

Review Article

From Digital Surveillance to Public Health Action: A Systematic Review and Implementation Readiness Framework for Communicable Disease Surveillance in Low- and Middle-Income Countries

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ABSTRACT

Background: Communicable and emerging disease surveillance is fundamental to outbreak preparedness and public health response, yet it remains constrained across low- and middle-income countries (LMICs). Technological advancements in digital health and Artificial Intelligence (AI) have provided the ability to increase real-time reporting opportunities, outbreak intelligence, predictive analytics, and anticipatory public health action. However, evidence is sparse on what conditions of implementation drive successful outcomes.

Methods: A systematic review was performed according to the PRISMA 2020 guidelines. A literature search was conducted in PubMed/MEDLINE, Web of Science, and Google Scholar for studies published between January 2015 and May 2026, which highlights surveillance systems in LMICs. The findings were narratively synthesized and recurring implementation determinants were identified and synthesized thematically to develop an implementation readiness framework.

Results: Seventeen empirical studies were included. Digital surveillance reported improvements in reporting timeliness, completeness, outbreak signal detection, and surveillance data generation. Cross-study synthesis identified six recurring readiness domains which informed the development of the Digital Surveillance and Artificial Intelligence Implementation Readiness Framework (DSIRF-AI) to guide stakeholders in enhancing surveillance outcomes.

Conclusion: Digital surveillance systems were associated with improved surveillance performance. The proposed DSIRF-AI provides an evidence-derived conceptual framework for implementation of communicable disease surveillance in LMIC settings.

Keywords: Communicable Disease Surveillance; Digital Surveillance; Outbreak Detection; Implementation Readiness; Public Health Action; LMICs; Artificial Intelligence

Introduction

Background and Rationale

Communicable disease surveillance is fundamental to outbreak preparedness and effective public health response, yet surveillance systems remain constrained across many low- and middle-income countries (LMICs), due to fragmented reporting pathways, inadequate infrastructure, limited analytical capacity, workforce shortages, and weak response systems [1, 2]. Advances in digital health technologies and artificial intelligence (AI) offer opportunities to strengthen real-time reporting, outbreak intelligence, predictive analytics, and public health decision-making. However, there is limited evidence on the implementation conditions and readiness factors required for these technologies to achieve sustainable improvements in surveillance performance and outbreak response.

Traditional surveillance frameworks, which were mostly paper-based, manually collated, and latency-driven impeded the capacity of health systems to produce real-time information insights and respond to new outbreaks [3, 4]. The Ebola outbreak in West Africa revealed how poor coordination of detection, poor integration of information systems, and inefficient linkage of the various Ebola surveillance and response components could compromise response, leaving vulnerable health systems more exposed [5, 6].

Advances in artificial intelligence (AI) and machine learning have strengthened digital surveillance by supporting anomaly detection, outbreak prediction, and analysis of large surveillance datasets to improve public health decision-making [7, 8]. AI applications have also expanded genomic surveillance, enabling earlier identification of emerging variants and improving preparedness for future outbreaks [8, 9]. However, successful implementation depends not only on technological capability but also on governance, infrastructure, workforce capacity, and sustained health-system integration [1, 10].

Evolution of Digital and AI-supported Disease Surveillance

Digital disease surveillance is the use of digital technologies for the collection, transmission, analysis, interpretation and communication of health information in disease prevention and control [5]. In LMICs, trends in surveillance communication patterns have increasingly transitioned surveillance from stand-alone reporting platforms to more integrated systems, which bring together multiple data sources and facilitate more coordinated public health responses. There are numerous surveillance systems currently in use, including electronic reporting platforms, mobile surveillance applications, event-based surveillance,

participatory surveillance, AI-based early-warning systems, and genomic surveillance models [2, 8, 11]. With improvements in surveillance systems, health facilities are better equipped to participate in routine surveillance activities through more timely reporting, enhanced visibility of health information via electronic surveillance platforms such as the District Health Information Software 2 (DHIS2) and electronic Integrated Disease Surveillance and Response (eIDSR), and improved communication between health facilities and public health authorities [3,4]. Mobile and community-based surveillance approaches have similarly widened the surveillance horizon, with frontline workers and communities reporting suspected events directly, thereby improving opportunities for earlier recognition of emerging threats in underserved populations [12-14].

AI-powered surveillance has emerged primarily as a complement to existing surveillance systems rather than a replacement. The use of machine learning has proven useful in applications to clinical records, mobility data, environmental data, digital traces, and genomic data inputs to improve analysis of large and heterogeneous data streams, thereby enabling the prediction of unusual disease patterns and early warning of potential cases of disease outbreaks [8]. Likewise, genomic surveillance has bolstered preparedness capability as it has facilitated tracking of pathogen evolution and aided the detection of new variants [8, 9]. However, experience of surveillance implementation has shown that the effectiveness of surveillance relies on both technological capability and the system conditions needed to support implementation and integration, as well as sustained public health use [1, 10].

From Digital Surveillance to Public Health Action: The Implementation Gap

While digital and AI surveillance capabilities have grown substantially, some questions remain over whether digital and AI innovations continuously deliver better communicable disease prevention and control. Process metrics such as timeliness and completeness of reports for surveillance activities, levels of system coverage, and signal detection capacity are the primary indicators assessed in existing surveys. Although these outcomes are relevant, they offer limited evidence of whether improvements in surveillance systems were linked to better outbreak management, better preparedness, and actual gains in population health benefits [15, 16].

