IIAR JOURNALS

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IIAR Journal of Health, Medicine, and Biomedical Research

Vol 1, No 1, 2026

AI-Enabled Disease Surveillance and Outbreak Prediction: A Theoretical Account of Signal, Noise and Action in Data-Sparse Settings

IGWE Emmanuel Sunday[1], NWOGBOJI Emmanuel Usulor[2], ATOLAGBE Umar Kawu[3]

[1,3] Veristzon Global Research Lab; [2] International Institute of AI and Research

ABSTRACT

Artificial intelligence (AI) is frequently presented as a means of detecting infectious-disease outbreaks earlier, yet the settings in which early detection matters most, including Nigeria and much of sub-Saharan Africa, are those in which surveillance data are incomplete, delayed and unevenly reported. Research on the subject has divided into technical studies reporting high forecasting accuracy and policy analyses calling for stronger governance, and neither explains what a model can infer from sparse reports or when its output leads to action. This paper addresses that gap. Using a conceptual, theory-building design, the study conducted a structured integrative review of peer-reviewed journal articles published between 2023 and 2026. Records were identified through purposive, criterion-based searches of PubMed/MEDLINE and Google Scholar using five pre-specified search strings, and 40 articles formed the final evidence base. Each article was verified against its Crossref, PubMed or publisher record, screened for retractions and corrections, and appraised with design-specific quality criteria, and every claim in the text was checked against the cited abstract. Findings were coded under signal, noise and action and synthesised abductively into propositions. The synthesis indicates that AI improves outbreak detection substantially, chiefly by drawing on data whose errors are independent of routine reporting, but improves the attribution of outbreaks to causes and places only modestly and locally, and contributes little to the public health response unless response pathways are agreed in advance. Data sparsity is accordingly reframed as a problem of identification created by under-ascertainment and reporting delay rather than as a mere shortage of observations. The paper advances seven testable propositions and a confidence-to-response framework linking signal confidence, data quality and corroboration to tiered action. Agencies adopting AI alerts should attach pre-agreed response protocols to each alert and fund data quality alongside modelling, and model developers should validate models over time, at the level at which decisions are made, under independent governance.

Keywords: disease surveillance; outbreak prediction; epidemic intelligence; artificial intelligence; early warning systems

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1. INTRODUCTION

Nigeria's national surveillance system recorded 6,288 confirmed cases of Lassa fever and 975 deaths between 2020 and 2025 (Tadema et al., 2026). During the same period, cholera, measles, mpox and seasonal malaria placed further demands on a surveillance system in which reporting is often incomplete and slow (Awoyale et al., 2026; Bakare et al., 2025, 2026; Opue et al., 2026). Artificial intelligence (AI) is frequently proposed as a remedy in such settings: models that combine case reports with other data sources can, in principle, identify outbreaks earlier than conventional surveillance (Villanueva-Miranda et al., 2025), and an international consensus exercise ranked AI-based outbreak prediction and early-warning systems among the highest research priorities for data science in global health (Song et al., 2026).

The central difficulty is that early warning is most valuable precisely where surveillance data are weakest. For COVID-19, the proportion of infections reported by African countries ranged from approximately one in two to one in several thousand (Kogan et al., 2023). This shortfall is not random. Stigma appears to have masked the true burden of mpox (Bragazzi et al., 2024), rural under-reporting and uneven coverage constrained mpox surveillance in Senegal (Faye et al., 2026), and the laboratory-confirmation rate for Lassa fever in Nigeria declined from 18.4% to 9.9% over five years, a trend interpreted by the original authors as consistent with, though not proof of, increasing under-ascertainment (Tadema et al., 2026). A model trained on such counts therefore learns the characteristics of the reporting system as well as the behaviour of the disease.

The existing literature has not addressed this problem directly. Technical studies commonly report high accuracy on short national or district series (Ahmad Amshi et al., 2024; Khan et al., 2024), whereas policy analyses contend that AI could transform preparedness in Africa once barriers of data, capacity and governance are removed (Alasow et al., 2026; Standley et al., 2025). Both bodies of work leave a prior question unresolved: what can a model legitimately infer from sparse and distorted reports, and under what conditions does its output alter the decisions of public health officials? Without an answer, accuracy is mistaken for usefulness, and governance recommendations ignore what models can and cannot know.

