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Digital Technologies for Global Disease Surveillance: A Scoping Review of Applications, Implementation Challenges, Equity, and Evidence Gaps

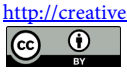
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Abstract

This scoping review mapped the evidence on digital technologies used in population-level disease surveillance and distinguished the findings from proposed or conceptual applications. It aimed to characterize applications, implementation contexts, reported benefits, barriers, equity implications, and evidence gaps. Using Arksey and O'Malley's framework, methodological guidance, and PRISMA-ScR, the authors searched PubMed/MEDLINE, Scopus, Web of Science, Google Scholar, and selected gray literature. These include empirical studies, reviews, conceptual papers, implementation protocols, and relevant nonpeer-reviewed sources. Data were charted according to publication type, setting, disease area, technology, surveillance function, outcomes, barriers, and ethical/equity considerations. The manuscript's extraction summary reports 10 sources in low- and middle-income country (LMIC) settings, nine in high-income country (HIC) settings, and three with global or multi-country scope; these geographical counts require reconciliation with the source-level extraction table before publication because several entries are labelled "global" or span multiple countries. Fifteen sources were reported as addressing infectious diseases, five chronic/non-communicable diseases, and two other surveillance areas; these disease-focus classifications should also be checked against the source-level records. Artificial intelligence/machine learning, participatory or social-media surveillance, and integrated/One Health platforms each appeared in five sources; mHealth appeared in four and EHR-based approaches in three. The review concluded that digital technologies may strengthen disease surveillance, but technological feasibility should not be equated with sustained public health effectiveness. Implementation depends on infrastruc-

ture, interoperability, workforce capacity, financing, governance, community trust, and equity. The included sources provide limited comparable quantitative evidence on effectiveness, economic value, subgroup coverage, or long-term outcomes. Future studies should prioritize real-world validation, implementation science, cost-effectiveness, interoperability, ethical governance, and longitudinal evaluation.

Keywords

Digital Disease Surveillance, Public Health Surveillance, Artificial Intelligence, Mobile Health, Electronic Health Records, Participatory Surveillance, One Health, Interoperability, Health Equity

1. Introduction

Disease surveillance is a core public health function that enables authorities to detect, monitor, assess, and respond to threats affecting populations. Surveillance data supports outbreak detection, risk assessment, policy development, resource allocation, and emergency response. Conventional systems including facility notifications, laboratory reporting, paper-based registers, and periodic aggregation remain important; however, their performance can be constrained by reporting delays, incomplete information, fragmented data flows, and limited population coverage, particularly in resource-constrained settings [1]-[4].

The expansion of digital technology has created additional surveillance opportunities. Artificial intelligence (AI) and machine learning, electronic health records (EHRs), mobile health (mHealth), geospatial systems, social media analytics, participatory reporting platforms, and integrated One Health systems can support automated signal detection, rapid reporting, predictive analysis, community-based event reporting, and the integration of heterogeneous data sources [5]-[8].

The COVID-19 pandemic has accelerated the deployment of digital surveillance tools including digital contact tracing, online symptom reporting, electronic notification systems, geospatial dashboards, and AI-supported analytics. Simultaneously, the pandemic has exposed limitations involving digital exclusion, fragmented information systems, privacy, public trust, governance, and unequal technological capacity [8] [9].

These limitations are particularly relevant in low- and middle-income countries (LMICs) where connectivity, electricity, health information infrastructure, technical workforce capacity, financing, interoperability, and regulatory arrangements may be constrained [2] [4] [10]. Therefore, the value of digital surveillance depends not only on the technology itself but also on the institutional and health system environment in which it is introduced.

The ethical considerations are equally important. Public health surveillance must balance collective protection with privacy, confidentiality, autonomy, fairness, and nondiscrimination [1] [9]. Digital systems may introduce additional

risks related to data ownership, cybersecurity, algorithmic bias, transparency, secondary use, and surveillance beyond legitimate public health purposes [11] [12].

Although previous reviews have examined specific technologies or applications, including social media, COVID-19 technologies, EHR-based surveillance, and the One Health System [5] [7] [8], the evidence remains heterogeneous. Therefore, broad mapping is useful for identifying a range of technologies, implementation challenges, and areas in which the evidence remains insufficient.