Although a surveillance system can provide large amounts of data, there is a risk that the generated data does not increase control measures unless health

systems can validate the data, interpret results, coordinate investigations, allocate resources, and take timely action [17, 18]. The distinction is of particular significance in LMIC contexts, where barriers to implementation often entail weak infrastructure, limited technical capacity, lack of interoperability, high staff turnover, complex governance structures, financing challenges, and weak data stewardship mechanisms as reported by Nguyen-Tien et al. (2025) [1]. New challenges arise when AI systems need to be explainable, undergo model validation, be transparent and accountable, monitored for bias, and remain subject to human oversight and regulation [19, 20]. These observations indicate that a high level of surveillance does not simply rely on the adoption of only digital technology. Instead, surveillance results seem to be influenced by what circumstances are needed to ensure surveillance data can be translated to operational public health action.

Thus, rather than asking what form of surveillance technology is the most effective, the central question becomes, “what conditions are necessary for digital and AI-assisted surveillance to achieve sustainable population health outcomes?” Accordingly, this review synthesises available evidence to identify the implementation conditions required for sustainable, equitable, and responsible digital and AI-assisted communicable disease surveillance in LMICs and to

develop an evidence-informed framework to guide response readiness.

Review Questions

This systematic review was guided by the following questions:

1. What digital and AI-assisted communicable disease surveillance approaches have been implemented in LMICs, and how effective are they in improving outbreak detection, reporting timeliness, surveillance outputs, and public health response?
2. What implementation barriers, facilitators, governance conditions, equity considerations, and sustainability factors influence surveillance effectiveness?
3. What health-system enabling conditions are required to support sustainable and responsible implementation of AI-integrated communicable disease surveillance in LMIC settings?

Study Objective

This review aimed to evaluate digital and AI-assisted communicable disease surveillance systems implemented in LMICs, identify the implementation conditions associated with successful surveillance, and develop an evidence-informed implementation readiness framework to support sustainable public health action.

Methods

Study Design

This study employed a systematic review design to examine readiness needs of digital and AI-based Communicable Disease Surveillance Systems (CDSSs) in LMICs. The review was carried out and reported following the guidelines provided by the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA 2020) [21]. Eligible studies were narratively synthesised, and recurring implementation determinants were thematically analysed to develop an evidence-informed

implementation readiness framework. The review was not prospectively registered in PROSPERO, and this is acknowledged as a methodological limitation.

Eligibility Criteria

The eligibility criteria were guided by the population, intervention, comparison, and outcome (PICO) framework for systematic reviews. Table 1 presents the PICO framework which guided the definition of the eligibility criteria for this study.

Table 1. PICO elements and eligibility criteria guiding study selection

Element	Description
Population (P)	Communicable/infectious disease surveillance systems operating in one or more LMICs. The unit of interest is the surveillance system/setting, not individual patients.
Intervention (I)	Digital and/or AI-supported surveillance approaches.
Comparison (C)	No formal comparator required (narrative/thematic synthesis, not meta-analysis).
Outcome (O)	Surveillance performance, implementation outcomes, downstream outcomes; development of implementation readiness domains (DSIRF-AI).

Inclusion Criteria

Studies were included if they were published between January 2015 and May 2026; conducted in one or more LMIC countries; assessed digital or AI-supported communicable disease surveillance interventions; used quantitative, qualitative, mixed method, implementation or operational study design; reported findings related to surveillance performance, implementation, preparedness, outbreak responses, equity, governance, or sustainability; and published in English.

Exclusion Criteria

Studies that were only concerned with clinical diagnosis, but not with applications to surveillance, as well as studies describing conceptual technologies with no evidence of implementation, studies without outcome measures for implementation or surveillance, or studies involving editorials, commentaries, conference abstracts, or protocols were excluded.

Search Strategy

A systematic literature search was conducted in PubMed/MEDLINE, Web of Science, and Google Scholar. The initial search was conducted on May 15, 2026, while an updated search was conducted on May 27, 2026 to identify additional eligible studies published or indexed since the initial search. Database-specific search strategies combined controlled vocabulary, where available, with free-text terms and Boolean operators. Complete search strategies, including database-specific syntax, search dates, and applied filters, are presented in Appendix Table A1. Keywords include “communicable disease surveillance,” “outbreak surveillance,” “digital surveillance,” “outbreak prediction,” “AI,” and “low- and middle-income countries” or “LMICs.”

The search concepts were structured using explicit Boolean logic, with synonyms within each concept combined using the OR operator and the main concepts combined using the AND operator. Parentheses were used to define the order of operations for each concept and to ensure that database-specific searches were reproducible. For Google Scholar, the predefined search terms were conducted as one combined search, and results were screened in order of relevance according to the predefined screening approach. A preliminary scoping search of IEEE Xplore and the ACM Digital Library predominantly identified algorithm-development and technical validation studies without implementation or health-system outcome data. Consequently, these databases were not included in the formal systematic search. Grey literature was searched through relevant institutional and organisational websites, including the World Health Organization (WHO) and Africa Centres for

Disease Control and Prevention (Africa CDC). The search was conducted using the predefined terms “digital disease surveillance,” “infectious disease surveillance,” “digital health surveillance,” “early warning systems,” “emerging infectious diseases,” “pandemic preparedness,” and “low- and middle-income countries” for publications between January 2015 and May 2026. Records identified through grey-literature searching were screened using the same eligibility criteria applied to database records. The complete search strings for the databases, the number of results reviewed for each search, and the date on which each search was conducted are reported in Appendix Table A1.