The present paper addresses that question. It distinguishes three inferential problems that are usually conflated: detecting that a change has occurred, attributing the change to a cause, place or driver, and determining a proportionate response. The central argument is that AI contributes substantially to the first, moderately to the second and only marginally to the third unless institutions are organised to act on probabilistic signals. In data-sparse settings, the value of a prediction consequently depends less on its accuracy than on whether it changes a decision. On this basis, the paper develops a signal–attribution–action framework, explains how the reporting process constrains what any model can learn, and proposes a means of matching the confidence of an AI-generated signal to the scale of response. Nigeria is the principal case.

2. LITERATURE REVIEW

2.1 CONCEPTUAL REVIEW

2.1.1 Disease surveillance and early warning

Routine surveillance in Nigeria, as in much of Africa, rests on indicator-based reporting of notifiable diseases through the Integrated Disease Surveillance and Response (IDSR) system. Event-based surveillance complements indicator-based reporting by capturing signals of unusual events from human, animal and environmental sources, and its principal contribution is earlier warning (Al Wahaibi et al., 2026). Digital epidemic intelligence applies this principle to open-source reports (MacIntyre et al., 2023; Quigley et al., 2025). In this paper, an early-warning system denotes any arrangement that links such data to a rule for flagging anomalies. The definition is deliberately broad, since the decision rule matters at least as much as the data. One Health surveillance broadens the frame to animal and

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environmental signals, which are particularly important for zoonoses such as Rift Valley fever and Lassa fever, where livestock or rodent reservoirs can reveal risk before human illness occurs (Diop et al., 2026; Layman et al., 2023).

2.1.2 AI-enabled surveillance

AI-enabled surveillance refers here to machine learning, deep learning, natural language processing and related methods to detect, forecast or characterise outbreaks (Kraemer et al., 2025). The category is broad, ranging from gradient-boosted trees applied to climatic and other covariates (Khan et al., 2024) through graph and recurrent neural networks (Fofanah et al., 2025) and computer vision applied to aerial imagery (Layman et al., 2023) to pretrained time-series foundation models (Kalahasti et al., 2026). It also extends upstream to data quality, as when an AI-enabled reader photographs malaria rapid diagnostic tests so that register entries can be checked against stored cassettes (Ngufor et al., 2025). Because AI and classical forecasting frequently share a pipeline, the two are treated here as a continuum, and statistical studies are drawn upon where these illuminate the same inferential problem (Bakare et al., 2025; Samson et al., 2024).

2.1.3 Data-sparse settings

The term "data-sparse" is readily mistaken for "small". The settings considered here often generate short or low-count series, but the more fundamental problem is that the available counts are partial, delayed and uneven. Only a fraction of infections are recorded, reports arrive irregularly or not at all, and both reporting and transmission vary across districts and seasons (Faye et al., 2026; Kogan et al., 2023). A subnational evaluation in Niger State found that only 66.5% of surveillance respondents reported fully accurate submitted forms and that transport delays were associated with surveillance failure (Awoyale et al., 2026). Such conditions are properties of the health system rather than of the dataset, and modelling alone cannot remove such conditions.

2.1.4 Signal, noise and action

In this paper, *signal* denotes information in the data about a genuine change in disease occurrence; *noise* denotes variation generated by testing, reporting and recording; and *action* denotes any decision taken in response to a signal, from verification by telephone to full deployment. Noise, however, is not random. The stigma, gaps in coverage and limited analytic capacity that distort reporting also constrain the capacity to respond (Bragazzi et al., 2024; Faye et al., 2026), which suggests that improvements in data and in response depend on many of the same investments.

2.2 THEORETICAL REVIEW

The analysis draws on three bodies of theory, the first being signal detection theory. Treating outbreak detection as discrimination between "change" and "no change" under uncertainty makes one trade-off unavoidable: wherever the alert threshold is placed, gains in sensitivity are obtained at the cost of false alarms. A Nigerian outbreak model operating at a sensitivity of 0.72 and a specificity of 0.82 still generated 2.8–3.6 false alerts per local government area per year (Opue et al., 2026). Signal detection reasoning also implies a ceiling, since no detector can recover information that the observation process has already removed. Recent reviews of AI in epidemic modelling emphasise explainability, accountability and validation (Kraemer et al., 2025) and the barriers that prevent outbreak data from being shared at all (Khurana et al., 2026). Adefolalu (2026) contributes a point about transportability in travel health that applies more widely: predictive validity in one setting does not establish that an inference is admissible in another, and appropriate responses range from supported inference to withholding the output altogether.