Aim and Review Questions

This scoping review aimed to map the applications of digital technologies in population-level disease surveillance and identify reported implementation approaches, benefits, limitations, ethical considerations, equity implications, and evidence gaps.

1) Which digital technologies have been applied to population-level disease surveillance?

2) Which diseases, surveillance functions, populations, and geographical settings have been addressed?

3) How have digital technologies been implemented or integrated into public health systems?

4) What benefits and outcomes have been reported and what types of evidence support these claims?

5) What technical, organizational, financial, ethical, legal, and equity-related barriers have been identified?

6) What evidence gaps and research priorities remain?

2. Methods

2.1. Study Design and Methodological Framework

A scoping review design was selected because the evidence encompassed heterogeneous technologies, surveillance functions, disease areas, geographical contexts, and publication types. This review was informed by Arksey and O'Malley [13], refined by Levac *et al.* [14], and reported in reference to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) [15]. The purpose was to map the breadth and characteristics of the evidence rather than calculate a pooled intervention effect.

A protocol was developed internally but was not prospectively registered.

2.2. Eligibility Criteria

Eligibility was structured using a population-concept context approach. The population comprised human populations represented in public health surveillance data. The concept comprises digital technologies used to identify, collect, integrate, analyze, communicate, or respond to population-level disease signals. The context included national, subnational, facility-linked, community-based, cross-border, and global surveillance systems in high-, middle-, and low-income settings, respectively.

The evidence base included empirical research; systematic or scoping reviews; conceptual frameworks; implementation protocols; selected policy or consensus sources; and selected non-peer-reviewed evidence, where the source provided relevant methodological, implementation, or system information. Because these source types differ substantially in evidentiary strength, they are not treated as equivalent evidence of effectiveness.

Sources were excluded if they focused exclusively on individual clinical care without a population surveillance function, addressed only clinical decision support, described technology without disease surveillance application, or lacked sufficient information to determine eligibility. The original review also excluded non-English publications; this restriction should be acknowledged as a potential source of language and geographical biases.

2.3. Information Sources and Search Strategy

We searched PubMed/MEDLINE, Scopus, Web of Science, Core Collection, WHO IRIS, CDC Stacks, medRxiv, bioRxiv, and Google Scholar databases. Database searches were conducted between January 2020 and June 2026.

2.4. Search Strategy

The search combined controlled vocabulary, where available, with free-text terms related to disease surveillance and digital technology. The manuscript records the following core search concepts; however, the complete database-specific strategies, exact search dates, source-level record totals, and Google Scholar/grey-literature selection rules must be supplied in the Supplementary Materials to make the search reproducible:

* ("Disease surveillance" OR "public health monitoring") AND ("technology" OR "digital health")

* ("Artificial intelligence" OR "AI" OR "machine learning") AND ("disease surveillance" OR "syndromic surveillance")

* ("Electronic health records" OR "EHR") AND ("infectious disease surveillance")

* ("Mobile health" OR "mHealth") AND ("outbreak tracking" OR "disease reporting")

* ("Social media" OR "participatory surveillance") AND ("disease tracking")

* ("One Health") AND ("digital surveillance" OR "zoonotic tracking")

2.5. Study Selection

All retrieved records (n = 119) were exported to Mendeley and de-duplicated using automatic and manual methods before import into Rayyan. Title/abstract screening was performed by a single reviewer; the manuscript does not document independent verification of those decisions. Full texts were assessed by one reviewer, and a second reviewer randomly verified 20% of full-text assessments. The extraction materials available for this revision do not identify the randomization

procedure or provide reviewer-level decision records. Disagreements were resolved through consensus where they were identified. Single-reviewer screening and partial full-text verification may have introduced selection or classification errors.

One primary reason for exclusion was recorded for each full text source. The selection process is illustrated in the PRISMA-ScR flow diagram (Figure 1).

