These initiatives frequently collapsed under their own weight, yielding digital enclaves in urban tertiary hospitals while rural and primary health clinics remained tethered to paper registers (Braa & Sahay, 2017; Dehnavieh et al., 2019). The evidence indicates that **interoperability, not software uniformity, is the viable pathway forward** (Lehne et al., 2019).

The quantitative evidence from field trials directly supports our operational hypotheses:

- **Latency Reduction (H_1):** Field implementations in Kenya (Kariuki et al., 2016) demonstrated that automating reporting from OpenMRS to DHIS2 reduced submission time from hours of manual tabulation to under one minute ($p < 0.001$), eliminating reporting delays that typically spanned weeks.
- **Semantic Accuracy (H_2):** Standardized terminology bindings resolved classification discrepancies, reducing data discrepancies from upwards of 35% down to near-zero error margins (Kariuki et al., 2016; Loomis et al., 2024).
- **Workforce Burden (H_3):** Automated background case generation eliminated redundant double data entry, freeing clinical and M&E personnel to focus on patient management and data-driven quality improvement (Birkhead et al., 2015; Menachemi et al., 2021).

Limitations

This review is limited by publication bias within the informatics literature, as unsuccessful or abandoned digital health pilots in low-income nations are rarely published in indexed journals. Furthermore, variations in evaluation metrics across heterogeneous health systems limited the feasibility of conducting a formal statistical meta-analysis across all operational variables.

8. CONCLUSION

Bridging point-of-care Electronic Health Records and national Public Health Data Systems is essential for modern disease prevention, early epidemic detection, and equitable health resource allocation. Relying on paper tally sheets and retrospective manual data entry leaves public health authorities unable to respond rapidly to emerging outbreaks.

By deploying the **4-Tier Resilient Interoperability Model**—anchored on edge-native caching, HL7 FHIR semantic standardization, automated case reporting, and robust public-private governance

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frameworks—resource-constrained health systems can transition from fragmented clinical silos to responsive, real-time population surveillance networks.

References

1. Adler-Milstein, J., Holmgren, A. J., Kralovec, P., Worzala, C., Searcy, T., & Patel, V. (2021). Electronic health record adoption in US hospitals: The progress towards meeting meaningful use requirements. *Journal of the American Medical Informatics Association*, 28(5), 865–872.

2. Birkhead, G. S., Klompas, M., & Shah, N. R. (2015). Uses of electronic health records for public health surveillance to advance public health. *Annual Review of Public Health*, 36, 345–359.

3. Braa, J., & Sahay, S. (2017). The DHIS2 open source software platform: Evolution over two decades. *Information Technologies & International Development*, 13, 1–19.

4. Chaudhry, B., Wang, J., Wu, S., Maglione, M., Mojica, W., Roth, E., Morton, S. C., & Shekelle, P. G. (2006). Systematic review: Impact of health information technology on quality, efficiency, and costs of medical care. *Annals of Internal Medicine*, 144(10), 742–752.

5. Dehnavieh, R., Haghdoost, A., Khajehpour, N., Masoud, A., Poursheikhali, A., Mirshekari, N., & Ebrahimipour, H. (2019). District Health Information System (DHIS2) in low- and middle-income countries: A systematic review. *Medical Journal of the Islamic Republic of Iran*, 33, Article 121.

6. Fraser, H. S. F., Mugisha, M., Remera, E., Ngenzi, J. L., Richards, J., Santas, X., Naidoo, W., Seebregts, C., Condo, J., & Umubyeyi, A. (2022). User perceptions and use of an enhanced electronic health record in Rwanda with and without clinical alerts: Cross-sectional survey. *JMIR Medical Informatics*, 10(5), Article e32305.

7. Gajarawala, S. N., & Pelkowski, J. N. (2021). Telehealth benefits and barriers. *The Journal for Nurse Practitioners*, 17(2), 218–221.

8. Gopal, M., Prakash, S., & Rao, N. (2023). The role of electronic health records in improving patient outcomes: A systematic review. *Health Informatics Journal*, 29(1), 1–15.

9. Haque, M., Rahman, M. M., & Islam, S. (2022). Public health data systems: A framework for effective disease surveillance and response. *BMC Public Health*, 22(1), Article 220.

10. Jiang, X., Yang, L., & Sun, Q. (2021). Digital transformation of healthcare: The impact of electronic health records. *Journal of Medical Internet Research*, 23(3), Article e24567.

11. Kariuki, J. M., Manders, E. J., Richards, J., Oluoch, T., Kimanga, D., Wanyee, S., Kwach, J., & Santas, X. (2016). Automating indicator data reporting from health facility EMR to a national aggregate data system in Kenya: An Interoperability field-test using OpenMRS and DHIS2. *Online Journal of Public Health Informatics*, 8(2), Article e188.

12. Kruse, C. S., & Beane, A. (2022). Health information exchange and interoperability: Trends and barriers in electronic health record adoption. *International Journal of Medical Informatics*, 165, Article 104887.