The second is decision theory. Information has value only if it can change a decision, so a forecast should be judged by how outcomes differ when action is conditioned on it, not by goodness of fit. Few studies in the present evidence base pose that question. The forecasting pipeline developed by Keshavamurthy et al. (2025), which selects a model for each setting and reports uncertainty to decision-makers, comes closest.

The third is sociotechnical theory. Surveillance operates as a system of people, rules, tools and resources, and a model performs only as well as it fits that system. Climate-informed early-warning systems for vector-borne disease have been undermined by fragmented data, limited stakeholder engagement and outputs too technical for practical use (Pham et al., 2026), and African governance

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analyses emphasise that data sovereignty, participatory governance and accountability shape whether model outputs are trusted (Alasow et al., 2026; Mohamed et al., 2026). Signal detection theory thus locates the ceiling on inference, decision theory specifies when a forecast is worth having, and sociotechnical theory explains whether it is acted upon.

2.3 EMPIRICAL REVIEW

2.3.1 Evidence on signal

The clearest gains arise from data that observe the epidemic through a channel other than the clinic. The addition of mobility data from phone records, GPS traces and social media reduced Ebola forecasting error by 5–10% relative to baselines (Fofanah et al., 2025). News and internet-search data improved forecasts of Kyasanur forest disease in India, and transfer learning outperformed baselines in newly affected areas that lacked any case history (Keshavamurthy & Charles, 2023). Open-source intelligence identified early signals where conventional surveillance was weak (Quigley et al., 2025), although that evaluation was produced by the team responsible for the system. A deep-learning framework combining COVID-19 case counts with search, news and satellite air-quality data improved 56-day forecasts in South Africa by up to 51% in R^2 relative to state-of-the-art models (Nia et al., 2025), and geospatial AI applied to surveillance data from the WHO African Region achieved an F1 score of 0.96 for malaria (Pezanowski et al., 2024). Neither abstract, however, reports a comparison with a model built without the auxiliary data, and the second figure concerns the weekly presence of an endemic disease, a lower threshold than anticipating a surge. Climate-informed models for malaria in northern Benin and The Gambia (Gbaguidi et al., 2024; Khan et al., 2024) and a probabilistic model of under-five malaria admissions in Ghana, validated on a rolling origin with explicit uncertainty bounds (Ansah-Narh et al., 2026), complete a picture of genuine but uneven progress.

2.3.2 Evidence on noise

Under-ascertainment of COVID-19 across African countries spanned more than three orders of magnitude (Kogan et al., 2023), and under-estimation of mpox in high-risk groups ranged from 25% to 93% across 16 countries (Bragazzi et al., 2024). Reporting may also change for reasons unrelated to transmission. During Nigeria's COVID-19 lockdown, confirmed Lassa fever cases fell immediately while suspected cases did not (Tadema et al., 2026); a model trained on confirmed counts would have interpreted the decline as reduced transmission.

Evaluation practice compounds the problem. In Nigeria, median quantile regression forecast confirmed Lassa fever cases more accurately than the best machine-learning model, although a support vector machine performed better for deaths (Samson et al., 2024). A Nigerian cholera model reported 99.6% accuracy after oversampling and outlier removal, without stating in the abstract whether these steps preceded the division of training and test data (Ahmad Amshi et al., 2024). A Gambian malaria model achieved 93.3% accuracy on a held-out test set after cross-validated training, again without indicating whether the split respected temporal order (Khan et al., 2024). Low counts introduce further fragility: an ARIMA model for mpox in Nigeria forecast approximately 13 cases per month (Bakare et al., 2025), a level at which a small number of missed reports alters the series materially. The climate signal also varies with scale. A Kogi State analysis found only weak associations with rainfall and humidity, and its proposed temperature and humidity thresholds derived from a model explaining less than 9% of the variance (John et al., 2026), whereas national data showed a clear inverse association with weekly rainfall ($r_s = -0.589$; Tadema et al., 2026). A review of the Lassa fever literature identifies short ecological series, under-reporting and the absence of linkage between rodent ecology and climate data as persistent gaps (Edo et al., 2026).

Some studies address noise directly. Stored malaria test cassettes, photographed with an AI-enabled reader and interpreted by a trained panel, remained sufficiently stable over one month to support audits of facility registers, with positive and negative predictive values of 96.3% and 93.8% (Ngufor et al., 2025). Topological features modestly improved surge prediction across 97 Nigerian local government areas under temporal hold-out, although prospective validation and threshold tuning were judged necessary before deployment (Opue et al., 2026).

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Pretrained foundation models outperformed standard models on limited and irregular series (Kalahasti et al., 2026), but the abstract reports no evaluation on African surveillance data, so the relevance of this approach to African settings remains untested.

