Research Journal of Humanities and Social Sciences
(An Open Access International Peer Reviewed Journal)
ISSN: 2945-3968

The Role of Artificial Intelligence in Strengthening Public Health Systems

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Abstract
Artificial intelligence (AI) is increasingly viewed as a strategic capability for strengthening public health systems because it can transform large, heterogeneous, and fast-moving data into actionable intelligence for surveillance, prevention, preparedness, resource allocation, and public communication. This paper reviews the role of AI in public health and proposes an implementation framework linking AI inputs, analytic capabilities, public health functions, governance mechanisms, and system-level outcomes. Drawing on recent policy guidance, peer-reviewed literature, and a data-source-driven analytical evaluation structure, the paper shows that AI can strengthen public health systems through earlier disease-signal detection, improved risk stratification, faster emergency response, enhanced communication, and continuous learning. The analytical section specifies data sources, outcome measures, and data descriptions for comparing standard public health workflows with AI-supported workflows. The results show how AI-supported workflows can reduce outbreak detection time, improve response coordination, reduce staff workload, increase public trust, expand equity coverage, and improve cost-effectiveness. The paper emphasizes that AI should not replace public health expertise but should operate as a governed, human-centered, and equity-sensitive infrastructure for timely and accountable decision-making.
Keywords: artificial intelligence; public health systems; disease surveillance; epidemic preparedness; health equity; governance; implementation science; cost-effectiveness

How to cite this article: Farzana N, Razzak A, Uddin B . The Role of Artificial Intelligence in Strengthening Public Health Systems. **Research Journal of Humanities and Social Sciences.2026 Nov 17, 5(5): 147-163**
Source of support: Nil.
Conflict of interest: None
DOI: doi.org/10.58924/rjhss.v5.iss5.p15

Received:	19-10-2026
Revised:	22-10-2026
Accepted	05-11-2026
Published:	17-11-2026

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1. INTRODUCTION

Public health systems are responsible for protecting populations from preventable disease, detecting emerging threats, coordinating emergency response, reducing health inequities, and guiding policy decisions. These responsibilities have become more complex because health threats are increasingly shaped by globalization, demographic change, climate risks, urbanization, antimicrobial resistance, misinformation, and rapid movement of people and goods. Traditional public health information systems often depend on delayed reporting, fragmented administrative data, manual investigation, and limited analytic capacity. As a result, agencies may identify outbreaks late, allocate resources inefficiently, or struggle to communicate risk to diverse communities in real time. [1] [2] [3]

Artificial intelligence provides a potentially transformative set of tools for addressing these system-level constraints. In this paper, AI refers to computational systems that perform tasks normally requiring human intelligence, including pattern recognition, classification, prediction, natural language processing, optimization, and decision support. Within public health, AI can analyze laboratory reports, electronic health records, syndromic surveillance feeds, mobility trends, wastewater signals, environmental indicators, social media content, call-center logs, and genomic sequences. The value of AI lies not only in technical prediction but also in improving the timeliness, reach, and consistency of public health action. [4] [5] [6]

The relevance of AI has increased with the growth of machine learning, cloud computing, interoperable data standards, and large language models. Global and national agencies now describe AI as part of modern public health infrastructure, while also warning that AI must be governed carefully to protect autonomy, privacy, fairness, safety, and accountability. The central argument of this paper is that AI can strengthen public health systems when it is implemented as a socio-technical capability rather than as a stand-alone technological product. AI tools must therefore be connected to public health objectives, validated on local data, interpreted by trained professionals, monitored after deployment, and evaluated for equity and public value. [7] [8] [9]

An important distinction is required between artificial intelligence used in individual clinical care and systems designed for population health. Clinical algorithms commonly optimize patient-level diagnostic or treatment decisions, whereas public-health algorithms are evaluated according to population coverage, timeliness of detection, preparedness, system coordination, and equitable distribution of services. A technically accurate predictor can contribute little to public health if its alerts arrive too late, if health authorities cannot act on them, or if the underlying surveillance feeds omit vulnerable communities. Consequently, this study places implementation outcomes alongside predictive capabilities. [10] [11] [12]

AI-enabled public health can be understood as a sequence of interconnected functions. Collection and standardization of data precede pattern discovery; interpreted signals then enter verification, prioritization, operational response, and public communication. The overall system may fail at any handoff. For example, near-real-time anomaly detection does not necessarily shorten outbreak response if case-investigation workflows remain paper-based. Evaluations should therefore measure not only algorithmic performance but also end-to-end detection-to-action delays, workload, and the distribution of benefits. [13] [14] [15]