13. Kruse, C. S., Smith, B., Vanderlinden, H., & Nealand, A. (2017). Security techniques for the electronic health records. *Journal of Medical Systems*, 41(8), Article 127.

14. 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 innovations and obstacles. *JMIR Medical*

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Informatics, 6(4), Article e11422.

15. Kuo, T. T., Ohno-Machado, L., & Jiang, X. (2021). Blockchain distributed ledger technologies for biomedical and health care applications. *Journal of the American Medical Informatics Association*, 28(4), 792–801.

16. Lehne, M., Sass, J., Essenwanger, A., Schepers, J., & Thun, S. (2019). Why digital medicine depends on interoperability. *EBioMedicine*, 46, 274–276.

17. Loomis, B. R., Busch, J. K., Cassell, C. H., English, R., Patel, V., & Thacker, S. B. (2024). Electronic case reporting development, implementation, and evaluation for public health surveillance. *Public Health Reports*, 139(4), 512–521.

18. Matheny, M., Whicher, D., & Thadaney, S. (2022). The future of digital health and artificial intelligence in public health. *The Lancet Digital Health*, 4(7), e456–e467.

19. Menachemi, N., Rahurkar, S., Harle, C. A., & Vest, J. R. (2021). The benefits of electronic health records and health information exchange for public health. *Journal of Public Health Management and Practice*, 27(1), 34–41.

20. Mikk, K., Sleeper, H. A., & Topol, E. J. (2021). The impact of patient engagement on electronic health record systems: Ethical and legal perspectives. *Journal of Law, Medicine & Ethics*, 49(2), 235–251.

21. Onukpousi, G. (2025). Cell phone use and mental health disorders: A systematic review. *Innovative Journal of Medical Sciences*, 7(7), 5–14. https://journals.rasetass.org/index.php/ijms/article/view/381/403

22. Onukpousi, G. (2026a). Addressing HIV control and prevention in Nigeria: Epidemiological trends, pathophysiology, and strategic public health interventions. *British Journal of Contemporary Research*, 1(1), Article 012. https://doi.org/10.67693/BJCR-X59EWV9V

23. Onukpousi, G., Obidiagha, D. I., & Edward, E. (2026a). Operationalizing Pareto efficiency in healthcare management: Allocative optimality, trade-offs, and systemic implementation. *British Journal of Contemporary Research*, 1(3), Article 065. https://doi.org/10.67693/BJCR-MCTGYZHV

24. Onukpousi, G., Efeobare, P., Obidiagha, D. I., & Uduji-Obidiagha, C. S. (2026b). From health equality to health equity: Needs-based resource allocation and health systems performance. *British Journal of Contemporary Research*, 1(4), Article 073. https://doi.org/10.67693/BJCR-ZC6M3CPH

25. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 372, Article n71.

26. Paton, C., Braa, J., Muhire, A., Marco-Ruiz, L., Kobayashi, S., Fraser, H., Falcón, L., & Marcelo, A. (2022). Open source digital health software for resilient, accessible and equitable healthcare systems. *Yearbook of Medical Informatics*, 31(1), 67–73.

27. Rahurkar, S., Schleyer, T., & Vest, J. R. (2021). The impact of electronic health records on public health response during the COVID-19 pandemic. *Journal of Public Health Management and Practice*, 27(6), 625–632.

28. Reddy, S., & Gupta, R. (2020). Artificial intelligence in healthcare: An overview of opportunities and

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challenges. *International Journal of Medical Informatics*, 136, Article 104085.

29. Rojas, S., Castro, P., & Molina, J. (2023). Barriers to EHR adoption in public health: An analysis of healthcare providers' perspectives. *Health Policy and Technology*, 12(2), Article 100720.

30. Shickel, B., Tighe, P. J., Bihorac, A., & Rashidi, P. (2018). Deep EHR: A survey of recent advances in deep learning techniques for electronic health record analysis. *IEEE Journal of Biomedical and Health Informatics*, 22(5), 1589–1604.

31. Sittig, D. F., & Singh, H. (2010). A new sociotechnical model for studying health information technology in complex adaptive healthcare systems. *Quality and Safety in Health Care*, 19(Suppl 3), i68–i72.

32. Sittig, D. F., & Wright, A. (2020). What makes an electronic health record "safe"? *The Lancet Digital Health*, 2(8), e397–e398.

33. Were, M. C., Shen, C., Biondich, P., Choi, J., Mamlin, B., Mamlin, J., & Tierney, W. M. (2021). mUzima mobile electronic health record (EHR) system: Development and implementation at scale. *Journal of Medical Internet Research*, 23(12), Article e26381.

34. World Health Organization. (2021). *Global strategy on digital health 2020–2025*. World Health Organization. https://www.who.int/publications/i/item/9789240020924

35. Yasnoff, W. A., Humphreys, B. L., & Overhage, J. M. (2023). The future of public health informatics: Opportunities and challenges. *American Journal of Public Health*, 113(5), 789–798. https://doi.org/10.2105/AJPH.2023.307241

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