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Artificial intelligence in zoonotic disease surveillance: A systematic review with One Health implications for low- and middle-income countries

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Abstract

Zoonotic diseases account for approximately 60% of known infectious diseases and 75% of emerging threats, disproportionately affecting low- and middle-income countries (LMICs). This systematic review synthesises evidence on artificial intelligence (AI) applications in veterinary surveillance relevant to zoonotic disease monitoring, with attention to LMIC implementation contexts. Following PRISMA 2020 guidelines and JBI methodology, we searched PubMed, Scopus, and Web of Science (January 2015–December 2025). Two reviewers independently performed screening, full-text assessment, and data extraction. Methodological quality was appraised using a six-item framework integrating JBI and PROBAST elements. Thirty empirical studies met inclusion criteria (20 primary empirical + 10 descriptive operational evaluations); 50.0% addressed LMIC settings. Four application domains were identified: predictive surveillance (30.0%), event-based surveillance (23.3%), automated monitoring (23.3%), and disease detection (23.3%). Fourteen studies (46.7%) demonstrated direct zoonotic relevance. A machine learning rabies risk-stratification approach yielded an approximately three-fold increase in epidemiologically useful surveillance data, and event-based syndromic classification achieved F1-macro of 0.9995 under retrospective validation. Edge AI and transfer learning approaches demonstrated feasibility for resource-constrained settings. AI-enabled approaches may strengthen zoonotic disease surveillance within One Health frameworks, particularly in LMIC settings, though most evidence reflects proof-of-concept and retrospective validation; prospective operational research is needed.

Introduction

Zoonotic pathogens constitute approximately 60% of known infectious diseases affecting humans and up to 75% of emerging infectious diseases (1, 2). The burden falls disproportionately on LMICs, where limited healthcare infrastructure and close human-animal interfaces create conditions conducive to pathogen emergence and spillover (3). Endemic rabies alone accounts for approximately 59,000 human deaths and $8.6

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billion in economic losses annually, with 95% of cases occurring in Africa and Asia (4). Traditional veterinary surveillance systems face limitations including under-ascertainment, inadequate workforce, and limited diagnostic capacity (5, 6).

Strengthening zoonotic disease surveillance at the animal-human interface is a key priority under the One Health framework. The One Health Joint Plan of Action emphasizes multisectoral collaboration and integrated surveillance approaches for addressing zoonotic threats (7).

Artificial intelligence has shown promise for pattern recognition, predictive modelling, and automated surveillance in healthcare (8). In veterinary medicine, deep learning has been applied for diagnostics and health assessment (9, 10). However, most AI development has occurred in high-income settings, raising questions about transferability (11, 12). Edge AI enables on-device inference without continuous connectivity (13), and transfer learning reduces data dependence (14) — approaches that may address LMIC constraints.

This systematic review synthesizes evidence on AI applications in veterinary surveillance with attention to zoonotic disease relevance and LMIC implementation contexts. Research questions: RQ1: What AI surveillance applications exist that are relevant to zoonotic disease monitoring? RQ2: What methodological approaches demonstrate feasibility for LMIC settings? RQ3: What is the demonstrated impact on surveillance performance?

Materials and Methods

This systematic review was conducted following the methodology for systematic reviews of the Joanna Briggs Institute (JBI; Aromataris & Munn, 2020) (19) and reported in accordance with the PRISMA 2020 statement (Page et al., 2021) (15). A completed PRISMA 2020 checklist is provided as Supplementary Material S2. We defined Eligibility criteria using the PECO framework (16). LMICs were classified according to World Bank criteria (17). Eligible study designs included: (i) primary empirical evaluations of AI-enabled veterinary surveillance systems (including diagnostic or prediction model development with internal/external validation, prospective or retrospective operational studies, and applied system assessments reporting performance data); (ii) retrospective validation studies; (iii) descriptive evaluations of implemented digital surveillance platforms reporting at least one quantitative performance indicator. Ineligible study designs included: narrative reviews, systematic reviews, scoping reviews, editorials, commentaries, opinion or perspective articles, conceptual or theoretical papers without empirical data, conference abstracts without subsequent peer-reviewed publication, bibliometric analyses, and digital platform descriptions without empirical evaluation outcomes. The complete eligibility framework is provided in Supplementary Material S2.