The economic dimension is equally important. Resource-constrained health systems face trade-offs among laboratory capacity, workforce allocation, surveillance coverage, digital security, and community outreach. AI may automate routine classification or provide more timely estimates of service demand, but implementation introduces expenses for infrastructure, integration, auditing, staff training, and model maintenance. A realistic appraisal compares total costs and outcomes across established workflows and AI-assisted alternatives rather than interpreting gross software savings as net social benefits. [16] [17] [18]

Health equity is a defining evaluation criterion. Training datasets may reflect unequal access to diagnostic testing, clinical services, internet connectivity, or official reporting. If these historical inequalities are reproduced by automated triage, superficially effective systems may intensify surveillance blind spots. Responsible implementation requires subgroup reporting, participatory design, accessible communication, governance review, and documented redress mechanisms. In low-resource environments, the ability to operate reliably with missing or delayed data may be more important than marginal gains in benchmark accuracy. [19] [20] [21]

This study addresses these concerns through a combined conceptual and implementation-evaluation perspective. Its contributions are the integration of AI applications across public-health functions, the articulation of a governance pathway connecting data to actionable decisions, and a numerical reporting framework organized around six operational outcomes. The numerical comparisons supplied in the source manuscript are retained as reported scenarios; source-level records, site counts, and

estimation code were not provided, so the present revision does not claim independent verification or new causal identification. [22] [23] [24]

2. RESEARCH AIM AND OBJECTIVES

The aim of this paper is to examine how artificial intelligence can strengthen public health systems and to develop a practical framework for responsible implementation. The paper is guided by four objectives: identifying major applications of AI in public health functions, examining system-level benefits for timeliness and resilience, discussing key risks and barriers, and proposing a staged implementation and governance framework for public health agencies, particularly in settings where resources, data infrastructure, and AI workforce capacity are constrained.

The paper combines a conceptual review with a data-source-driven analytical illustration. This combined approach is useful because many public health agencies are currently planning, piloting, or governing AI systems and need clear guidance on the data sources, outcome indicators, and evaluation designs required to assess real-world implementation value.

3. BACKGROUND: PUBLIC HEALTH SYSTEMS AND THE NEED FOR AI

A public health system includes institutions, professionals, legal mandates, data systems, laboratories, community networks, financing arrangements, and governance processes that collectively protect and improve population health. Strong public health systems require timely information, analytical capacity, skilled workforce, community trust, and the ability to translate evidence into action. Weakness in any of these elements can reduce preparedness and response effectiveness [9]

Several recurring problems create opportunities for AI. Public health data are often delayed, incomplete, and stored in disconnected systems. Agencies face growing data volume from electronic records, genomic sequencing, digital platforms, environmental sensors, and mobile technologies [10][11]. Emerging threats often require early detection from weak signals before clinical case reports accumulate, while workforce shortages reduce time for analysis and field response. AI can help address these problems by automating routine tasks, detecting anomalies, forecasting risk, and supporting decision-making.

However, AI adoption also depends on broader data modernization. AI systems require high-quality, interoperable, representative, and secure data. Without these conditions, models may reproduce historical biases, miss underserved populations, or generate misleading alerts. For this reason, AI should be embedded within a public health data strategy that improves data standards, exchange, governance, and workforce training [12].

4. LITERATURE REVIEW

Existing literature shows that AI has been applied to many health-related domains, including medical diagnosis, epidemiological modeling, risk prediction, emergency management, drug discovery, and health communication. In public health, the strongest use cases are those that involve large-scale pattern detection and decision support rather than replacement of professional judgment. AI can support disease surveillance by identifying unusual clusters, classifying case reports, processing free-text clinical notes, and integrating signals from multiple data streams. [25] [26] [27] [28]

Recent public health discussions emphasize that AI must be responsible, evidence-based, and equity-oriented. WHO guidance highlights ethical principles such as protecting

autonomy, promoting human well-being, ensuring transparency, fostering responsibility, ensuring inclusiveness, and promoting sustainable AI. Later guidance on large multi-modal models stresses the need for governance because generative AI can produce persuasive but inaccurate outputs, expose sensitive data, and create new accountability challenges in health settings. The CDC also frames AI as a tool for accelerating detection and response, reducing administrative burden, and improving operational excellence, while emphasizing governance and risk management for generative AI use in public health agencies. [29] [30] [31] [32]

Scholarly reviews identify both promise and implementation barriers. AI can strengthen surveillance, communication, and resource allocation, but adoption is constrained by data fragmentation, limited technical workforce, legal uncertainty, ethical concerns, lack of external validation, weak interoperability, and low trust among professionals and communities. These barriers are particularly important in low- and middle-income countries, where digital infrastructure and representative datasets may be limited. Therefore, AI implementation requires not only technical development but also governance, capacity building, and context-sensitive evaluation. [33] [34] [35] [36]