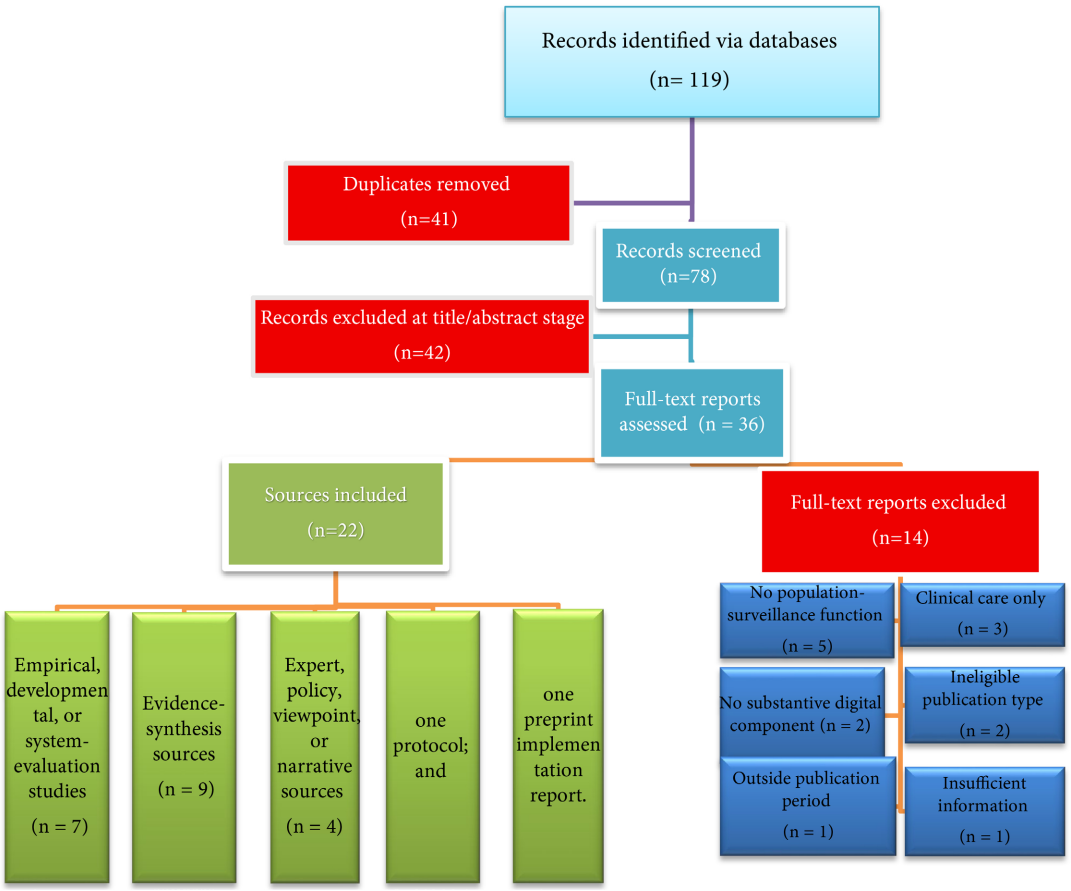


Figure 1. The PRISMA flow chart clearly outlines study selection process from initial record identification down to final inclusion. (n = 22).

2.6. Data Charting

Data were charted using a structured approach. The variables included full citations, publication year, country or region, World Bank income classification, publication type, peer-review status, disease or condition, population and surveillance level, digital technology, data source, surveillance function, implementation setting, stakeholders, reported benefits, measured outcomes, implementation barriers, ethical and privacy concerns, equity implications, financing and sustainability considerations, and the authors' reported limitations.

2.7. Analysis and Synthesis

Evidence was synthesized descriptively using counts and percentages. Each source

was assigned a primary technology category for the purpose of mutually exclusive descriptive percentages; secondary technologies were recorded separately, where applicable. The qualitative thematic synthesis organized barriers and opportunities into seven domains: infrastructure and connectivity, data quality and interoperability, workforce and organizational capacity, financing and sustainability, ethics, privacy and governance, equity and digital inclusion, and validation and evaluation.

No meta-analysis was performed because of substantial heterogeneity in publication type, study design, technology, setting, outcomes, and reporting.

Overlap between primary studies and evidence syntheses could not be quantified from the available extraction table. Where an included review may have summarized primary studies also included independently, findings were not statistically combined and were interpreted narratively. Descriptive counts and percentages refer to included publications/sources, not to independent surveillance systems, unique populations, or participants. This limitation should be considered when interpreting the distribution of technologies and settings.

2.8. Critical Appraisal

Consistent with the mapping purpose of the scoping review, formal risk-of-bias appraisal was not undertaken. Consequently, the review describes the nature and distribution of reported evidence but does not grade certainty or draw causal conclusions about effectiveness.