Three electronic databases (PubMed, Scopus, Web of Science Core Collection) were searched on the following dates: PubMed on 15 March 2026; Scopus on 16 March 2026; Web of Science on 17 March 2026. The search covered publications from 1 January 2015 to 31 December 2025. Searches were limited to publications in English; this language restriction is acknowledged as a limitation in Section 4.6.

Grey literature was not systematically searched, because peer-reviewed publications constitute the principal source of empirically evaluated systems with reproducible methodology in this rapidly evolving field. Reference lists of included studies were hand-searched to mitigate this limitation (acknowledged in Section 4.6) partially.

In addition to database searches, the websites of WOAH, FAO, WHO, and UNEP were consulted on 18 March 2026 for relevant policy documents and One Health surveillance frameworks. Documents identified informed the contextual framing (Sections 1.1, 4.2) but were not eligible for inclusion in the quantitative synthesis as they did not constitute primary empirical evaluations.

Two reviewers independently screened records with substantial inter-rater agreement (κ=0.87 title/abstract; κ=0.92 full-text) (18). A post-screening eligibility re-assessment was conducted using the explicit empirical eligibility criterion defined in Supplementary Material S2; this evaluation identified 9 articles that did not meet the empirical criterion (5 narrative/conceptual reviews, 2 perspective/opinion articles, 1 bibliometric analysis, 1 conceptual framework paper). These articles were removed from the quantitative synthesis and are documented in Supplementary Material S4. The final synthesis comprises 30 studies (20 primary empirical evaluations + 10 Descriptive operational evaluations).

Data were extracted independently by two reviewers using a standardised extraction form. Discrepancies were resolved through discussion and consensus. Due to methodological heterogeneity, quantitative meta-analysis was not appropriate. Data synthesis followed the four sequential elements proposed by Popay et al. (2006) (21). First, a preliminary synthesis was developed by tabulating study characteristics and grouping studies into four surveillance application domains (disease detection, predictive surveillance, automated monitoring, event-based surveillance) and by AI methodological family. Second, relationships within and between studies were explored by cross-tabulating methodological approach against surveillance objective, geographical setting, and reported performance metrics. Third, the robustness of the synthesis was examined through a post-screening eligibility re-assessment using the predefined empirical eligibility criterion. Fourth, the synthesised findings were integrated into a conceptual framework (Supplementary Figure S1).

Each included study was assigned a unique Article ID solely to facilitate cross-referencing between the manuscript tables, Supplementary Materials, and the accompanying master extraction dataset.

Results

The search yielded 512 records across three databases. After removing 147 duplicates, screening 365 records, and excluding 285 at title/abstract review and 41 at full-text, 39 articles were initially retained (Figure 1). Following application of the predefined empirical eligibility criterion, nine articles were reclassified as ineligible (conceptual reviews, perspective articles, narrative reviews, or bibliometric analyses; documented in Supplementary S4). The revised synthesis includes 30 empirical studies. Summary characteristics are presented in Supplementary Table S3. Studies were published between 2015 and 2025, with publications concentrated in 2023–2025 reflecting rapid growth. Fifteen of the 30 included studies (50.0%) were conducted in HIC settings and 15 (50.0%) in LMIC settings. Quality ratings: high (70.0%), moderate (30.0%), low (0.0%). Following eligibility re-assessment, all included studies were rated as moderate or high quality according to the predefined appraisal framework.

Methodological quality was independently appraised by two reviewers using a standardised six-item framework integrating JBI and PROBAST elements adapted for AI surveillance research (20). Full per-study appraisal outcomes and item-level scores are provided in Supplementary Table S7.