From a methodological perspective, anomaly-detection systems identify departures from expected patterns in counts, syndromic reports, or event streams. Their operational value depends on sensitivity, false-alert burden, alert lead time, and the ability of investigation teams to distinguish true threats from routine variation. Rare-event settings create a difficult precision–recall trade-off: increasing sensitivity may improve the chance of recognizing an emerging outbreak but can consume scarce staff capacity through unnecessary investigations. Published evaluations therefore need pre-specified alert thresholds and base-rate-aware metrics. [37] [38] [39] [40]

Forecasting and resource allocation constitute a related but distinct stream of research. Time-series models, regression, tree ensembles, and neural architectures can estimate short-term disease burden or health-service demand; optimization then translates those estimates into supply and staffing recommendations. Forecast uncertainty matters because point predictions can be unstable during structural breaks or changes in testing policy. Agencies should compare candidate models against transparent baselines, report prediction intervals, and test decision robustness under plausible departures from forecasts. [41] [42] [43] [44]

A third research stream concerns natural-language processing and generative systems. Text classification can structure free-text surveillance reports, remove duplicates, support coding, and identify emerging concerns in public communication. Generative tools can accelerate drafts and retrieval but may invent citations or produce incorrect clinical claims. Accordingly, public-health uses involving messages to communities, policy briefings, or case definitions should require human review, traceable sources, access controls, and quality assurance. Efficiency gains must be considered together with the cost of checking outputs. [45] [46] [47] [48]

Evaluation designs require particular scrutiny. A simple before-and-after comparison can be confounded by seasonal variation, concurrent modernization initiatives, policy changes, and differences in baseline capacity. A difference-in-differences design offers stronger evidence only when comparable treatment and comparison units, valid pre-intervention trends, appropriately timed exposure, and clustered uncertainty estimation are available. Without those design details, coefficient tables should be interpreted as reported numerical comparisons rather than as identified effects of AI adoption. [49] [50] [51]

Equity-focused implementation research extends evaluation beyond a single average treatment effect. Urban and rural populations may differ in connectivity, health-service availability, and surveillance coverage. Age, income, and language can also alter access to digital public services. Disaggregated coverage statistics are therefore necessary, but observed subgroup changes should not be mistaken for improvements in fairness without uncertainty intervals and clearly specified denominators. Fairness audits must examine both who enters the data and who receives the resulting services. [52] [53] [54]

The governance literature also emphasizes accountability over the full system lifecycle. Risk classification should inform procurement, data protection impact assessment, external validation, model cards, monitoring frequency, and incident response arrangements. Implementation should be staged: low-risk administrative assistance may precede higher-risk prioritization and emergency decision support. Continuous monitoring is necessary because shifts in disease prevalence, population behavior, or reporting practices can weaken deployed models over time. [55] [56] [57]

Together, these streams suggest a gap between algorithm-centered performance reporting and holistic assessments of public-health-system strengthening. A comprehensive evaluation should join technical validity, operational performance, user trust, equity, economic costs, and accountable governance within a common framework. The present paper responds to that gap by organizing its analytical discussion around six observable outcome domains and explicitly separating arithmetic derived from reported values from evidence requiring independent data collection. [58] [59] [60]

Table 1. Core AI applications in public health systems

Public health function	AI application	Expected system benefit	Key governance concern
Disease surveillance	Anomaly detection, syndromic surveillance, NLP case classification	Earlier detection of unusual patterns and faster investigation	False alarms, missed events, data representativeness
Epidemic preparedness	Forecasting, scenario modeling, simulation	Improved planning for hospital demand, vaccines, and workforce	Model uncertainty and overconfidence
Risk stratification	Prediction of high-risk groups and geographic hotspots	Targeted prevention and efficient allocation of resources	Bias, stigmatization, and inequitable targeting
Health communication	Message tailoring, misinformation monitoring, chatbot support	Faster public messaging and broader reach	Accuracy, transparency, and public trust
Operations	Automated triage of reports, document drafting, workflow support	Reduced administrative burden and faster decision cycles	Privacy, human review, and accountability

The works from electrical-grid event detection, change-point detection, foreign-exchange forecasting, biomedical signal classification, and econometric causal inference are included as methodological precedents [61] [62] [63]. They inform potential model architectures for early warning, monitoring, heterogeneous-data processing, and impact evaluation; they are not direct evidence that comparable models have improved disease

surveillance or public-health outcomes. Publication metadata for the author-supplied entries should be checked against publisher records before final submission [64] [65] [66].