2.9. Use of Review Software and Artificial Intelligence

Rayyan was used for record management, deduplication support, and screening workflows. All eligibility decisions were verified by human reviewers. Rayyan was not treated as an autonomous reviewer. No generative-AI system was used to determine study eligibility, synthesize findings, or formulate conclusions.

2.10. Data Availability

The complete search strategies, screening decision log, excluded full-text list with reasons, data-charting form, and extracted dataset are provided in the Supplementary Materials.

3. Results

3.1. Study Selection and Characteristics

In total, 119 records were identified. After removing 41 duplicates, 78 unique records were subjected to title and abstract screenings. Forty-two records were excluded and 36 full-text sources were assessed. Fourteen full-text sources were excluded, as shown in (**Figure 1**), leaving 22 sources for final synthesis.

The 22 included sources covered diverse geographical contexts, disease foci, and technological domains. According to the manuscript's aggregate coding, 10 sources (45.5%) were classified as LMIC-focused, nine (40.9%) as HIC-focused,

and three (13.6%) as global or multicountry. The unit of analysis is publications/sources, not patients. These geographical counts should be reconciled with the source-level extraction table before final submission (Figure 2).

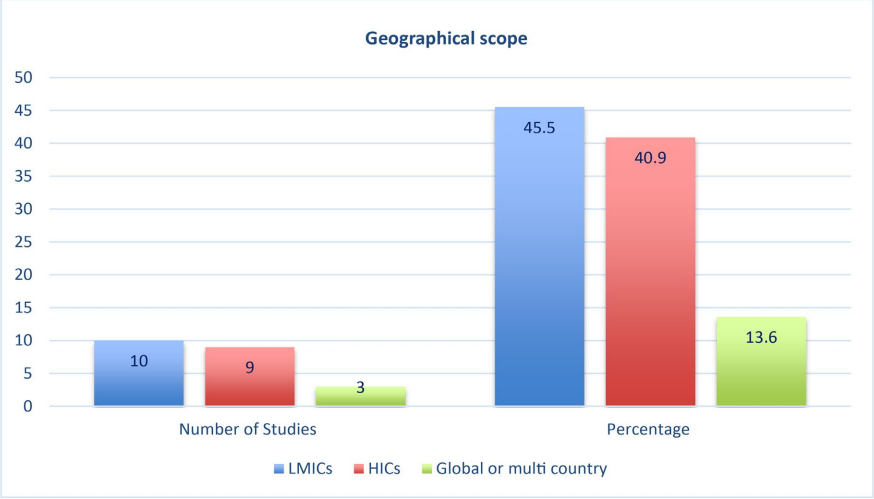


Figure 2. Distribution of studies by geographical scope (n = 22).

The distribution of included sources by primary disease focus is presented in Figure 3.

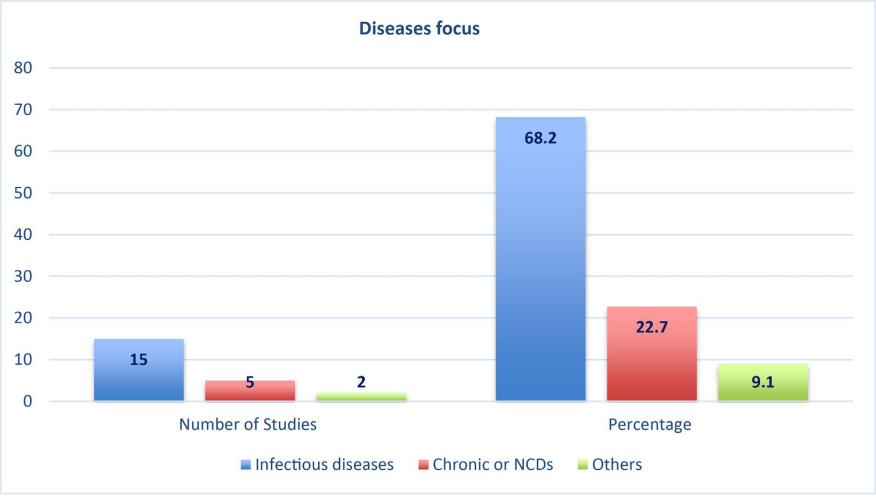


Figure 3. Distribution of studies by primary diseases focus (n = 22).