2.3.3 Evidence on action

At the point of action, evidence becomes sparse. A review of epidemic intelligence systems, not all of which are AI-based, found that most supply unfiltered data and that uptake by public health authorities has been slow (MacIntyre et al., 2023; see also "Corrigendum," 2023). In Senegal, an AI-supported One Health platform detected Rift Valley fever signals days to weeks before official confirmation, yet delayed validation and weak cross-sector coordination limited the response; notably, the AI component was largely heuristic (Diop et al., 2026). An evaluation of the mpox surveillance system in Senegal concluded that stakeholder involvement, transparency, workforce capacity and ethical data safeguards are prerequisites for predictive modelling (Faye et al., 2026).

The most persuasive example of a signal translated into action involved no AI. During Uganda's 2025 Martyrs' Day gathering, wastewater detections by the Ministry of Health led to drainage, chlorination and vendor relocation on the same day, followed by sanitation upgrades, risk communication and on-site clinical screening (Nsawotebba et al., 2026). The decisive factor appears to have been response capacity already in place rather than analytical sophistication. Elsewhere, forecasts have been proposed for timing seasonal malaria chemoprevention and net campaigns in Nigerian states (Bakare et al., 2026), and changes in malaria-control policy have been modelled as predictors of incidence in Rivers State (Egbom et al., 2026), but neither study reports a decision that changed as a result.

Perspective and policy papers largely fill this gap with recommendations rather than evidence, calling for data sovereignty, privacy-by-design and phased regional roadmaps (Alasow et al., 2026), governance that keeps pace with adoption (Mohamed et al., 2026), investment in infrastructure and skills in fragile states (Tahlil et al., 2026), federated analysis that pools data without transferring it across borders (Khurana et al., 2026) and offline-first One Health tools suited to low-infrastructure settings (Mukherjee et al., 2025). Such recommendations are reasonable but mostly untested.

2.3.4 Synthesis and gap

The studies collectively show genuine but uneven progress in detection, pervasive and structured noise, and a weak and largely untheorised link to action. None of the predictive modelling studies reported how a forecast had changed a public health decision; the closest were Bakare et al. (2025, 2026), who recommended specific interventions on the basis of the forecasts produced. Most modelling abstracts also omitted a validation design, a baseline or a measure of uncertainty. In short, the field has asked whether models fit the data more often than whether models support decisions.

3. MATERIALS AND METHODS

3.1 RESEARCH DESIGN

The study adopts a conceptual, theory-building design. A structured integrative review of recent peer-reviewed literature provided the evidence base, and abductive reasoning, which moves iteratively between empirical patterns and candidate explanations, was used to derive propositions from that evidence. As the study involved no human participants or primary data, ethical approval was not required.

3.2 POPULATION, SOURCES AND SEARCH

Searches for English-language, peer-reviewed journal articles published between 2023 and 2026 were conducted on 20 October 2026 in PubMed/MEDLINE and Google Scholar using five pre-specified search strings: a core string and one string each for signal, noise, action and Nigerian priority diseases. Two supplementary PubMed title-and-abstract strings were also run. The PubMed strings returned 1,639 records before de-duplication, of which the 208 highest-ranked were screened at title and abstract. In Google Scholar, the top 20 records for each string were screened and resolved to Crossref; of these 100 records, 20 had no Crossref match and 24 were not journal articles or fell outside the date window. Scopus and Web of Science could not be accessed through an institutional library at the

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time of searching, a limitation discussed in Section 4.2.

3.3 INCLUSION AND EXCLUSION CRITERIA

Eligible records were peer-reviewed articles with a registered DOI, including original research, reviews and conceptual, perspective and policy papers, that addressed AI or forecasting for outbreak surveillance, the quality and sparsity of surveillance data, or the translation of predictions into action. Studies from LMICs, Africa and Nigeria were prioritised, and global methodological papers were admitted when the argument transferred to data-sparse settings. Preprints, conference material, book chapters, theses, letters, editorials, records without a DOI and outlets whose indexing could not be confirmed were excluded. Screening excluded 83 records at title and abstract, held 34 eligible records in reserve and advanced 40, one of which was subsequently removed as a meeting report. Claim-level verification then led to the withdrawal of two further articles, one whose abstract could not be retrieved and one published in a journal not yet indexed in Scopus, and to the addition of three verified, Scopus-indexed articles identified through PubMed (Al Wahaibi et al., 2026; Awoyale et al., 2026; Tadema et al., 2026). The final evidence base comprised 40 articles.