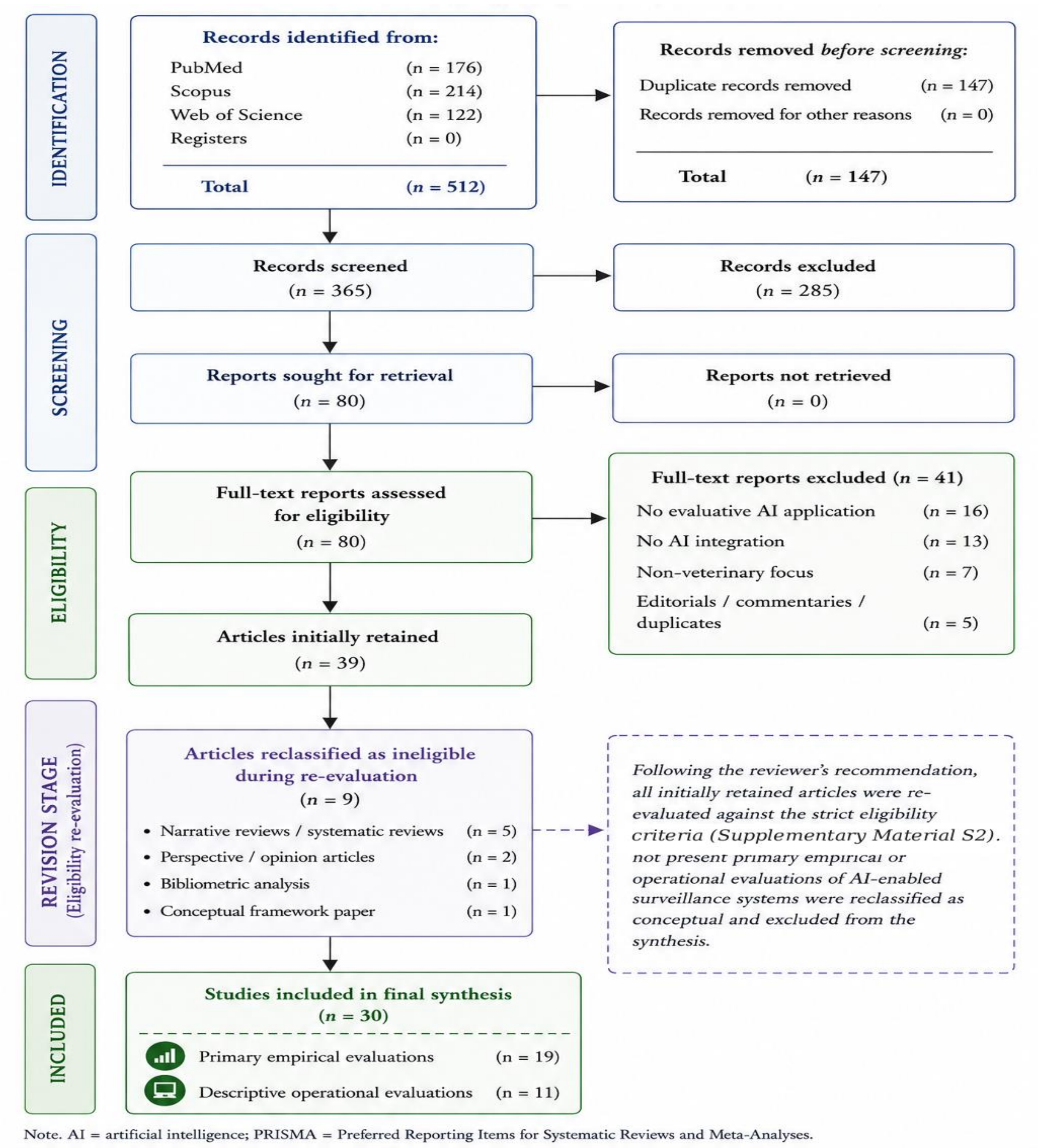

Fig. 1. PRISMA 2020 flow diagram for the systematic review of artificial intelligence applications in veterinary surveillance with One Health implications for LMICs. The highlighted boxes indicate the post-screening eligibility re-assessment that reclassified 9 articles as ineligible (Supplementary Material S4), reducing the final synthesis from 39 initially retained articles to 30 studies meeting the empirical eligibility criterion (Supplementary Material S2). Article IDs correspond to Supplementary Table S3 and the accompanying master extraction dataset. Adapted from Page et al. (2021), PRISMA 2020 statement.