Study Selection

All identified records were exported to Endnote reference management software and duplicate studies were removed. Titles, abstracts, and full-texts were independently screened by two reviewers who were blinded to each other's decisions. Disagreements were resolved through discussion and, where necessary, adjudication by a third reviewer. Pre-formal review pilot screening/calibration exercises were held before full screening. A PRISMA flow diagram was used for documenting the selection process. The study selection process is shown in the PRISMA diagram (Figure 1).

Data Extraction

Two independent reviewers extracted the data with a structured extraction template developed for this review. Information extracted included: study characteristics (author/year); country, study type, type of digital technology/surveillance system, communicable disease focus, and key findings. Additional information pertinent to assessing the risk of bias was also abstracted. Disagreements between reviewers were resolved through consensus, and where necessary, a third reviewer was involved.

Data Synthesis

Because of the methodological variety of the studies included, no meta-analysis was conducted. Rather, narrative synthesis of findings was performed through three sequential stages: descriptive synthesis of study characteristics and outcomes, comparative thematic synthesis of implementation determinants, and development of implementation readiness framework based on recurring implementation themes.

Framework Development Process and Theoretical Positioning

The Digital Surveillance and Artificial Intelligence Implementation Readiness Framework (DSIRF-AI) was developed through an iterative thematic synthesis of implementation determinants identified across the included studies. Thematic

synthesis procedure employing Thomas & Harden (2008) principles was used for the organization and interpretation of the results from various studies to give high level concepts [22]. Two reviewers independently identified implementation barriers, facilitators, and enabling conditions, which were iteratively grouped into candidate domains. Repeated review and refinement continued until the reviewers considered the thematic structure sufficiently comprehensive and stable. The final DSIRF-AI comprised six interrelated readiness domains representing the most consistently reported implementation requirements across the included studies. As an evidence-derived conceptual framework, DSIRF-AI has not undergone external validation through Delphi consensus, stakeholder consultation, expert review, or pilot testing and should therefore be considered for future validation.

Digital health and implementation science principles such as the World Health Organization (WHO) guidance on digital health (2019) [23], Consolidated Framework for Implementation Research (CFIR), and the Nonadoption, Abandonment, Scale-up, Spread, and Sustainability (NASSS) Framework were used to inform the development of the framework [24, 25]. While these existing frameworks shed light on technology, organizational, and contextual dimensions, they lacked evidence with regard to the specific aspects of AI technologies, such as algorithm control, model validation, explainability, fairness, and human oversight. Six recurring domains emerged from the thematic synthesis of the included evidence, while CFIR, NASSS, and WHO digital health guidance informed the conceptual interpretation and positioning of these domains. These domains informed the development of the evidence-based conceptual framework - Digital Surveillance and Artificial Intelligence Implementation Readiness Framework (DSIRF-AI). The DSIRF-AI builds upon these established implementation science frameworks, while

extending them to address the AI-specific implementation requirements.

Quality Assessment

Due to the heterogeneous study designs, design-appropriate quality appraisal tools were selected according to study methodology, rather than one generic tool. The methodological quality and risk of bias were assessed using the following tools: MMAT for mixed-methods studies [26]; ROBINS-I for non-randomised studies of interventions [27]; ROB 2 for randomised trials [28]; Cochrane EPOC risk-of-bias criteria for interrupted time-series studies [29]; CASP checklists for qualitative and cohort studies [30]; PROBAST+AI for prediction-model studies [31]; and appropriate JBI critical appraisal tools for descriptive, cross-sectional, and operational studies [32]. Evaluation included the clarity of the objectives, suitability of the study design, data collection procedures, reporting of outcomes, implementation level of the study, and risk of bias. Individual assessments were interpreted according to the criteria of the respective appraisal tools. For synthesis across heterogeneous study designs, study-level judgements were summarised as low, moderate, or high risk of bias based on the overall pattern of domain-level concerns. Study-level assessments are presented in Appendix Table A3.

Quality assessment informed interpretation of findings but did not determine study exclusion. Studies with higher risk of bias remained included in the synthesis, but their findings were interpreted more cautiously. Findings supported by studies with lower or moderate risk of bias were considered more robust, while findings supported mainly by studies with higher risk of bias were reported with appropriate caution. Similarly, the development and interpretation of the DSIRF-AI framework considered the overall strength and limitations of the underlying evidence, without excluding domains identified from studies with higher risk of bias.

Results

Study Selection

There were a total of 348 records identified during the database search. Following duplicate removal, 333 records underwent title and abstract screening, after which the remaining 81 records were reviewed for full-text eligibility. Seventeen studies met the eligibility criteria and were included in the final synthesis. Also, 35 grey-literature records were identified, 22 were screened after removal of clearly irrelevant records, and none was included in the final synthesis. In addition, the reference lists of all studies meeting the eligibility criteria were manually screened to identify potentially relevant additional studies.