3.4 VERIFICATION AND INTEGRITY SCREENING

Each DOI was checked against the corresponding Crossref record for authors, journal, volume, issue, pagination or article number and dates, and the Crossref value was preferred where it differed from PubMed; this procedure resolved one DOI discrepancy. Crossref update records, which incorporate Retraction Watch data, were used to screen for retractions, corrections and expressions of concern, and the three later additions were checked against PubMed and publisher records. No retractions or expressions of concern were identified. One correction was identified and is cited alongside the original article. A spot-check also corrected one author list in which honorifics had been parsed as initials.

3.5 APPRAISAL AND BASES OF JUDGEMENT

Each article was assessed against six eligibility criteria (date, peer review, topic fit, relevance to data-sparse settings, indexed venue and integrity) and a five-item checklist matched to study design. Items for predictive modelling studies drew on TRIPOD+AI (Collins et al., 2024) and PROBAST+AI (Moons et al., 2025) and addressed data description, validation beyond the training data, metrics with uncertainty and a baseline, leakage-free handling of missing data, and acknowledgement of limitations. Reviews were appraised using items derived from AMSTAR 2 (Shea et al., 2017), and perspective papers using items derived from the JBI approach to text and opinion (McArthur et al., 2015). These methodological tools are cited in the original versions irrespective of date; all substantive evidence falls within 2023–2026. Items were scored 1, 0.5 or 0, yielding ratings of high (4 or above), moderate (2.5–3.5) or low (2 or below). Low-quality studies were retained only where no stronger study addressed the point, and such studies are used as evidence of patterns in the field, such as evaluation artefacts, rather than as evidence of methodological effectiveness.

3.6 DATA EXTRACTION AND ANALYSIS

The literature matrix recorded the setting, design, disease, method, data sources, findings, pillar and verification status of each article. Findings were first classified under the signal, noise and action pillars and then coded within each pillar into mechanisms such as auxiliary-data fusion, under-ascertainment and pre-committed response. Comparison of these mechanisms across pillars yielded the propositions and the framework. Metadata were verified through the Crossref REST API, PubMed E-utilities and publisher pages, and every claim in the text was checked against the abstract of the cited article.

3.7 CONSTRUCTS AND MEASUREMENT

Because the study is theoretical, its variables are constructs, defined to permit measurement in subsequent empirical work. *Signal confidence* (C) is the posterior probability that a genuine change in disease occurrence underlies an alert and can be estimated from calibrated model outputs. *Data-quality grade* (Q) summarises completeness,

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timeliness and ascertainment for a reporting unit and can be derived from IDSR indicators or from verification audits of the kind described by Ngufor et al. (2025). *Corroboration* (K) is the number of independent streams, such as case reports, event-based signals, laboratory results or environmental samples, that indicate the same change. The *cost and reversibility* of a response (c) capture the resources an action commits and the ease with which it can be reversed, and the *response tier* is the action ultimately selected (Table 3).

3.8 RELIABILITY AND VALIDITY

An audit trail comprising the search strings, yields, screening log, verification dates and appraisal rubric is available on request. The theory was assessed against three criteria: whether each proposition rests on several included studies, as set out in Section 2.3 and Table 2; whether the propositions are mutually consistent; and whether each is stated in a form that evidence could refute. Screening and appraisal were conducted by a single reviewer with AI assistance and at abstract level, which limits reliability.

3.9 AI USAGE DISCLOSURE

A generative AI assistant (Claude, Anthropic) was used to run searches, retrieve and compare metadata, organise the literature matrix, check claims against sources and assist in drafting the text. All AI-assisted output was reviewed and edited by the authors, who accept full responsibility for the content. No AI tool is listed as an author.

4. RESULTS AND DISCUSSION

4.1 RESULTS

4.1.1 Characteristics of the evidence base

Table 1 summarises the 40 included articles. Half were published in 2026, indicating a rapidly developing field. Predictive modelling studies formed the largest group (16), followed by perspective, narrative and policy papers (12), observational and evaluation studies (10) and systematic reviews (2). Eleven articles included a Nigerian setting, and a further 15 originated elsewhere in Africa. Signal and action were each addressed by approximately two-thirds of the articles, and noise by fewer than half. The quality profile is concerning: 18 articles were rated low, 10 moderate and 12 high, and low ratings were concentrated among modelling studies whose abstracts reported no validation design, baseline or measure of uncertainty. The literature thus reports model fit considerably more often than the effect of reporting errors on that fit.