Among the 30 included studies, 14 (46.7%) demonstrated direct relevance to zoonotic disease surveillance through explicit focus on zoonotic pathogens, vector surveillance, or One Health applications (Table 1). The remaining 16 (53.3%) studies addressed animal health surveillance with indirect zoonotic relevance via documented spillover pathways: poultry health monitoring is relevant to avian influenza (H5N1/H7N9) surveillance (51); livestock disease detection supports brucellosis/Q fever/Rift Valley fever monitoring; aquaculture monitoring is relevant to foodborne zoonoses; vector surveillance directly supports outbreak risk assessment for vector-borne zoonotic pathogens. Full study characteristics for all 30 included studies are documented in Supplementary Table S3 (25, 27–29, 34, 36–42, 45, 46, 48).

Table 1. Studies with direct zoonotic disease surveillance relevance (n = 14).

Article ID	Disease/Context	Country	Zoonotic Relevance	Application	Key Finding
B5-A01	Rabies	Haiti	Direct zoonosis	Predictive surveillance	ML risk stratification (XGBoost) yielded ~3-fold more epidemiologically useful surveillance data **(43)**
B1-A01	Multiple zoonoses	France	Event-based detection	Event-based surveillance	PADI-web multilingual surveillance system; retrospective F1-macro = 0.9995 **(22)**
B1-A02	Zoonotic diseases	Kenya	Syndromic surveillance	Event-based surveillance	Mobile-based syndromic system at animal-human interface (descriptive One Health evaluation) **(23)**
B3-A03	Multiple zoonoses	Cameroon	One Health platform	Event-based surveillance	Digital platform integrating animal and human health data (descriptive operational evaluation) **(35)**
B3-A01	Rodent-borne (leptospirosis)	Brazil	Vector surveillance	Predictive surveillance	ML-enhanced rodent surveillance for leptospirosis risk **(33)**
B5-A02	Zoonotic blood parasites	Thailand	Zoonotic parasites	Detection	Self-supervised learning for zoonotic blood parasite ID **(44)**
B6-A01	Kyasanur Forest Disease	India	Vector-borne zoonosis	Event-based surveillance	Transfer learning event-based prediction in resource-limited setting **(47)**
B6-A03	Dengue	Multi-country	Vector-borne	Predictive surveillance	Spatial ML for dengue epidemic wave prediction **(49)**
B6-A04	Avian influenza	United States	Direct zoonosis	Predictive surveillance	Gradient-boosted trees estimated AIV isolation probability from wild bird surveillance samples and supported sample prioritization **(50)**
B1-A03	Multiple zoonoses	HIC	Syndromic surveillance	Event-based surveillance	Automated syndromic ML from lab data; F1-macro = 0.9995 **(24)**
B2-A01	Disease trends	HIC	NLP surveillance	Event-based surveillance	Text mining for earlier disease-trend detection **(26)**
B2-A07	Surveillance indicators	HIC	Adoption barriers	Predictive surveillance	Identification of timeliness and completeness as key indicators **(32)**
B2-A05	Multi-disease big data	HIC	Big data surveillance	Predictive surveillance	Big data analytics for proactive targeted surveillance **(30)**
B2-A06	Animal diseases	HIC	Decision support	Event-based surveillance	Visual analytics for complex epi data integration **(31)**

Note: Article IDs are cross-reference labels linking each entry to Supplementary Table S3 and the master extraction dataset; they are not citation identifiers. The previous Ohia et al. (2025) entry was reclassified as a perspective/policy article and removed from the synthesis following eligibility re-assessment (Supplementary S4).

AI application categories (RQ1)

Four surveillance application categories were identified (Supplementary Table S5): predictive surveillance (n=9, 30.0%), event-based surveillance (n=7, 23.3%), automated monitoring (n=7, 23.3%), and disease detection and diagnosis (n=7, 23.3%). The roughly equal distribution across categories reflects the methodological diversity of AI applications in veterinary surveillance.

AI methodological approaches and LMIC feasibility (RQ2)

Six AI methodological categories were identified (Figure 2, Table 2). Traditional ML (40.0%) and Deep Learning/CNN (30.0%) were most common. Edge AI/TinyML (10.0%) and Transfer Learning (3.3%) explicitly addressed LMIC constraints, including limited connectivity, computational resources, and labelled training data scarcity.