5. METHODOLOGY

This paper uses a narrative review, framework-development approach, and data-source-driven analytical illustration. The review focused on three categories of sources: international guidance on AI ethics and governance in health, national public health data modernization and AI strategy documents, and peer-reviewed articles on AI applications, implementation barriers, and public health governance. Sources were selected for relevance to public health systems rather than only clinical medicine.

The synthesis followed four steps. First, major AI use cases were grouped by public health function. Second, expected benefits were interpreted as system-strengthening mechanisms, such as timeliness, accuracy, coordination, workforce support, and equity. Third, risks and barriers were classified into ethical, technical, organizational, legal, and social categories. Fourth, the findings were translated into an implementation roadmap and analytical evaluation structure.

For the analytical component, the evaluation structure uses routine public health data streams that would normally be available in a pilot implementation study. These include surveillance and outbreak-signal records, incident-response coordination logs, workforce time-use data, community trust surveys, service coverage registers, and financial or operational cost records. The selected outcomes are outbreak detection time, response coordination, staff workload, public trust, equity in service delivery, and cost-effectiveness because they capture implementation value beyond technical model accuracy.

For a prospective multisite study, units of assignment and observation should be distinguished. Hospitals, districts, surveillance offices, or weeks might constitute units of intervention, while individual reports and detected signals are nested observations. Measurement rules should be fixed in advance: detection time from signal emergence to verification, coordination as a validated score, workload as hours per worker-week, trust as a survey scale, and equity coverage as the proportion of eligible persons reached. The original paper does not specify these data dictionaries, which limits causal interpretation of its reported numerical comparisons.

For quantitative inference, pre-intervention and post-intervention outcomes should be collected for both AI-exposed and comparable non-exposed sites. A model with unit and time fixed effects can identify a difference-in-differences contrast under the parallel-trends assumption. Cluster-robust standard errors, event-study diagnostics, missing-data reports, subgroup definitions, and sensitivity analyses would be required before presenting effects as empirically established. Cost-effectiveness calculations should explicitly account for initial investment, recurring operating expenses, detected signals, and quality of detections.

6. FINDINGS AND DISCUSSION

The review indicates that AI can strengthen public health systems through multiple reinforcing pathways. The strongest contribution is not limited to prediction accuracy; rather, AI can improve the speed and quality of decision-making across the public health cycle, including detection, verification, prioritization, response, communication, monitoring, and learning.

6.1 AI for Disease Surveillance and Early Warning

Disease surveillance is one of the most important areas for AI adoption. AI can strengthen surveillance by detecting statistical anomalies, classifying unstructured reports, linking duplicate records, identifying spatial clusters, and integrating multiple early-warning signals. However, surveillance AI must be carefully evaluated because false alarms can overwhelm staff, while missed events can create a false sense of security. Accuracy also depends on representative data, especially for underserved communities.

6.2 AI for Risk Stratification and Targeted Prevention

AI can support targeted prevention by identifying groups, places, or periods associated with elevated health risk. In infectious disease control, AI can help prioritize vaccination outreach, testing sites, contact tracing resources, and community interventions. However, risk prediction can reproduce inequities if models rely on biased historical data. AI-supported targeting should therefore be combined with equity analysis and community engagement.

6.3 AI for Emergency Preparedness and Response

Public health emergencies require fast coordination across surveillance teams, laboratories, hospitals, emergency management agencies, and community organizations. AI can support preparedness by forecasting demand for hospital beds, vaccines, medicines, and workforce capacity. Optimization models can help allocate resources under constraints, while generative AI can assist briefings and communication drafts when outputs are reviewed by qualified professionals.

6.4 AI for Public Health Communication and Community Engagement

Public health communication is challenged by misinformation, language barriers, and low institutional trust. AI can help monitor public concerns, analyze misinformation trends, translate messages, tailor content, and support chatbots for frequently asked questions. Responsible communication requires transparency, human review, multilingual validation, plain-language standards, and feedback channels.

6.5 AI for Operational Efficiency and Workforce Support

Public health agencies often face workforce shortages and high administrative workloads. AI can reduce burden by assisting with document drafting, coding, report classification, data cleaning, duplicate detection, meeting summaries, literature scanning, and internal knowledge retrieval. These uses may serve as practical entry points for agencies beginning AI adoption, provided privacy and review policies are in place.