Table. 1. Characteristics of the included articles (n = 40)

Characteristic	Category	n
Publication year	2023	4
	2024	6
	2025	10
	2026	20
Design	Predictive modelling	16
	Perspective, narrative or policy	12
	Observational or evaluation	10
	Systematic review	2
Setting	Nigeria (alone or with other countries)	11
	Other African settings	15
	Global, LMIC-general or non-African	14
Pillar addressed	Signal	26
	Noise	18
	Action	25
Quality (abstract level)	High (score ≥4)	12
	Moderate (2.5–3.5)	10
	Low (≤2)	18
Integrity status	Published correction	1
	Retraction or expression of concern	0

Note. Pillar counts sum to more than 40 because an article can address more than one pillar. Quality scores follow the rubric in Section 3.5.

4.1.2 What AI adds at each inferential stage

Table 2 relates the evidence to the three inferential stages. Gains in detection were consistent, and the most persuasive arose from data whose errors are independent of routine reporting. Gains in attribution were smaller and more local, for the reasons set out in Section 2.3.2. At the action stage, the single clear instance of rapid response came from a non-AI system with response capacity already in place, whereas the AI-supported examples stalled at validation and coordination.

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Table. 2. AI contribution and limiting noise at each inferential stage

Stage	AI contribution and main limit	Illustrative evidence
Detection	Substantial where independent auxiliary streams are fused; bounded by ascertainment and delay in routine reports	Diop et al. (2026); Fofanah et al. (2025); Keshavamurthy & Charles (2023); Layman et al. (2023); Quigley et al. (2025)
Attribution	Modest and local; drivers vary between places, and interpretability describes the model rather than the cause	Adefolalu (2026); Egbom et al. (2026); John et al. (2026); Pezanowski et al. (2024); Tadema et al. (2026)
Action	Rarely demonstrated; follows when response capacity is already in place, stalls when validation and coordination lag	Diop et al. (2026); Faye et al. (2026); MacIntyre et al. (2023); Nsawotebba et al. (2026); Pham et al. (2026)
Noise (all stages)	Under-ascertainment structured by stigma, coverage and confirmation capacity; evaluation choices can inflate accuracy on short series	Ahmad Amshi et al. (2024); Bragazzi et al. (2024); Kogan et al. (2023); Samson et al. (2024); Tadema et al. (2026)

4.1.3 The signal–attribution–action framework

Figure 1 summarises the framework, which rests on a simple observation model. Let $Y_{s,t}$ denote true incident infections in place s at time t, $\pi_{s,t}$ the probability that an infection is ascertained and reported, and $f_s(d)$ the distribution of reporting delay d. The expected reported count is then:

$$E\left[Y_{s,t}^{obs}\right]=\pi_{s,t}\sum_{d=0}^{D} f_s(d)\,Y_{s,t-d} \qquad (1)$$

Equation (1) recasts data sparsity as a problem of identification rather than of sample size. An increase in reported cases may reflect more infections, improved ascertainment (for example, a testing campaign) or a change in delay. Where π and f vary across places and over time, as the evidence reviewed above indicates, reported counts cannot distinguish between these explanations, irrespective of the model applied. A more flexible model fits the joint process more closely but cannot recover a distinction that the data do not contain. Only streams whose errors are independent of π and f contribute that information. With X_1, …, X_K denoting such streams, signal confidence becomes:

$$C=Pr\left(outbreak_{s,t}\,|\,Y^{obs},X_1,\ldots,X_K\right) \qquad (2)$$

The decision to act follows from an expected-loss argument: if an action at tier j costs c_j and, by assumption, averts an avoidable loss L, the action is justified when the expected loss averted exceeds the cost:

$$C\cdot L>c_j \Leftrightarrow C>\frac{c_j}{L} \qquad (3)$$

Because verification is inexpensive relative to deployment ($c_1 \ll c_3$), a weak signal may justify verification well before it justifies the dispatch of a response team. Table 3 translates this logic into response tiers.