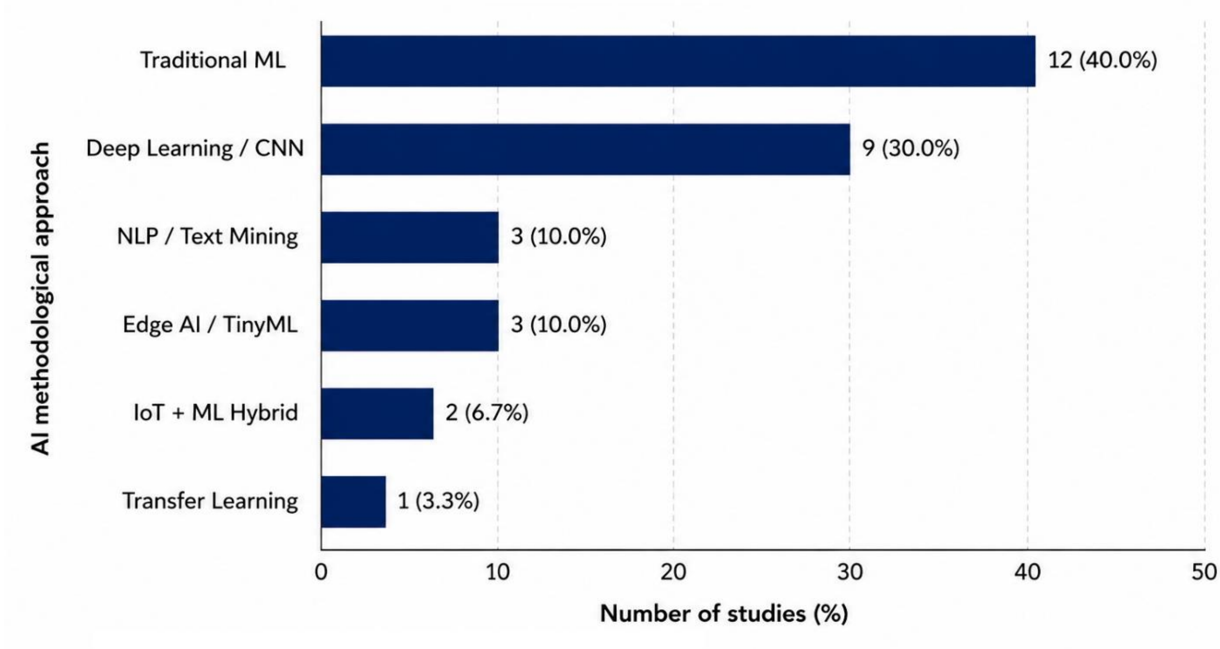

Fig. 2. Distribution of AI methodological approaches identified across the 30 included studies. Bar lengths represent the proportion of included studies applying each methodological category.

Surveillance performance indicators (RQ3)

Twenty studies (66.7%) reported quantitative performance metrics (Supplementary Table S6). Detection sensitivity exceeded 90% for deep learning approaches under controlled conditions. The machine learning rabies risk-stratification study reported an approximately 3-fold increase in epidemiologically useful surveillance data under low-surveillance field conditions in Haiti (43). Under retrospective validation, event-based syndromic classification achieved F1-macro of 0.9995 (24); prospective operational performance requires independent validation before conclusions can be drawn about routine automated zoonotic threat detection.

Table 2. AI methodological approaches and LMIC feasibility assessment (n=30).

AI Approach	n	%	Compute	Data Req.	Connectivity	LMIC Feasibility[1]
Traditional ML	12	40.0	Low	Moderate	Not required	High
Deep Learning / CNN	9	30.0	High	High	Often required	Moderate
NLP / Text Mining	3	10.0	Moderate	Moderate	Required	Moderate
Edge AI / TinyML	3	10.0	Very Low	Moderate	Not required	Very High
IoT + ML Hybrid	2	6.7	Moderate	Moderate	Periodic	Moderate
Transfer Learning	1	3.3	Moderate	Low	Initial only	High

[1] LMIC feasibility reflects expert judgment based on technical characteristics (computational requirements, data dependencies, connectivity) reported in included studies. These ratings do not constitute empirical evidence of operational feasibility from routine deployments; sustainability and cost-effectiveness under real-world LMIC conditions remain areas requiring further investigation.