3.2. Digital Technology Domains

Five broad technological categories are identified. Artificial intelligence and machine learning were represented by five sources (22.7%), participatory surveillance and social media approaches by five (22.7%), integrated digital and One Health platform by five (22.7%), mHealth by four (18.2%), and EHR-based approaches by three (13.6%). These percentages sum to 100%, because each source was assigned a primary technology category (Figure 4, Table 1).

Table 1. Technologies used in disease surveillance across included sources.

Technology category	Sources (n)	Main applications	Key limitations
AI and machine learning	5	Outbreak prediction; syndrome discovery; risk mapping; early warning; syndromic surveillance	Limited prospective validation; data-quality problems; bias; transparency and calibration concerns
mHealth	4	Mobile reporting; symptom reporting; health monitoring; community reporting	Scalability; dependence on pilots/external funding; connectivity and digital-literacy barriers
Electronic health records	3	Automated reporting; case identification; clinical-data linkage; longitudinal monitoring	Interoperability; coding inconsistency; incomplete records; fragmented systems
Participatory surveillance/social media	5	Community reporting; symptom reporting; event monitoring; risk communication	Misinformation; representativeness; privacy; platform and algorithmic bias
Integrated/One Health platforms	5	Human-animal-environmental surveillance; zoonoses; pandemic preparedness	Institutional silos; incompatible systems; financing; data-sharing and governance barriers

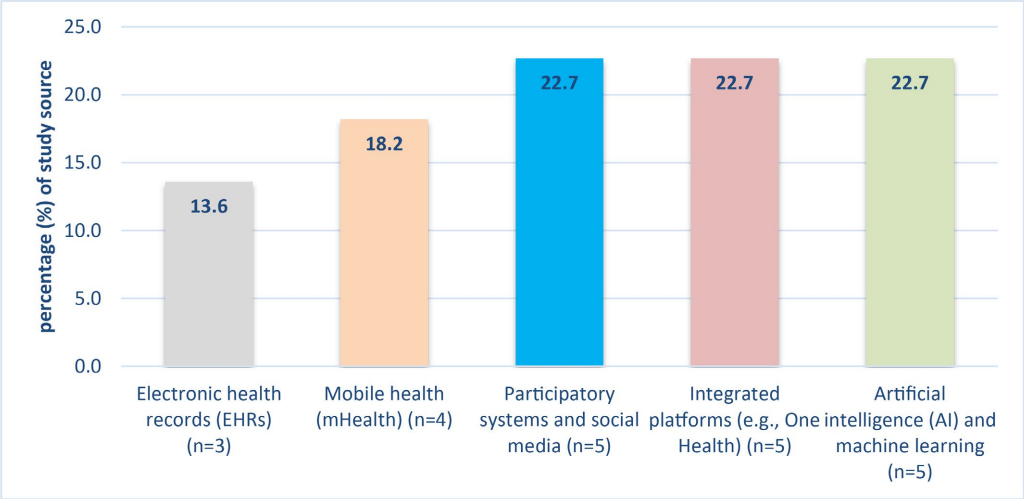


Figure 4. Distribution of studies by primary digital technology category (n = 22).

3.3. Nature and Strength of the Evidence

The 22 included sources were methodologically heterogeneous. The source-level extraction table identifies the following design labels (some categories overlap and should not be treated as mutually exclusive): conceptual/review; observational survey with geospatial analysis; expert consensus; review/overview; Delphi protocol; scoping review; system evaluation; applied system report; mixed-methods synthesis; qualitative study; viewpoint/session report; narrative recommendations; review; narrative review; policy overview; development study; implementation lessons (preprint); system-transformation report; prospective cohort; and scoping review. The manuscript's previous grouped totals (nine reviews/evidence syntheses, seven empirical/developmental/system-evaluation sources, four expert/policy/viewpoint/narrative sources, one protocol, and one preprint report) should

not be presented as verified mutually exclusive study-design counts: the preprint is also an implementation report, and several source labels overlap.

- nine reviews or evidence-synthesis sources;
- seven empirical, developmental, or system-evaluation studies;
- four expert, policy, viewpoint, or narrative sources;
- one protocol; and
- one preprint implementation report.