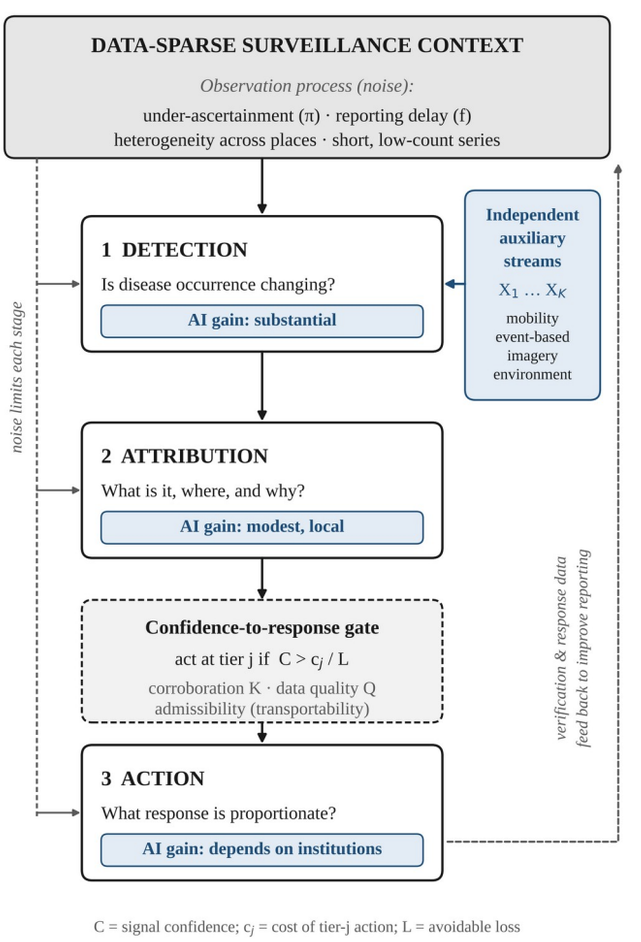


Figure. 1. The signal–attribution–action framework. Noise from the observation process limits every stage; independent auxiliary streams raise the detection ceiling; a confidence-to-response gate links signal confidence to tiered action.

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4.1.4 Propositions

Seven propositions follow from the synthesis; the studies underpinning each are presented in Section 2.3 and Table 2.

P1 (Detection ceiling). In data-sparse settings, the reporting process rather than model complexity sets the limit on the improvement in outbreak detection attainable from AI; further gains derive chiefly from data streams whose errors are independent of routine reporting (Fofanah et al., 2025; Keshavamurthy & Charles, 2023).

P2 (Simplicity under sparsity). On short, low-count series, flexible machine-learning models will not reliably outperform parsimonious statistical models out of sample, and near-perfect reported accuracy is more likely to indicate an evaluation artefact than genuine predictive skill (Samson et al., 2024).

P3 (Attribution is local). Drivers learned from surveillance data in one setting do not transfer to another without re-estimation, and interpretability tools describe the model rather than the cause (Adefolalu, 2026).

P4 (Structured noise). Because under-ascertainment follows stigma, coverage and confirmation capacity, models trained on reported counts learn the surveillance system as well as the disease, and a change in reporting can either mimic or conceal an outbreak (Tadema et al., 2026).

P5 (Pre-commitment). A prediction improves outcomes only where the responsible actors, the threshold for action and the resources to be committed are specified in advance (Nsawotebba et al., 2026).

P6 (Proportionality). The confidence required before acting should increase with the cost and irreversibility of the action, so that weak signals prompt inexpensive verification rather than either inaction or full response (Opue et al., 2026).

P7 (Governance as a precondition). Validation, accountability and data-sovereignty arrangements determine whether accurate predictions are trusted and used, independently of predictive accuracy (Mohamed et al., 2026).

Table. 3. Confidence-to-response framework

Tier	Signal condition	Proportionate action
0 Monitor	C below the verification threshold, or output not admissible for the setting (failing data-quality grade; model not validated locally)	Routine monitoring; log the alert; flag the data-quality problem for correction
1 Verify	Low-to-moderate C from a single stream, or any signal for a high-consequence pathogen	Check data entry; call the reporting facility; investigate cases; collect samples
2 Prepare	Moderate C corroborated by at least two independent streams ($K \geq 2$) or by verification	Alert facilities and laboratories; place rapid response team on standby; pre-position supplies; brief health workers
3 Respond	High C with laboratory or field confirmation	Deploy rapid response; vaccination, case management or WASH measures; public risk communication

Note. Thresholds for each tier follow from Equation (3) and should be set in advance by the responsible agency, given local costs of action and the consequences of delay.