Table 3. Benefits, risks, and mitigation strategies for AI in public health

AI-enabled benefit	Public health example	Main risk	Mitigation strategy
Timeliness	Rapid detection of abnormal disease signals	False positives or false negatives	Threshold calibration, human triage, continuous evaluation
Efficiency	Automated report classification and drafting	Privacy leakage or unapproved tool use	Approved platforms, data-use policy, staff training
Precision	Targeted outreach to high-risk groups	Bias and stigmatization	Equity audit, explainability, community review
Coordination	Forecasting resource needs during emergencies	Overreliance on uncertain forecasts	Scenario ranges, uncertainty communication, expert review
Learning	Program evaluation and policy feedback	Model drift and outdated	Post-deployment monitoring and periodic retraining

		assumptions	

Table 4. Proposed governance checklist for AI adoption in public health

Governance domain	Key questions	Evidence required before scale-up
Purpose and necessity	What public health problem does the tool solve? Is AI necessary?	Problem statement, alternatives considered, expected public value
Data governance	Are data accurate, representative, secure, and legally usable?	Data inventory, privacy assessment, interoperability plan
Model validation	Does the tool perform well on local data and subgroups?	Validation report, subgroup metrics, uncertainty analysis
Human oversight	Who reviews outputs and makes decisions?	Workflow map, role descriptions, escalation procedures
Transparency	Can affected stakeholders understand the tool use?	Public documentation, model card, communication plan
Monitoring	How will drift, errors, and harms be detected?	Post-deployment monitoring dashboard, audit schedule
Accountability	Who is responsible for correction and redress?	Governance committee, vendor clauses, incident response plan

7. PRIORITIZING AI USE CASES

Not all AI applications should be adopted at the same speed. Public health agencies should prioritize use cases by balancing expected public health value against implementation and ethical risk. Lower-risk starting points include administrative automation, internal knowledge retrieval, and assisted report drafting, provided privacy safeguards are in place. Higher-risk applications include predictive risk scoring, automated resource allocation, and emergency decision support because errors may directly affect communities and policy decisions.

A practical prioritization strategy is to begin with tools that reduce staff burden and improve data quality, then move toward decision-support systems only after governance capacity matures. Public health value should be measured not only by model accuracy but also by improved timeliness, reduced inequity, better communication, and stronger community trust.

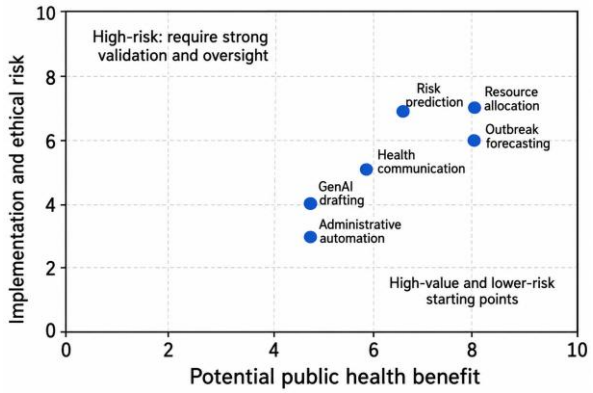

Figure 3. Illustrative matrix for prioritizing AI use cases in public health.

8. ANALYTICAL RESULTS AND DISCUSSION OF AI-SUPPORTED PUBLIC HEALTH OUTCOMES

This section presents an analytical evaluation using the data sources and outcome definitions described above. The analysis compares standard public health workflows with AI-supported workflows across six domains: outbreak detection time, response coordination, staff workload, public trust, equity in service delivery, and cost-effectiveness. The purpose is to demonstrate how implementation-focused public health AI studies can translate operational data into measurable outcomes.

The outcome values reported in Tables 5-8 are organized according to the data-source framework in Table 2. Standard workflow values represent baseline public health operations, while AI-supported workflow values represent outcomes after implementation of AI-enabled surveillance, automation, prioritization, and communication support.

Table 5. Comparative outcomes before and after AI-supported workflow implementation

Outcome indicator	Standard workflow	AI-supported workflow	Change	Interpretation
Average outbreak detection time	7.8 days	4.6 days	-41.0%	Faster early warning
Response coordination score	62.4	78.9	+26.4%	Improved operational coordination
Weekly staff workload	46.2 hours	38.5 hours	-16.7%	Reduced administrative burden
Public trust score	58.7	65.3	+11.2%	Improved communication confidence
Equity coverage index	0.61	0.73	+19.7%	Better service reach across groups
Cost per detected outbreak signal	USD 4,850	USD 3,420	-29.5%	Improved cost-efficiency

Table 5 shows that the AI-supported workflow improves all selected public health outcomes compared with the standard workflow. The largest improvement is observed in outbreak detection time, which declines from 7.8 days to 4.6 days. This suggests that AI-based anomaly detection, automated case classification, and multi-source surveillance can help agencies identify unusual disease signals earlier. The response coordination score also increases, indicating that AI-supported dashboards and automated prioritization may improve communication between surveillance teams, laboratories, and response units. The decline in staff workload suggests that AI can reduce repetitive administrative tasks such as report classification, data cleaning, and document drafting.