The extraction table shows a heterogeneous evidence base that includes reviews, conceptual and narrative sources, expert/policy sources, protocols, empirical studies, and system reports. The protocol by Denny *et al.* describes planned assessment and has no results yet; it should therefore be interpreted as a proposed evaluation, not evidence of effectiveness. The Wu 2025 source is explicitly labelled a preprint and an implementation-lessons source; preprint status is a publication-status attribute, not a study design. The extraction table summarizes reported findings qualitatively but does not consistently provide numerical measures of timeliness, coverage, sensitivity, specificity, false-signal rates, or operational impact. Accordingly, claims of benefit are presented as source-reported or potential contributions, not as established comparative effects. The limited availability of standardized outcome measures, prospective validation, economic evaluation, and long-term follow-up is a finding of this evidence map.

3.4. Reported Barriers

Infrastructure and Workforce Capacity: Digital surveillance depends on electricity, connectivity, functioning hardware, technical support, trained personnel, and reliable data systems. Deficits in these areas constrain their implementation, particularly in resource-limited settings.

Interoperability and Data Quality: Inconsistent coding, incompatible systems, incomplete records, duplicate data, and weak linkages between clinical, laboratory, and public health databases limited integration.

Financial Sustainability: Several technologies have been implemented through time-limited pilots or external funding. Information regarding recurrent costs, national budget integration, maintenance, procurement, and cost-effectiveness is limited.

Privacy and Governance: Reported concerns include data ownership, unauthorized secondary use, cybersecurity, inadequate consent processes, limited transparency, algorithmic bias, and unclear institutional accountability.

Digital exclusion and equity: The extraction table identifies representativeness as a limitation for the Lebanon digital-tracing study (Bassim *et al.*) and identifies underreporting and fragmentation in the Sudan COVID-19 system evaluation (Izzoddeen *et al.*). It also notes limited prospective/operational evaluation and validation across several technology areas. However, the available extraction does not report measured subgroup coverage, missingness, participation rates, or differential surveillance performance by age, sex, disability, displacement, socioeconomic

status, language, or rurality. Therefore, inequitable representation is a plausible risk highlighted by the literature, but the current extracted data do not establish its magnitude or demonstrate that it was measured consistently across included sources. People without internet access, mobile devices, digital literacy, language accessibility, or trust in public institutions may be omitted or underrepresented.

4. Discussion

4.1. Principal's Findings

This scoping review mapped five major digital technology domains of disease surveillance: AI and machine learning, mHealth, EHRs, participatory or social media surveillance, and integrated digital or health platforms. Applications include automated case identification, mobile reporting, syndromic monitoring, predictive analysis, risk mapping, community event reporting, and the integration of human, animal, and environmental information.

Taken together, the included sources describe potential or reported contributions to timeliness, signal detection, community reporting, and data integration, but the extraction table rarely supplies comparable quantitative outcome measures. The prospective cohort by Valerio (2024) is described as enabling early detection of cholera-like diarrhoeal outbreaks in rural Malawi, although no numerical detection or timeliness measure is recorded in the extraction table. Bassim *et al.* (2025) report early-pandemic digital-tracing insights using survey and geospatial data, while the extraction notes representativeness and validation against gold standards as limitations. Kang *et al.* (2024) and Zhang *et al.* (2026) are described as applied/system-transformation reports, but the extraction table does not provide standardized effect estimates. These are source-specific descriptions rather than proof of comparative effectiveness. The evidence base does not establish that one technology is more effective than another or that benefits are sustained at population level.

4.2. Artificial Intelligence and Predictive Surveillance

AI and machine learning are among the most frequently used domains. Reported applications include outbreak forecasting, syndrome identification, risk classification, geospatial prediction, and analysis of large or heterogeneous data streams [16]-[18]. These approaches may also combine laboratory, EHR, epidemiological, environmental, mobility, wastewater, and social media information [17] [18].

The principal limitation is the gap between technical performance and operational effectiveness. Good performance on retrospective datasets does not establish its usefulness in routine surveillance. Performance may change when models are transferred across countries, populations, diseases, or information systems. Data incompleteness, distributional changes, limited external validation, poor calibration, and limited explainability may reduce the practical value. Algorithmic bias may also reinforce existing inequities when training data do not adequately represent the affected populations [11] [12] [19].

Future evaluations should report data provenance, model development procedures, external validation, subgroup performance, calibration, uncertainty, human oversight, and post-deployment monitoring. AI should support, not replace, epidemiological judgement and accountable public health decision-making.

4.3. Mobile Health and Community-Based Surveillance

mHealth can support rapid reporting by community health workers, symptom monitoring, communication between communities and health authorities, and replacement or supplementation of paper-based reporting [20] [21]. Participatory systems may extend surveillance beyond formal healthcare facilities and capture community-level events that would otherwise reach the health system later [21] [22].

