SUPPLEMENTARY MATERIALS

Artificial Intelligence in Zoonotic Disease Surveillance: A Systematic Review with One Health Implications for Low- and Middle-Income Countries

Following application of the explicit empirical eligibility criterion, the eligibility criteria were strictly re-applied to all retrieved articles. Nine articles previously included were identified as conceptual reviews, perspective articles, or bibliometric analyses that did not meet the empirical eligibility criterion (Supplementary eligibility framework). These have been removed from the quantitative synthesis and are documented in Supplementary Material S4. The revised synthesis includes 30 empirical and operational studies (20 primary empirical evaluations + 10 descriptive operational evaluations).

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Contents

Supplementary Material S1: Complete database-specific search strategies

This supplementary material presents the complete, reproducible search strategies for all electronic databases consulted in this systematic review. The search concept was structured around three thematic blocks combined with AND, with synonyms within each block combined with OR. Truncation symbols capture morphological variants. All searches were developed iteratively in consultation with an academic librarian.

S1.1. PubMed (via NCBI)

Date of search execution: 15 March 2026

URL: *https://pubmed.ncbi.nlm.nih.gov/*

```
(   ("artificial intelligence"[MeSH Terms] OR "machine learning"[MeSH Terms]    OR "deep learning"[Title/Abstract] OR "neural network*"[Title/Abstract]    OR "convolutional neural network*"[Title/Abstract] OR "computer vision"[Title/Abstract]    OR "natural language processing"[Title/Abstract] OR "transfer learning"[Title/Abstract]    OR "self-supervised learning"[Title/Abstract] OR "edge computing"[Title/Abstract]    OR "TinyML"[Title/Abstract] OR "Internet of Things"[MeSH Terms])    AND    ("veterinary surveillance"[Title/Abstract] OR "animal disease surveillance"[Title/Abstract]    OR "syndromic surveillance"[Title/Abstract] OR "event-based surveillance"[Title/Abstract]    OR "Zoonoses"[MeSH Terms] OR "One Health"[MeSH Terms] OR "livestock disease*"[Title/Abstract] OR "poultry disease*"[Title/Abstract]    OR "wildlife disease*"[Title/Abstract] OR "aquaculture"[MeSH Terms]    OR "vector surveillance"[Title/Abstract])    AND    ("detection"[Title/Abstract] OR "prediction"[Title/Abstract]    OR "monitoring"[Title/Abstract] OR "outbreak*"[Title/Abstract] OR "early warning"[Title/Abstract] OR "risk assessment"[Title/Abstract]    OR "spillover"[Title/Abstract]) )  AND ("2015/01/01"[Date - Publication] : "2025/12/31"[Date - Publication]) AND English[Language] NOT ("editorial"[Publication Type] OR "letter"[Publication Type]      OR "comment"[Publication Type] OR "news"[Publication Type])
```

Records retrieved: 176

S1.2. Scopus (via Elsevier)

Date of search execution: 16 March 2026

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(TITLE-ABS-KEY ("artificial intelligence" OR "machine learning" OR "deep learning"   OR "neural network*" OR "convolutional neural network*" OR "computer vision"   OR "natural language processing" OR "transfer learning" OR "self-supervised learning"   OR "edge computing" OR "TinyML" OR "Internet of Things")  AND TITLE-ABS-KEY ("veterinary surveillance" OR "animal disease surveillance"   OR "syndromic surveillance" OR "event-based surveillance"   OR "zoonos*" OR "One Health" OR "livestock disease*" OR "poultry disease*"   OR "wildlife disease*" OR "aquaculture" OR "vector surveillance")  AND TITLE-ABS-KEY ("detection" OR "prediction" OR "monitoring"   OR "outbreak*" OR "early warning" OR "risk assessment" OR "spillover"))  AND PUBYEAR > 2014 AND PUBYEAR < 2026 AND LANGUAGE (english) AND NOT DOCTYPE ("ed" OR "le" OR "no" OR "sh")
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Records retrieved: 214

S1.3. Web of Science Core Collection

Date of search execution: 17 March 2026

```
TS = (("artificial intelligence" OR "machine learning" OR "deep learning"   OR "neural network*"
OR "convolutional neural network*" OR "computer vision"   OR "natural language processing" OR
"transfer learning" OR "self-supervised learning"   OR "edge computing" OR "TinyML" OR "Internet
of Things")  AND ("veterinary surveillance" OR "animal disease surveillance"   OR "syndromic
surveillance" OR "event-based surveillance"   OR "zoonos*" OR "One Health" OR "livestock
disease*" OR "poultry disease*"   OR "wildlife disease*" OR "aquaculture" OR "vector
surveillance")  AND ("detection" OR "prediction" OR "monitoring"   OR "outbreak*" OR "early
warning" OR "risk assessment" OR "spillover"))  AND PY = 2015-2025 AND LA = (English) NOT DT =
(Editorial Material OR Letter OR News Item OR Correction)
```

Records retrieved: 122

S1.4. Targeted website searches (organisational sources)

Websites of WOAH, FAO, WHO, and UNEP were consulted on 18 March 2026 for relevant One Health policy documents. Documents identified were used for contextual framing only and were not included in the quantitative synthesis.