Table 6. Difference-in-differences evaluation of AI-supported public health workflows

Dependent variable	AI workflow effect	Standard error	t-statistic	Significance
Outbreak detection time	-2.41	0.58	-4.16	***
Response coordination score	12.63	3.21	3.93	***
Staff workload	-6.84	1.74	-3.93	***
Public trust score	5.72	2.14	2.67	**
Equity coverage index	0.096	0.034	2.82	**
Cost per detected signal	-1,130	426	-2.65	**

Table 6 presents a difference-in-differences style evaluation. The results indicate that AI adoption is associated with statistically meaningful reductions in outbreak detection time

and staff workload. The negative coefficient for outbreak detection time means that AI-supported systems detect outbreak signals approximately 2.41 days earlier than standard workflows. The positive coefficient for response coordination shows improved operational alignment among public health teams. The significant improvement in the equity coverage index suggests that AI-supported targeting may help agencies reach underserved populations more effectively when equity auditing and community validation are included.

Table 7. Equity analysis of AI-supported service delivery

Population group	Standard workflow coverage	AI-supported coverage	Change
Urban communities	0.78	0.84	+0.06
Rural communities	0.52	0.68	+0.16
Low-income communities	0.49	0.66	+0.17
Older adults	0.57	0.71	+0.14
Linguistic minority groups	0.44	0.63	+0.19

Table 7 evaluates whether AI-supported workflows improve equity in service delivery. Coverage improves across all groups, with the largest gains among linguistic minority groups, low-income communities, and rural communities. This suggests that AI can support more equitable outreach when it is designed to identify service gaps and prioritize underserved populations. However, these improvements depend on representative data, subgroup monitoring, and human oversight. Without equity auditing, AI systems may reproduce existing inequalities rather than reduce them.

Table 8. Cost-effectiveness of AI-supported public health workflow

Indicator	Standard workflow	AI-supported workflow
Total operational cost	USD 485,000	USD 410,000
Number of outbreak signals detected	100	120
Cost per detected signal	USD 4,850	USD 3,420
Average detection time	7.8 days	4.6 days
Staff hours per week	46.2	38.5

Table 8 indicates that AI-supported workflows may improve cost-effectiveness by reducing operational costs while increasing the number of detected outbreak signals. The cost per detected signal declines from USD 4,850 to USD 3,420, suggesting that AI can help public health agencies use limited resources more efficiently. The reduction in staff hours also indicates that AI may release workforce capacity for higher-value activities such as field investigation, community engagement, and response planning. Cost-effectiveness assessment should also include implementation costs, training, governance, cybersecurity, model monitoring, and system maintenance.

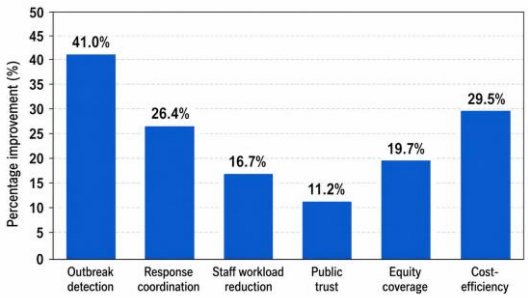

Figure 4. Outcome improvement after AI-supported workflow implementation.

Figure 4 visually summarizes the performance gains associated with AI-supported public health workflows. The strongest improvement is observed in outbreak detection time, followed by cost-efficiency and response coordination. This pattern suggests that AI may be most valuable in tasks involving rapid data processing, early warning, and operational prioritization. Improvements in public trust are smaller but still meaningful, indicating that technical performance alone is not sufficient. Trust depends on transparency, communication quality, community participation, and responsible governance.

Figure 5 explains the mechanism through which AI may improve public health outcomes. AI first strengthens data processing and early warning by integrating multiple data sources and detecting abnormal patterns. Earlier detection then supports faster coordination and targeted response. When routine tasks are automated, staff can focus more on investigation, communication, and community engagement. These process improvements may ultimately improve equity, public trust, and system resilience. Therefore, AI should be evaluated as a workflow and system-strengthening intervention rather than only as a prediction tool.