Discussion

This systematic review identified 30 studies on AI in veterinary surveillance, with 50.0% addressing LMIC contexts and 14 (46.7%) studies demonstrating direct relevance to zoonotic disease monitoring. The approximately three-fold increase in epidemiologically useful rabies surveillance data achieved through ML-based risk stratification and near real-time event detection for zoonotic threats suggest AI-enabled approaches may help address the documented under ascertainment of zoonotic disease burden. However, most studies were proof-of-concept evaluations rather than operational deployments.

AI-enabled surveillance tools may complement conventional surveillance infrastructures by enabling automated anomaly detection across animal health, environmental, and vector monitoring datasets. Event-based surveillance systems demonstrated capacity for automated detection of zoonotic disease signals. Beyond the empirically evaluated systems in the synthesis, perspective and policy contributions (e.g., conceptual articles reclassified following eligibility re-assessment and documented in Supplementary S4) provide useful conceptual framing of multi-sectoral zoonotic surveillance challenges and have been retained as contextual references where relevant.

AI-supported systems may serve as complementary analytical tools rather than replacements for conventional surveillance infrastructures. AI-based surveillance systems should be interpreted as decision-support and signal-enhancement tools rather than autonomous replacements for veterinary epidemiological expertise.

A conceptual synthesis (Supplementary Figure S1) illustrates how AI methodological approaches align with surveillance objectives and resource constraints. The framework was constructed inductively from recurring implementation themes identified across the 30 included studies, with each component grounded in evidence from at least two independent studies. The framework should be interpreted as a heuristic synthesis rather than a prescriptive implementation model.

Edge AI/TinyML demonstrated feasibility for field deployment without continuous connectivity. Transfer learning reduced labeled data dependence. Self-supervised approaches addressed annotator shortages. Notably, the revised synthesis shows balanced HIC–LMIC representation (15 of 30 studies, 50.0%, in each setting), confirming strong LMIC representation in the AI veterinary surveillance literature. However, sustainability under routine conditions remains uncertain, and cost-effectiveness has not been rigorously evaluated.

Study heterogeneity precluded quantitative meta-analysis. Publication bias likely favors positive findings. The search was limited to English. Grey literature was not systematically searched, which may have excluded relevant operational reports. Many included studies evaluated AI models under experimental conditions rather than routine surveillance workflows, limiting conclusions regarding operational feasibility. Unsuccessful or negative AI surveillance implementations are likely underreported. Following eligibility re-assessment, 9 articles initially retained were reclassified as ineligible (Supplementary S4). This re-evaluation also functioned as a sensitivity analysis: the principal findings (balanced HIC–LMIC representation, dominant application domains, role of Edge AI and transfer learning for LMICs, calibrated strength-of-evidence for surveillance impact) remained robust across both the initial (n=39 retained) and revised (n=30) frames.

Supplementary Table S8 presents a synthesis of identified gaps across surveillance application domains.

Priority areas include: (1) comparative evaluations under operational conditions; (2) cost-effectiveness analyses; (3) transferability assessment across contexts; (4) One Health integration frameworks; (5) governance standards for ethical AI deployment in zoonotic disease surveillance.

Conclusion

This review synthesised 30 empirical studies (20 primary empirical + 10 descriptive operational evaluations) on AI applications in veterinary surveillance relevant to zoonotic disease monitoring; 50.0% addressed LMIC settings and 14 (46.7%) demonstrated direct zoonotic relevance. Applications spanned predictive surveillance (30.0%), event-based surveillance (23.3%), automated monitoring (23.3%), and disease detection (23.3%); Edge AI/TinyML, transfer learning, and self-supervised learning recurrently aligned with LMIC constraints. Key operational signals included a ~3-fold increase in epidemiologically useful rabies surveillance data (Haiti) and PADI-web retrospective F1-macro = 0.9995. AI-enabled approaches appear methodologically promising for strengthening zoonotic surveillance within One Health frameworks, particularly in LMICs, but current evidence is dominated by proof-of-concept and retrospective evaluations. Prospective operational studies, cost-effectiveness analyses, transferability assessments, and governance frameworks remain priority research directions.

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Conflict of Interest

The authors declare no competing interests.

Ethical approval

Ethical approval was not required for this systematic review based exclusively on published literature.

Artificial Intelligence Statement

The authors used a generative artificial intelligence tool to assist with language editing and formatting of the manuscript. All content was subsequently reviewed, verified, and approved by the authors, who take full responsibility for the integrity and accuracy of the work.

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