S1.5. Summary of search yield and study selection

Stage	Records (n)	Records excluded (n)
Total records from databases	**512**	—
Duplicates removed	—	147
Records after deduplication	365	—
Title/abstract screening — excluded	—	285
Full-text retrieved	80	—
Full-text excluded	—	41
Articles initially retained	39	—
Reclassified during revision (not primary empirical)	—	9
Studies included in final synthesis	**30**	—

Reasons for full-text exclusion (n = 41): non-evaluative AI applications (n = 16); no AI integration (n = 13); non-veterinary focus (n = 7); editorials, commentaries, or duplicates (n = 5). Reclassification during revision (n = 9): articles identified as conceptual reviews, perspective articles, narrative reviews, or bibliometric analyses that did not meet the empirical eligibility criterion (see Section S4 below). Final synthesis: 30 empirical and operational studies (20 primary empirical + 10 descriptive operational evaluations).

Supplementary Material S2: Eligibility Framework and PRISMA 2020 Checklist

This completed PRISMA 2020 checklist reports the location (section/paragraph) in the main manuscript and/or in this Supplementary Materials document where each PRISMA 2020 item is addressed. Reference: Page MJ, et al. The PRISMA 2020 statement. BMJ. 2021;372:n71.

Eligibility framework (PECO)

The eligibility framework was defined using the PECO structure and applied during the final revision-stage eligibility re-assessment.

PECO element	Definition	Eligibility requirement	Notes
Population	Animal populations, veterinary surveillance systems, and zoonotic vectors relevant to animal health or zoonotic disease surveillance.	Studies addressing veterinary/animal health surveillance or an animal–human interface.	Included livestock, poultry, aquaculture, multiple-species systems, and zoonotic vectors.
Exposure / intervention	AI-enabled methods used for disease detection, prediction, monitoring, or event-based surveillance.	AI had to be integrated into a surveillance or surveillance-relevant empirical/operational application.	Methods included ML, deep learning/CNN, NLP, Edge AI/TinyML, IoT–ML, and transfer learning.
Comparator	Conventional, baseline, alternative model, or pre-existing surveillance approach, where applicable.	Comparator was not mandatory because some studies were descriptive operational or single-arm model evaluations.	Where available, comparative or baseline performance information was extracted.
Outcome	Quantitative surveillance performance or operational indicator.	At least one quantitative indicator, such as accuracy/sensitivity, F1-score, reporting timeliness, early detection, risk-prediction performance, or operational performance.	Studies without empirical evaluation outcomes were excluded.

Eligible study designs comprised (i) primary empirical evaluations of AI-enabled veterinary surveillance systems, (ii) retrospective validation studies, and (iii) descriptive evaluations of implemented digital surveillance platforms reporting at least one quantitative performance indicator. Ineligible designs included narrative, systematic, or 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.

Item #	Item	Reporting requirement	Location
TITLE			
1	**Title**	Identify the report as a systematic review.	*Title page*
ABSTRACT			
2	**Abstract**	See the PRISMA 2020 for Abstracts checklist.	*Abstract*
INTRODUCTION			
3	**Rationale**	Describe rationale in context of existing knowledge.	*Section 1.1–1.2*
4	**Objectives**	Provide an explicit statement of the objectives.	*Section 1.3 (RQ1–RQ3)*
METHODS			
5	**Eligibility criteria**	Specify the inclusion and exclusion criteria.	*Section 2.1; Supplementary eligibility framework*
6	**Information sources**	Specify all sources and dates searched.	*Section 2.2; Supp. S1*
7	**Search strategy**	Present full search strategies for all databases.	*Section 2.2; Supp. S1.1–S1.3*
8	**Selection process**	Specify methods used to decide whether a study met criteria.	*Section 2.2 (two independent reviewers; κ=0.87/0.92)*
9	**Data collection process**	Specify methods used to collect data.	*Section 2.3*
10a	**Data items — outcomes**	List and define all outcomes.	*Section 2.3; Supp. S3*
10b	**Data items — other variables**	List and define all other variables.	*Section 2.3; Supp. S3*
11	**Study risk of bias assessment**	Specify the methods used to assess risk of bias.	*Section 2.2; Supp. S7*
12	**Effect measures**	Specify effect measures used.	*Section 2.3 (narrative; no meta-analysis)*
13a	**Synthesis methods — eligibility**	Describe processes used to decide eligibility.	*Section 2.3; Supp. S1.5*
13b	**Synthesis methods — preparation**	Describe data preparation.	*Section 2.3*
13c	**Synthesis methods — visualisation**	Describe tabulation methods.	*Section 2.3; Tables 1–2*
13d	**Synthesis methods — synthesis**	Describe synthesis methods.	*Section 2.3 (Popay et al., 2006)*
13e	**Synthesis methods — heterogeneity**	Describe heterogeneity exploration.	*Section 2.3; Section 4.6*
13f	**Synthesis methods — sensitivity**	Describe sensitivity analyses.	*Section 2.3 (eligibility re-evaluation)*
14	**Reporting bias assessment**	Describe methods for missing-results bias.	*Section 4.6*
15	**Certainty assessment**	Describe certainty assessment.	*Section 3.1; Section 4.6*
RESULTS			
16a	**Study selection — flow**	Describe selection results with flow diagram.	*Section 3.1; Figure 1; Supp. S1.5*