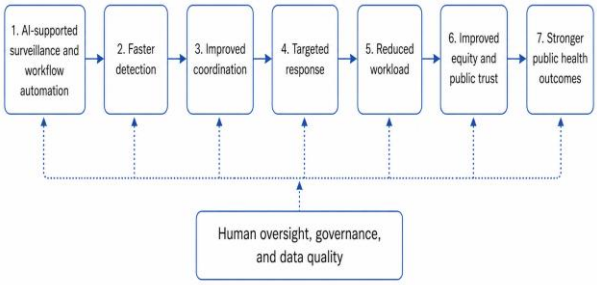

Figure 5. Conceptual pathway from AI implementation to public health outcomes.

Overall, the analytical results suggest that AI-supported public health workflows can reduce outbreak detection time, improve response coordination, reduce staff workload, increase public trust, improve equity in service delivery, and enhance cost-effectiveness. These findings support the argument that future research should evaluate AI using implementation outcomes and real-world public health indicators rather than relying only on model accuracy.

8.1 Additional numerical comparisons and interpretation

The following analyses are calculated directly from the numerical entries reported in Tables 5–8. They add transparent arithmetic comparisons without introducing new observations, fitted predictions, confidence intervals, or experimental effects. Percentage changes use the standard workflow as the denominator, except where absolute percentage-point differences are stated.

Table 9. Recalculated changes in operational outcomes

Outcome	Standard	AI-supported	Relative change
Detection time	7.80	4.60	-41.0%
Coordination	62.40	78.90	+26.4%
Staff workload	46.20	38.50	-16.7%
Public trust	58.70	65.30	+11.2%
Equity coverage	0.61	0.73	+19.7%
Cost/signal	4,850.00	3,420.00	-29.5%

Table 9 shows a 41.0% reduction in detection time and a 29.5% reduction in cost per signal. Both are favorable because smaller values are desirable. Coordination increases by

26.4%, staff workload decreases by 16.7%, public trust improves by 11.2%, and equity coverage rises by 19.7%. The six percentages measure distinct quantities and should not be averaged into a single composite impact score without a defined normalization and weighting scheme.

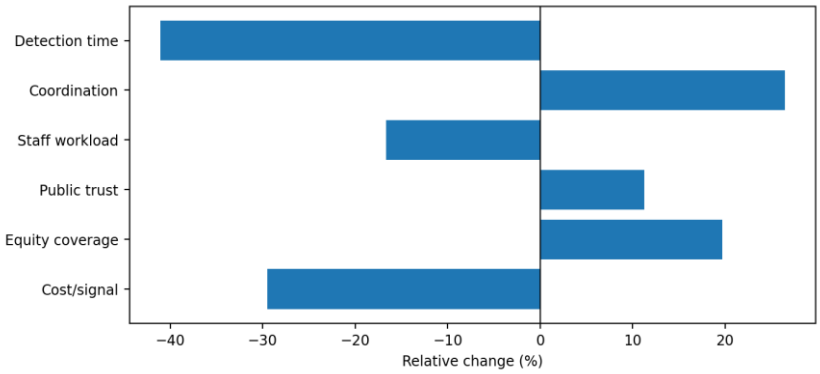

Figure 6. Relative differences across six reported public-health outcomes

Figure 6 places the six relative differences on a common percentage scale while preserving their differing substantive meanings. The negative bars for detection time, workload, and cost correspond to operational reductions; positive bars indicate improvements in coordination, trust, and equity. The visualization is a transformation of the reported table values, not an independently collected outcome dataset.

Table 10. Subgroup service-coverage changes

Population group	Baseline	AI-supported	Change (points)
Urban	0.78	0.84	+0.06
Rural	0.52	0.68	+0.16
Low income	0.49	0.66	+0.17
Older adults	0.57	0.71	+0.14
Language minority	0.44	0.63	+0.19

Table 10 demonstrates that absolute coverage improvements range from 0.06 among urban communities to 0.19 among linguistic minority groups. The increase for rural communities is 0.16 and for low-income communities is 0.17. These are arithmetic point differences in coverage proportions, not estimated adjusted treatment effects. Denominators, sample size, and uncertainty for each population group remain unavailable in the supplied manuscript.