Reference-list screening identified 18 additional records, of which 3 met the eligibility criteria and were included in the final synthesis. Overall, 17 studies were included in the final synthesis. Records identified through database searching, grey-literature searching, and citation searching were incorporated into the study-selection process and are reported in the PRISMA flow diagram (Figure 1).

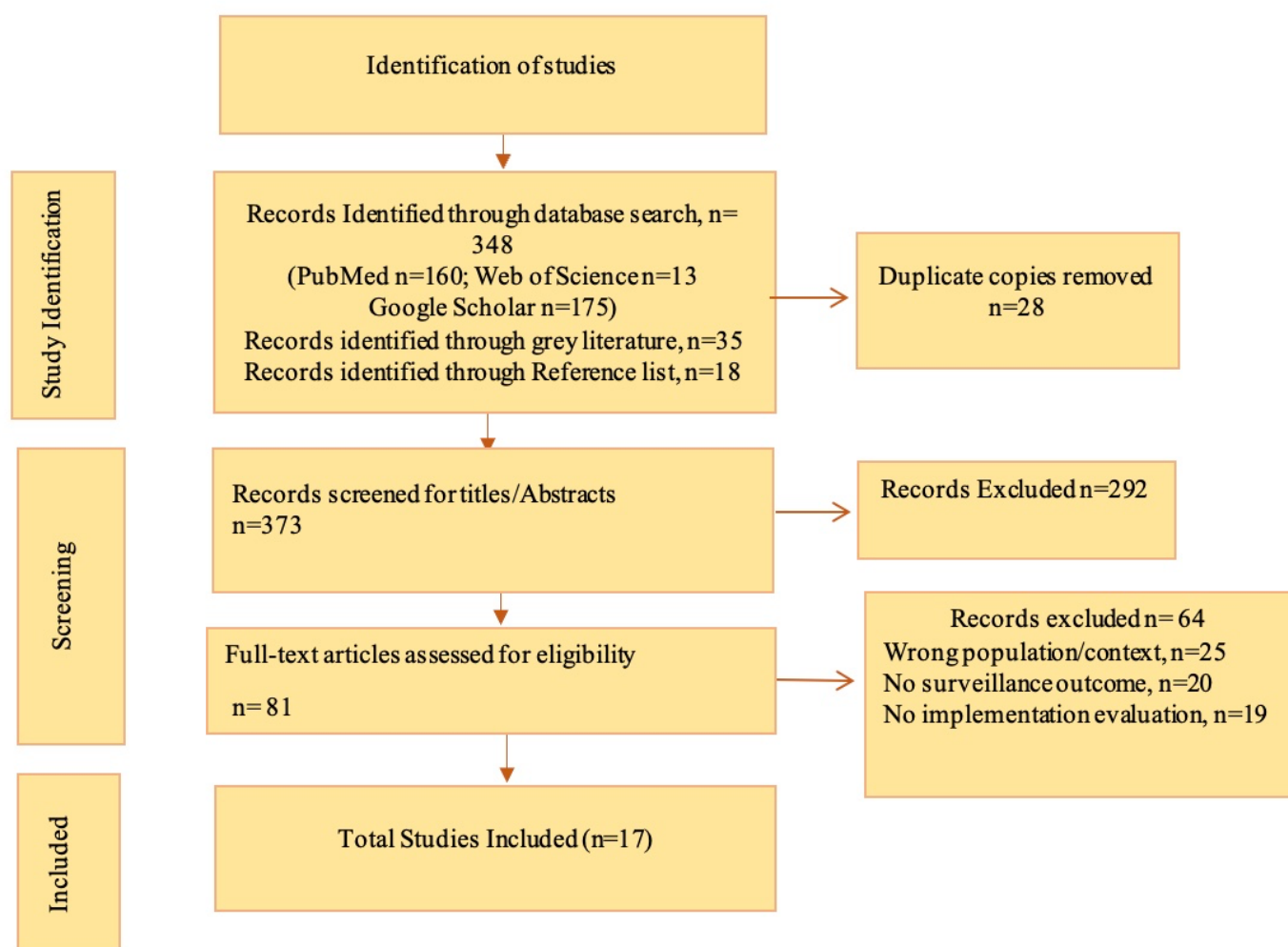


Figure 1. Showing PRISMA flowchart for study selection

Characteristics of Included Studies and Evidence Profile

The included studies had a wide variety of study designs, including qualitative, mixed-methods, pilot, time series, and implementation studies. The majority of the studies were conducted from Africa (n=15), with only a few from other LMIC regions (n=2). Overall methodological quality was moderate across most studies. Fifteen studies were judged to have moderate risk of bias, while two studies were judged to have high risk of bias. The main concerns included absence of comparator groups, selection and reporting bias, confounding, limited baseline or follow-up data, and limitations in generalisability. Table A2 presents the characteristics of included studies, while Table A3 presents the methodological/risk of bias assessment (Appendix).

Digital surveillance interventions were associated with improvements in reporting timeliness, reporting completeness, surveillance data availability, and outbreak signal detection [3, 11, 13, 33-36]. By contrast, evidence supporting AI-assisted surveillance was limited and largely confined to prediction and decision-support applications [37, 38]. Most studies

evaluated process indicators rather than epidemiological or health outcomes, with few assessing impacts on outbreak control, disease transmission, or health system performance [2, 11-13, 33-35, 39]. A small number of studies focused on processes of implementation, governance, sustainability, and population-level outcomes related to outbreak surveillance and response [4, 10, 17, 18, 36, 40].