4.2 DISCUSSION

The synthesis supports the central argument of the paper and also resolves an apparent contradiction in the literature. Studies that add mobility or event-based data report gains in forecasting (Fofanah et al., 2025; Keshavamurthy & Charles, 2023), whereas a Nigerian comparison found that a simple quantile regression matched or outperformed machine learning (Samson et al., 2024). Interpreted through Equation (1), these findings are compatible: the former studies introduced information with independent errors, while the latter asked a more flexible model to extract more from the same reports. Transfer learning and pretrained foundation models perform relatively well under sparsity for a similar reason, since both import structure learned elsewhere (Kalahasti et al., 2026; Keshavamurthy & Charles, 2023). Such borrowing assists detection, but P3 marks its limit: the rainfall signal that is clear in national Lassa fever data is weak in Kogi State (John et al., 2026; Tadema et al., 2026), and a borrowed driver remains an assumption rather than a finding.

The evidence also indicates a need to change how models are evaluated. Very high accuracy obtained on small or resampled datasets, or on splits that disregard temporal order, warrants scepticism rather than acceptance. It is instructive that the studies

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employing temporal or rolling-origin validation with explicit uncertainty were also those that stated limitations most clearly: Opue et al. (2026) called for prospective validation before deployment, and Ansah-Narh et al. (2026) acknowledged constraints arising from data quality and the absence of environmental covariates. Modelling studies should, in addition, report quantities of direct use to district officers, such as lead time gained, false alerts per true event and performance under realistic reporting delays.

Action remains the weakest link. When AI-supported detection is followed by institutional delay, as in the Rift Valley fever response in Senegal (Diop et al., 2026), the usual inclination is to improve the model. Under P5, the more probable cause is the absence of an agreed decision rule and of the coordination required to implement it. The Ugandan case supports the same conclusion from the opposite direction: with response capacity already deployed, even a simple laboratory signal produced action within the day (Nsawotebba et al., 2026). The tiers in Table 3 extend this lesson to probabilistic outputs, making uncertainty a basis for proportionate action rather than delay.

Three implications follow for Nigeria. The divergence between state and national climate associations, together with spatially varying drivers elsewhere in the region (Pezanowski et al., 2024), favours state-level models nested within national surveillance over a single national model. Investment in data quality and verification (Awoyale et al., 2026; Ngufor et al., 2025) raises the ceiling on what any model can detect and should form part of AI budgets rather than compete with AI investment. The governance principles articulated in African policy analyses (Alasow et al., 2026; Standley et al., 2025; Tahlil et al., 2026) become operational only when translated into pre-agreed thresholds, designated responsible officers and published validation reports for every model in use.

The analysis has several limitations. The evidence was drawn from two databases and appraised at abstract level by a single reviewer, so relevant studies may have been omitted, and claims were checked against abstracts rather than full texts. Many studies were rated low quality, which is why such studies are treated as evidence of patterns rather than of effectiveness. Equation (3) assumes that action fully averts loss, whereas real responses are partial and the associated costs fall on different actors. Retrospective replays that simulate decisions under each tier, comparisons of model performance before and after documented changes in reporting, and prospective trials of pre-committed response protocols in Nigerian states would each provide a rigorous test of the propositions.

5. CONCLUSION AND RECOMMENDATION

AI can help data-sparse health systems detect outbreaks earlier, but only within the limits imposed by the reporting process and only where institutions are prepared to act on uncertain signals. The value of a prediction in such settings lies in the decision it changes.

The most immediate recommendation is that public health agencies, including the Nigeria Centre for Disease Control and Prevention and state ministries of health, attach a pre-agreed, tiered response protocol to any AI alert adopted, specifying the thresholds, the responsible officers and the resources committed at each tier. Investment in AI should be accompanied by investment in data quality, including completeness and timeliness audits and the verification of routine reports, since better data raise the ceiling for every model. Model developers, journals and funders should require temporal or rolling-origin validation, baselines, measures of uncertainty and testing under realistic reporting delays. Models should be developed and validated at the level at which decisions are made, usually the state or district, with national models reserved for coordination. Governance should precede deployment: independent validation, data-sovereignty safeguards and public documentation of operational models should be in place before predictive outputs are used to allocate resources.

6. CONTRIBUTION TO EXISTING KNOWLEDGE

The principal contribution of the paper is the separation of detection, attribution and action, together with an explanation of why the contribution of AI diminishes from the first stage to the last, which accounts for the frequent failure of gains in accuracy to translate into gains in public health. By treating

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data sparsity as a problem of identification arising from the reporting process, the paper also explains when AI can add information and why comparisons of machine learning with simpler models reach divergent conclusions. The confidence-to-response framework offers decision-makers a principled basis for acting on uncertain predictions, and the seven propositions establish a testable agenda for research on AI-enabled surveillance in Africa and in other data-scarce settings.

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