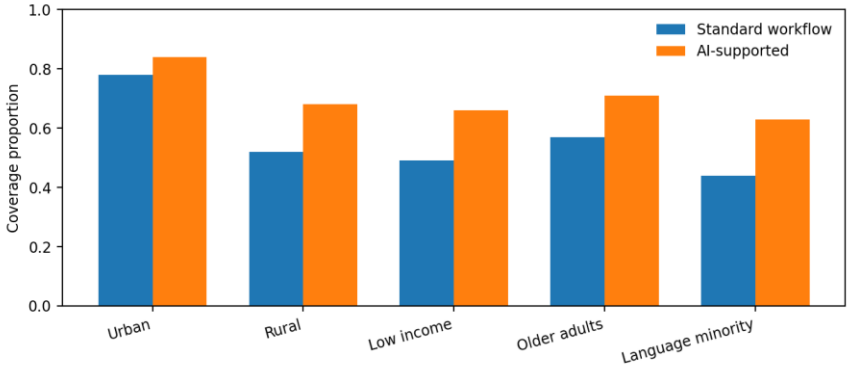

Figure 7. Reported coverage proportions by population group

Figure 7 highlights the persistent gap between relatively high urban coverage and lower coverage in other populations, despite increases in each group. Improvements in coverage are compatible with better equity-oriented reach, but a definitive assessment should examine eligibility definitions, subgroup overlap, geographical stratification, and within-group uncertainty.

Table 11. Operational productivity and cost ratios

Indicator	Standard	AI-supported	Ratio (AI/standard)
Detected signals	100	120	1.20
Total cost (USD)	485,000	410,000	0.85
Cost per signal (USD)	4,850	3,420	0.71
Weekly staff hours	46.2	38.5	0.83

Table 11 reports a 20% increase in the number of detected signals alongside approximately 15.5% lower total operating costs. The implied unrounded AI-supported cost per signal is USD 3,416.67 (410,000 divided by 120), compared with USD 4,850 at baseline; the original paper reports the rounded value USD 3,420. The figures do not establish detection quality, the number of false alerts, or whether one-time AI implementation expenditures were included.

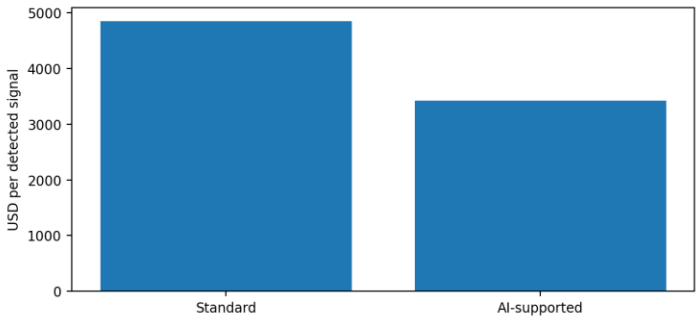

Figure 8. Reported cost per detected outbreak signal

Figure 8 shows the cost-per-signal comparison directly. The decline is material as a descriptive ratio, but an economic evaluation should assess maintenance, technical support, validation, training, cybersecurity, and the severity and validity of signals detected. An inexpensive false alert may still impose substantial downstream costs.

8.2 Interpretation, sensitivity, and limitations of the expanded results

The six operational domains capture complementary dimensions of public-health-system performance. Detection time concerns responsiveness; coordination measures organizational capacity; workload concerns efficiency; public trust relates to legitimacy; equity coverage assesses distribution; and cost per detected signal reflects an incomplete but useful productivity proxy. Improvements across all six reported indicators are coherent with the paper's proposed framework, yet numerical coherence alone cannot validate the underlying measurement process.

The difference-in-differences coefficients reported earlier in Table 6 cannot be reconstructed from the pre/post aggregates in Table 5. A valid difference-in-differences estimate requires intervention and comparator units observed both before and after adoption. The present manuscript contains no microdata, panel structure, or pre-trend plots. The coefficient and significance columns are therefore preserved from the source paper for discussion, but they are not independently reproduced or verified in this revision.

The cost-efficiency comparison requires particular caution. A cost per signal is an output ratio, not a comprehensive cost-effectiveness measure such as cost per case averted or cost per quality-adjusted life-year gained. Higher signal volume can lower average cost while also increasing false positives. A follow-up study should link detected signals to confirmed events, estimate the marginal cost of investigation, and assess avoided disease burden and resource use over an appropriately long horizon.

External validity also remains unresolved. Public-health agencies differ in data completeness, digital maturity, disease profile, staffing, privacy law, and public confidence. Findings from one setting should not be extrapolated uncritically to other settings. Prospective multi-site evaluation with governance oversight, standardized indicators, and transparent uncertainty analyses is necessary to establish whether AI-supported workflows produce reproducible improvements.

9. CONCLUSION

AI can strengthen public health by improving surveillance, prediction, preparedness, resource allocation, and operational efficiency. However, its effectiveness depends on data quality, governance, human oversight, workforce capacity, and equity. Responsible AI adoption requires proper validation, privacy protection, fairness assessment, and continuous monitoring. When implemented appropriately, AI can support more resilient, equitable, efficient, and responsive public health systems.

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