Comparative Performance of Digital and AI-Supported Surveillance Approaches

Five main trends in surveillance were identified. Instead of presenting as competing technologies, these approaches reflected different stages in the maturity of the surveillance capability, as well as differing in how much complexity is involved in the implementation.

Electronic Surveillance and Reporting Systems

This category of electronic surveillance and reporting systems was the most consistently assessed category across the evidence base. Electronic reporting systems represented the largest category of interventions and demonstrated consistent operational improvements across multiple LMIC settings. Studies

highlighted that successful implementation depended on governance, infrastructure, workforce capacity, and technical support [3, 18, 34, 35]. This was reflected in the use of electronic systems for integrated design and architecture, which aimed to replace fragmented paper-based systems [40, 41]. On the implementation angle, however, there were limitations found regarding poor technical support, weak digital infrastructure, and fragmented accountability [10, 17].

Mobile and Participatory Surveillance Systems

Mobile and participatory surveillance systems broadened surveillance beyond traditional reporting lines as highlighted by Yano et al. (2018) [11]. The findings suggest that community-generated reports and use of mobile technologies were effective at identifying events, broadening geographic reach, and enabling earlier recognition of unusual signs of disease outbreak [12, 13, 33]. These approaches were more strongly associated with increasing surveillance sensitivity and engagement of communities, relative to routine electronic reporting systems. Several studies reported high levels of community engagement and participation over repeated surveillance periods, although evidence on long-term implementation support and comparative performance remained limited [11, 13, 33]. The results indicate that expanding surveillance reach is not always tied to increased quality of surveillance data, unless that information can also be validated, integrated, and utilized in established response processes.

Event-Based Surveillance and Outbreak Intelligence Systems

Event-based surveillance systems were associated with more comprehensive disease intelligence by integrating formal and informal information sources. Tetuh et al. (2023) suggested that adding health facility alerts, community alerts, environmental observations, media alerts, and laboratory information may improve sensitivity to rare events and enhance situational awareness [2]. Compared with routine reporting systems, event-based systems seemed effective for enabling early public health action, which included being more involved in detecting new threats rather than waiting for reports to be made [38]. But effectiveness was based on the capacity of sectors to receive signals and trigger response actions. These findings emphasise that rapid detection must be accompanied by timely public health response. Improvement in surveillance can only be recorded when decision-makers can act on the information and have the means to respond effectively and on time.

AI-Supported Surveillance and Predictive Intelligence

Only a small proportion of the included studies directly evaluated AI-assisted surveillance systems [37, 38]. Consequently, findings relating to AI should be interpreted cautiously, as the current evidence base remains substantially smaller than that for broader digital surveillance interventions. Evidence of AI-supported surveillance showed increasing interest in expanding surveillance from observations to prediction and automated signal detection. Applications included outbreak forecasting and early detection using machine learning and epidemic intelligence approaches [37, 38]. Incorporating AI tools in surveillance can offer maximum benefit in scenarios involving large and complex surveillance data that surpass what traditional analytical methods can handle. Evidence on direct public health impact was more tenuous, though. The results illustrate that the utility of AI for communicable disease surveillance is not so much driven by the complexity of the algorithms and models, but by how easily health systems are able to utilize, understand, and integrate AI outputs. Overall, AI applications remain promising, but evidence from real-world LMIC implementation studies is currently insufficient to determine effectiveness across diverse settings.

Genomic and Integrated Surveillance Platforms

The most advanced surveillance architectures found in this study included systems based on genomic and integrated surveillance [18, 39]. These integrated systems drew on combinations of epidemiological, laboratory, environmental, and digital information streams to potentially facilitate pathogen characterization, enhance outbreak detection and attribution, and inform planning for outbreaks and other events [18, 35, 39]. These techniques have the potential to strengthen surveillance information; however, they require a significantly greater amount of resources to implement. Critical infrastructure investments, specialised technical capacity and interoperability, organisational governance maturity, and institutional commitment played a key role in successful implementation [10, 17, 18, 36]. The evidence suggests that capability for integrated surveillance is a reflection of the stages of health system readiness, rather than technology development [17, 18, 36].

Implementation Determinants and Emergence of Readiness Domains

Although surveillance technologies differed substantially across studies, implementation determinants showed notable consistency. These recurring determinants informed the development of six readiness domains within the DSIRF-AI framework.

Importantly, these determinants did not operate independently - infrastructure influenced data quality; governance shaped accountability; workforce capability affected interpretation; algorithmic readiness influenced trust and adoption; and sustainability

determined long-term system performance. These determinants formed the conceptual basis for the development of the Digital Surveillance and Artificial Intelligence Implementation Readiness Framework (DSIRF-AI).

Development and Presentation of the Digital Surveillance and Artificial Intelligence Implementation Readiness Framework (DSIRF-AI)

From Evidence Synthesis to Framework Development

Building on the recurring implementation determinants identified, the findings were translated into development of the DSIRF-AI framework. Electronic reporting systems performed best where infrastructure and governance arrangements supported routine operation [3, 18]. Participatory and mobile surveillance approaches depended on workforce engagement, digital access, and institutional integration [12, 13, 33]. Event-based and integrated surveillance systems relied on interoperability, information governance, and response coordination [2, 38]. Emerging AI-supported systems introduced additional requirements relating to predictive modeling, model governance, transparency, validation, explainability, and human oversight [37].