Sustainability requires more than just deployment of mobile devices. Long-term financing, training, supervision, technical maintenance, integration with national information systems, network availability, digital literacy, language accessibility, and community trust influence participation and data quality [20] [21]. Without these components, mHealth initiatives may remain small-scale pilots that are difficult to sustain or scale [23] [24].

Evaluations should therefore report participation, missingness, representativeness, retention, false-signal rates, verification processes, costs, and integration with routine response mechanisms.

4.4. Electronic Health Records and Interoperability

EHRs contain routinely collected demographic, diagnostic, laboratory, treatment, and outcome information, and can support automated case detection, reporting, and near-real-time monitoring when linked appropriately to public health systems [25] [26]. However, their surveillance value depends on the completeness, coding consistency, semantic interoperability, data quality, and timely exchange.

Interoperability is broader than adoption of a single technical standard. Effective exchange requires common terminology, data quality rules, patient-matching approaches, governance agreements, cybersecurity safeguards, clear institutional responsibilities, and workforce capacity [25] [27] [28]. Standards such as the HL7 FHIR may facilitate exchange, but implementation outcomes depend on a wider organizational and governance environment.

In LMICs, EHR-based surveillance should be accompanied by investment in foundational digital infrastructure, workforce development, maintenance, data quality, and integrated national health-information systems [3,10,26].

4.5. Participatory Surveillance, Social Media, and Public Trust

Participatory surveillance and social media monitoring can broaden the range of information available to public health authorities and may identify community-level signals before formal healthcare contact [22] [29] [30]. Therefore, their value is complementary rather than necessarily substitutive to conventional surveil-

lance.

Important limitations include noisy data, demographic under-representation, platform and keyword bias, misinformation, privacy concerns, and limited access among people without reliable Internet, smartphones, or sufficient digital literacy [29] [31] [32]. Public participation also depends on trust in the institutions collecting and using data. Therefore, transparent communication, proportionate data use, privacy safeguards, appropriate consent processes, and meaningful community engagement are central to sustainable implementation [1] [33].

4.6. One Health and Integrated Surveillance

The emergence of zoonotic diseases, antimicrobial resistance, food safety threats, and climate-sensitive health risks have reinforced the importance of health surveillance [6] [7] [34]. Integrated digital platforms can connect humans, animals, the environment, food, and other relevant data streams, potentially supporting a coordinated detection and response.

Operational barriers are frequently institutional rather than purely technical barriers. Agencies may use different definitions, operate under different legal mandates, have unequal resources, or lack mechanisms for data sharing [7] [35]-[37]. Therefore, effective implementation requires political commitment, interoperable standards, clear institutional roles, defined data access arrangements, cross-sector governance, sustainable financing, and multidisciplinary workforce capacity.

4.7. Equity, Ethics, Governance, and Public Trust

Equity should be treated as both an implementation requirement and an outcome to be evaluated. A technically accurate digital system may still produce biased surveillance intelligence if rural, low-income, displaced, migrant, minority language, or otherwise digitally marginalized populations are systematically underrepresented [32] [38]-[40]. Digital surveillance should, therefore, supplement, rather than replace, conventional facilities, laboratories, and community surveillance, where digital exclusion is likely.

Ethical risks include privacy and confidentiality, consent, data ownership, secondary use, cybersecurity, stigmatization, discriminatory use, and surveillance beyond legitimate public health purposes [1] [33] [41] [42]. AI adds to concerns regarding bias, transparency, explainability, contestability, and accountability [11] [12] [19] [36]. Governance should be incorporated at the design stage and address necessity, proportionality, transparency, security, access controls, retention periods, auditing, incident response, independent oversight, and community engagement.

4.8. Policy and Practice Implications

- Integrate digital surveillance tools into national surveillance strategies and routine workflows rather than maintaining isolated pilots.

- Invest foundational infrastructure, workforce capacity, maintenance, and local technical leadership, particularly in LMICs.
- Treat interoperability as a strategic requirement and combine technical standards with semantic alignment and enforceable governance agreements.
- Establish privacy, security, transparency, accountability, and community engagement requirements before deployment.
- Evaluate digital surveillance using operational and public health outcomes, equity, cost, sustainability, and usefulness, not technical performance alone.

These implications should be presented as policy considerations arising from a heterogeneous evidence map rather than as causal conclusions supported by pooled effectiveness evidence.

4.9. Future Research

- Longitudinal evaluation of operational sustainability, costs, and public health impacts beyond the pilot phases.
- Implementation-science research examining organizational, behavioral, and structural determinants of integration into routine workflows.
- Equity-focused evaluation measures coverage, missingness, performance, and outcomes across population groups.
- Cost-effectiveness and return-on-investment analyses to inform resource allocation.
- Practical ethical-governance frameworks addressing privacy, consent, data ownership, bias, transparency, and accountability.
- Greater attention is paid to digital surveillance of chronic and non-communicable diseases, which remains less represented than infectious disease surveillance.
- Operational health research evaluating cross-sector data-sharing arrangements and integrated surveillance platforms.

5. Strengths and Limitations

This review can be used to map multiple technological categories, disease areas, geographical contexts, and publication types. It also explicitly considers implementation, equity, ethics, interoperability, and sustainability, rather than focusing only on technical performance.

Nevertheless, this study has several limitations. First, restrictions in English-language literature may introduce language and geographical biases. Second, the field is rapidly evolving, creating a risk that newly published or poorly indexed evidence will be missed. Third, Google Scholar and grey literature searches can be difficult to reproduce without detailed documentation. Fourth, the included sources were heterogeneous and should not be treated as equivalent to the evidence of effectiveness. Fifth, if formal critical appraisal was not undertaken, the methodological quality and risk of bias could not be systematically compared. Sixth, assigning each source to a single primary technology category may underrepresent

the systems that combine multiple technologies. The supplied extraction table does not document quantitative equity indicators (such as subgroup coverage, missingness, participation, or differential model performance) for most sources; equity conclusions therefore primarily identify reported representativeness concerns and anticipated risks, not measured population-level inequities.

6. Conclusions

Digital technologies have been applied across disease surveillance through automated reporting, syndromic monitoring, mobile and community-based reporting, predictive analytics, EHR-based surveillance, social media monitoring, and integrated health platforms. The reviewed evidence suggests that these technologies may support timely data collection, broader reporting coverage, improved data integration, and the earlier identification of potential public health signals.

However, evidence does not justify equating technological feasibility with sustained public health effectiveness. Infrastructure limitations, fragmented information systems, weak interoperability, workforce constraints, uncertain financing, ethical and cybersecurity risks, and digital exclusion remain as significant barriers. Future developments should prioritize integration with existing public health systems, local technical capacity, transparent governance, community engagement, interoperability, and protection of populations that are poorly represented in digital data. Research should move beyond technical demonstrations toward rigorous assessment of real-world effectiveness, equity, cost, scalability, and long-term sustainability.

Author Contributions

Amjad A. I. Dawood: Conceptualization, methodology, literature search, screening and data charting, synthesis, writing—original draft, and writing—review and editing. The author approved the submitted version and accepts accountability for the work.

Ethics Statement

The study did not involve direct interactions with human participants, animal experiments, or the collection or processing of identifiable private clinical data or biological tissues.

Copyright & Rights

The PRISMA-ScR checklist and documentation were copyrighted by the Unity Health Toronto and St. Michael Hospital (2019). The checklist and flow diagram are freely available for non-commercial academic use, credit is provided, and the original paper is cited.

Self-Citation and Scientific Independence Statement

The author declares that no self-published works or prior personal papers were

included in the reference list of this scoping review to influence citation metrics. All the studies included in this review were selected strictly based on predefined eligibility criteria using a standard search syntax across public databases.

Conflicts of Interest

Dawood declares no competing financial interests or personal relationships that could have influenced the work reported in this scoping review. All institutional affiliations, including Liverpool John Moores University and the Carter Center, are academic and programmatic in nature, and do not pose any commercial or conflicting interests regarding the findings or conclusions of this study.

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Abbreviations

AI—Artificial Intelligence
COVID-19—Coronavirus Disease 2019
EHR—Electronic Health Record
eIDSR—Electronic Integrated Disease Surveillance and Response
HIC—High-Income Country
ICT—Information and Communication Technology
IDSP—Integrated Disease Surveillance Programme
LMIC—Low- and Middle-Income Country
mHealth—Mobile Health
PRISMA-ScR—Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews
WHO—World Health Organization