Conceptual Structure of the DSIRF-AI

The DSIRF-AI framework comprises six interrelated readiness domains, namely: governance, technology, workforce, data intelligence, algorithmic, and sustainability readiness. Governance readiness reflects the presence of clear leadership, accountability structures, policy alignment, intersectoral coordination, institutional ownership, and ethical oversight needed to guide and support surveillance implementation. Technology readiness reflects the availability, interoperability, functionality, and maintenance of digital infrastructure. Workforce readiness encompasses human resource capacity, digital competencies, training, and organisational support. Data intelligence readiness addresses data quality, integration, interoperability, security, analytics, and the translation of surveillance data into actionable intelligence. Algorithmic readiness relates to the transparency, validation, fairness, explainability, monitoring, and human oversight of AI algorithms. Sustainability readiness considers long-term financing, institutional ownership, scalability, continuous system improvement, and resilience.

Detailed Description of Readiness Domains Emerging from Evidence Synthesis

Governance Readiness

Governance readiness was identified as one of the determinants most commonly reported across surveillance approaches. The evidence consistently

made reference to structures that need to be in place to help organize, share, and integrate surveillance information into decision-making and ensure ownership [4, 10, 17]. The synthesis revealed four shared needs of governance: plans for operational accountability and inter-sectoral coordination, policy alignment, leadership structures, and ethical oversight [4, 10, 17]. Governance ensures oversight over AI-supported surveillance systems, in order to maintain trust in the surveillance process. These are reflected in surveillance arrangements, guidelines for national implementation, and accountability structures [4, 10, 17].

Technology Readiness

Studies consistently demonstrated that reliable infrastructure, interoperability, connectivity, and user-centered system design were essential for effective implementation [3, 18, 36]. Meanwhile, a study by Kaburi et al. (2023) indicated that weak support during implementation was not associated with sustained improvement after technology implementation. Indicators include interoperability, infrastructural coverage, platform reliability, availability of technical support, and integration into the regular workflow.

Workforce Readiness

Workforce readiness centred on ensuring that personnel possessed the technical, analytical, and implementation competencies required to operate surveillance systems effectively. Barriers such as technical skills shortages, surveillance competence, analytic competence, and implementation support skills were identified as factors that hindered conducting effective surveillance [3, 17]. Aside from competency in operational surveillance, workforce readiness was required in integrated surveillance for investigation, analysis, and interpretation [18, 36]. Indicators include digital literacy, capacity to investigate outbreaks, analytical competence, training coverage, and support systems for implementation [3, 10, 17].

Data Intelligence Readiness

Evidence consistently highlighted data quality and interoperability as prerequisites for translating surveillance information into timely public health action [38]. Data completeness, timeliness, interoperability, representativeness, validation, and

governance structures were identified as important determinants of the quality, reliability, and usability of surveillance systems [35]. Institutions required mechanisms for information interpretation, output validation, and linkage of findings to operational action [18, 36]. Illustrative indicators include data quality, analytic workflows, governance processes and system interoperability success.

Algorithmic Readiness

AI-focused studies identified additional implementation requirements extending beyond conventional digital readiness. Studies describing predictive surveillance and automated analytics identified additional requirements, including validation, transparency, and monitoring [37, 38]. Institutional capacity was required to govern model outputs and integrate predictions into operational decision processes. Indicators include documented validation procedures, model monitoring processes, audit structures, and human oversight mechanisms.

Sustainability Readiness

Sustainability readiness reflected the long-term institutional capacity required to maintain surveillance systems beyond initial implementation. Different implementation contexts recorded recurring challenges, such as fragmented ownership, workforce instability, infrastructure limitations, weak institutional integration, and sustainability of implementation [4, 10, 36]. Surveillance gains were more sustainable when implementation was integrated within routine systems [4, 18, 36]. Examples of indicators include maintenance planning, institutional ownership, financing continuity, workforce retention, and policy integration.

Table A4 presents a summary of the readiness domains along with their operational indicators (Appendix).

Relationship Between DSIRF-AI and Implementation Science Frameworks

The DSIRF-AI extends established implementation science frameworks by incorporating AI-specific implementation requirements identified through this review. It is important to note that technology, users, organization, policy, and health-system context do not exist in isolation, rather, they interact in ways that facilitate successful adoption and implementation of health innovations [24, 25].

Studies by NASSS and the WHO shed some light on the role of contextual factors, organizational readiness, and processes of implementation in predicting intervention implementation success [24]. However, they lack information about new requirements on the use of artificial intelligence (AI) in surveillance, like testing of algorithms, explainability, analysis of bias, accountability, and human oversight.

Based on these findings, DSIRF-AI extends these insights and incorporates AI-readiness lessons into communicable disease monitoring. This comparison is provided in Table A5 (Appendix).

Applying DSIRF-AI to Surveillance Planning and Implementation

Intended Users and Practical Application of DSIRF-AI

DSIRF-AI may be used by policy makers, programme managers, surveillance teams, and implementing organizations during surveillance planning, deployment, and evaluation. At the implementation level, programme managers, surveillance coordinators, and implementation teams may use the framework before deployment to assess whether enabling conditions are sufficiently established to support successful implementation. For operational users, including surveillance officers, public health practitioners, and outbreak response teams, the framework may support routine evaluation of surveillance outputs and how they are translated into actionable decisions and response activities. In practical terms, engagement with the framework follows four implementation steps:

Step 1: Assess readiness across the six domains.

Step 2: Identify implementation gaps and prioritize corrective actions.

Step 3: Align surveillance deployment with identified implementation prerequisites.

Step 4: Monitor implementation performance and refine system capability over time.

Through this process, DSIRF-AI functions not as a maturity scoring tool but as a structured implementation approach designed to strengthen the conversion of surveillance output into sustainable public health outcomes. Figure 2 presents the DSIRF-AI, while Table 2 presents the practical engagement pathways with DSIRF-AI.

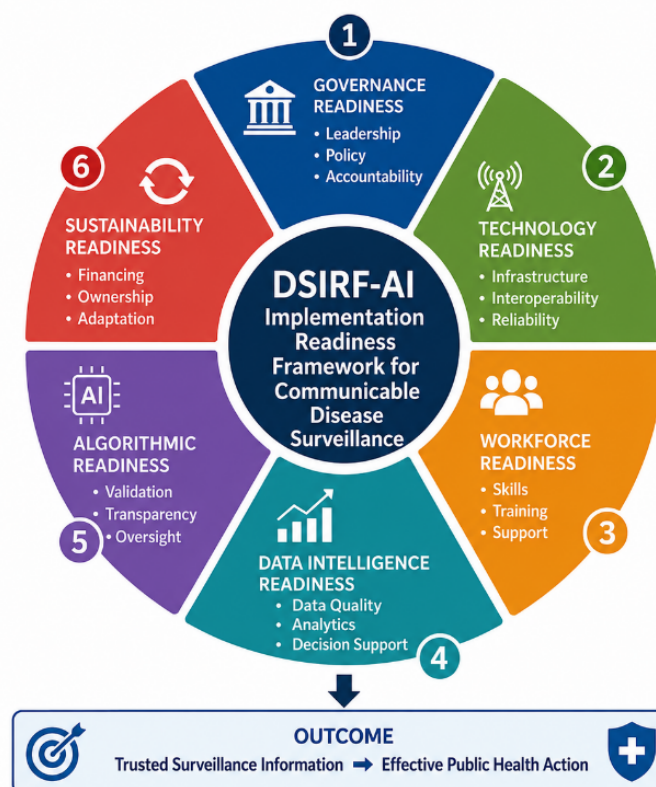


Figure 2. The Digital Surveillance and Artificial Intelligence Implementation Readiness Framework (DSIRF-AI).

The framework illustrates how the proposed readiness domains may facilitate digital surveillance implementation and support the translation of surveillance data into actionable intelligence. The

framework aims at being an implementation plan and evaluation framework, requiring empirical testing and validation.

Table 2. Practical Engagement Pathway for DSIRF-AI Implementation.

Source: Developed from evidence synthesis and informed by implementation science frameworks including CFIR, NASSS, WHO digital health guidance, and surveillance implementation literature) [23, 10, 24, 25].

DSIRF-AI Domain	Implementation Question	Key Engagement Activities	Expected Implementation Outcomes
Governance Readiness	Is the health system prepared to govern, own, and lead digital and supported surveillance?	Develop surveillance policies; define leadership roles; establish governance and accountability structures; align digital and AI tools with national surveillance priorities; establish ethical and regulatory oversight	Strong ownership, institutional integration, trusted implementation, and improved decision governance
Technology Readiness	Is the digital environment capable of supporting interoperable and scalable surveillance systems?	Assess connectivity; select context-appropriate technologies; ensure interoperability; establish maintenance mechanisms; prepare infrastructure for AI-informed analytics	Reliable data flow, reduced reporting delays, stronger system integration
Workforce Readiness	Are users capable of operating, interpreting, and acting on digital and AI-supported surveillance outputs?	Conduct training; strengthen supervision; develop digital and analytical skills; build AI literacy; establish technical support networks	Improved data quality, better system utilization, stronger interpretation of surveillance results

DSIRF-AI Domain	Implementation Question	Key Engagement Activities	Expected Implementation Outcomes
Data Intelligence Readiness	Can surveillance information be transformed into timely and actionable public health intelligence?	Establish analytics workflows; define alert thresholds; strengthen data governance; integrate surveillance with response teams; improve information feedback loops	Faster outbreak recognition, improvement in prioritization, evidence-informed public health decisions
Algorithmic Readiness	Is the system prepared to implement AI-supported surveillance responsibly and effectively?	Validate models; establish explainability procedures; monitor bias; define oversight processes; maintain human review and performance monitoring	Trust in AI-supported decision-making, safer implementation, improvement in predictive surveillance capability
Sustainability Readiness	Can the surveillance system remain functional after initial implementation and adapt over time?	Develop financing plans; institutionalize systems; monitor performance; establish continuous learning and adaptation mechanisms	Long-term surveillance resilience, sustainable public health value

Discussion

Interpretation of Principal Findings

This review examined the implementation of digital and AI-assisted communicable disease surveillance in LMICs, and synthesised evidence on their reported implementation experiences and outcomes. Digital surveillance was shown to be associated with operational surveillance functions, including timely reporting of findings, reporting completeness, visibility of surveillance data, and timely detection of the presence of outbreaks indicators, whereas only a small proportion of studies directly evaluated AI-assisted systems [37, 38]. Consequently, conclusions relating to AI should be interpreted cautiously and should not be extrapolated beyond the current implementation evidence.

Evidence focused more on process performance than public health outcomes. A range of improvements to reporting speed, information flows, and detection of outbreaks were frequently reported but relatively few studies assessed the impact of such improvements on outbreak control process, transmission, and mortality [15, 16]. The findings showed that rather than being viewed as a standalone technological intervention that directly improves health outcomes, digital disease surveillance should be seen as a supporting system, which yields benefits when information generated from surveillance is analyzed, managed, fed into decision-making, and applied to public health interventions [10, 17]. Much of the existing reviews had concentrated on effectiveness of the digital surveillance systems, however, this review draws on existing evidence to identify and synthesize the determining conditions that enable successful implementation to develop the readiness framework (Figure 2).

AI-Supported surveillance: Opportunity, Constraint, and Readiness

Enhanced efforts were found in the integration of AI into communicable disease surveillance including predictive analytics, automated signal detection, outbreak forecasting, surveillance prioritization, and incorporation of various data flow streams [8, 42-44]. However, most evidence related to AI was derived from a limited number of implementation-focused studies, and the available evidence remains substantially smaller than that supporting broader digital surveillance interventions. AI alone was not shown to directly yield improvements in outbreak response according to the evidence presented in this review. Instead, changes to implementation outcomes (e.g., reliability of infrastructure, information interoperability, data quality, capacity of governance, analytical, and institutional readiness) were found to be more closely associated with factors that promote implementation [1, 10]. The evidence illustrates that AI may support surveillance effectiveness, but implementation and preparedness in the health-system are crucial if the promise of AI is going to be realized, through effective governance and human oversight. Implementation efforts in the future should focus on how digital surveillance approaches contribute to enhancing equity in access, representation, and decision-making. However, surveillance technologies alone are unlikely to produce sustained public health benefits without appropriate governance, workforce capacity, data intelligence, algorithmic oversight, and long-term sustainability mechanisms.

The findings should also be interpreted in the context of substantial heterogeneity across the included studies, which varied in surveillance systems, diseases,

geographical settings, study designs, and outcome measures. This variation limits direct comparison of findings across settings. Future research should prioritise robust implementation evaluations using interrupted time-series analyses, controlled before-and-after studies, pragmatic implementation trials, and longitudinal evaluations that directly link surveillance performance with outbreak response and population health outcomes.

Comparison with Existing Systematic Reviews

The present findings are broadly consistent with previous systematic reviews, which reported that successful digital surveillance depends on governance, workforce capacity, interoperability, and sustainable implementation [10, 16, 45]. Unlike earlier reviews, this review synthesised these recurring implementation determinants into the evidence-derived DSIRF-AI framework, providing a structured implementation readiness perspective for LMIC surveillance systems. Where differences were observed, they largely reflected variation in surveillance platforms, implementation contexts, study designs, and outcome measures rather than contradictory evidence.

Limitations of the Study

This review has several limitations. First, the review was not prospectively registered, however it followed the PRISMA checklist for systematic reviews. Second, the inclusion of only English-language publications may have introduced language-selection

bias and may have resulted in the exclusion of relevant evidence published in other languages. Third, publication bias cannot be excluded because unpublished studies and studies reporting null or unfavourable findings may be underrepresented in the available literature. Fourth, search or database bias may have occurred because the formal search was limited to a selected number of bibliographic databases and relevant studies indexed elsewhere may have been missed. Although supplementary searching was undertaken, differences in database coverage and indexing practices may have affected the completeness of the evidence base. Fifth, despite the use of independent review procedures and iterative discussion during synthesis, some degree of reviewer or synthesis bias may remain because thematic synthesis, interpretation of findings, and the development of framework domains involve judgement. Finally, the DSIRF-AI is an evidence-derived conceptual framework and has not yet undergone external validation through stakeholder consultation, expert consensus, Delphi processes, or empirical pilot testing. These limitations may affect the completeness of the evidence identified, the interpretation of the findings, and the generalisability and practical applicability of the proposed framework. Future research should therefore validate and refine the DSIRF-AI across diverse LMIC settings and with relevant stakeholders."

Conclusion

Digital surveillance systems were associated with improvements in surveillance performance across diverse LMIC settings, whereas evidence supporting AI-assisted surveillance primarily reflects early implementation experience rather than established effectiveness. Evidence suggested that surveillance processes were more dependent on the interpretability of the outputs, governance processes, embedding in operational processes, and maintenance within existing

health systems than the technology itself. The review was designed to close the implementation gap through the development of the DSIRF-AI. The DSIRF-AI offers an evidence-informed conceptual framework to guide implementation planning and sustainability. Sustainable implementation will require appropriate health-system and governance conditions alongside technological capability.

Supplementary Materials

Supplementary file available via: <https://www.journalehdi.com/supplfile/773/ehdi056-suppl-file-APPENDIX.pdf>

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