Item #	Item	Reporting requirement	Location
16b	**Study selection — exclusions**	Cite excluded studies and reasons.	*Section 3.1; Supp. S4*
17	**Study characteristics**	Cite each included study and present characteristics.	*Table 1; Supplementary Table S3 (all 30 studies)*
18	**Risk of bias in studies**	Present risk of bias assessments per study.	*Supplementary Table S7*
19	**Results of individual studies**	For all outcomes, present per-study data.	*Supp. S3; Supp. S6*
20a	**Results of syntheses — characteristics**	Summarise characteristics for each synthesis.	*Sections 3.2–3.5*
20b	**Results of syntheses — statistical**	Present statistical syntheses.	*Sections 3.2–3.5 (narrative)*
20c	**Results of syntheses — heterogeneity**	Present heterogeneity investigations.	*Section 4.6*
20d	**Results of syntheses — sensitivity**	Present sensitivity analyses.	*Section 3.1*
21	**Reporting biases**	Present bias assessments per synthesis.	*Section 4.6*
22	**Certainty of evidence**	Present certainty assessments.	*Sections 3.1, 4.6, 5*
DISCUSSION			
23a	**Discussion — interpretation**	Provide interpretation in context.	*Sections 4.1–4.5*
23b	**Discussion — limitations of evidence**	Discuss limitations of evidence.	*Section 4.6*
23c	**Discussion — limitations of processes**	Discuss process limitations.	*Section 4.6*
23d	**Discussion — implications**	Discuss implications.	*Sections 4.3, 4.8, 5*
OTHER INFORMATION			
24a	**Registration and protocol**	Provide registration information.	*Section 2.1 (not registered; rationale provided)*
24b	**Protocol access**	Indicate protocol access.	*Section 2.1*
24c	**Amendments**	Describe amendments.	*Revision: study count from 35→34→30 (Supp. S1.5, S4)*
25	**Support**	Describe sources of support.	*Funding statement (manuscript)*
26	**Competing interests**	Declare competing interests.	*Conflict of Interest Statement (manuscript)*
27	**Availability of data, code, materials**	Report data/code/materials availability.	*Data Availability Statement; Supp. S3*

Supplementary Table S3: Per-study evidence table (n = 30)

This table presents, for each of the 30 included studies (20 primary empirical + 10 descriptive operational evaluations), the following variables: (1) sequential number; (2) Article ID from the master extraction dataset; (3) short title; (4) DOI; (5) study design / evidence type (E = primary empirical evaluation; O = descriptive operational evaluation); (6) country / income setting (HIC / LMIC); (7) AI methodological category; (8) surveillance application category; (9) target animal/population; (10) zoonotic relevance (Direct / Indirect via spillover pathway); (11) quality appraisal score (0–6); (12) overall quality rating. Studies are presented according to their unique Article IDs to facilitate cross-referencing with the master extraction dataset. Full bibliographic citations corresponding to each DOI are available in the master extraction file submitted with this revision.

Abbreviations: AI = artificial intelligence; CNN = convolutional neural network; DL = deep learning; HIC = high-income country; IoT = Internet of Things; LMIC = low- or middle-income country; ML = machine learning; NLP = natural language processing; SSL = self-supervised learning.

Article ID	Short title	DOI	Type	Setting	AI method	Surv. category	Species (zoonotic)	Q
B1-A01	PADI-web 3.0	10.1016/j.onehlt.2021.100357	**E**	HIC	NLP / Text Mining	Event-based	Multi-species (D)	**6 H**
B1-A02	Kenya Animal Health Surveillance System	10.1371/journal.pone.0244119	**E**	LMIC	Traditional ML (Syndromic)	Event-based	Multi-species (D)	**6 H**
B1-A03	Automated syndromic ML (Lab data)	10.1371/journal.pone.0057334	**E**	HIC	Traditional ML	Event-based	Multi-species (D)	**5 H**
B1-A04	ACMSPT Poultry Monitoring	10.3390/agriengineering7030086	**O**	LMIC	Deep Learning / CNN	Automated Monitoring	Poultry (I)	**4 M**
B2-A01	Text mining veterinary clinical data (Part II)	10.1016/j.prevetmed.2014.01.017	**E**	HIC	NLP / Text Mining	Event-based	Multi-species (D)	**5 H**
B2-A02	Automated dead chicken detection (ViT)	10.3390/app15010136	**E**	HIC	Deep Learning / CNN	Disease Detection	Poultry (I)	**5 H**
B2-A03	AI-based laying hen behavior monitoring	10.3390/agriculture15181963	**O**	HIC	Deep Learning / CNN	Automated Monitoring	Poultry (I)	**5 H**
B2-A04	IoT-driven hybrid AI for cows	10.1007/s44163-025-00610-4	**E**	LMIC	IoT + ML Hybrid	Automated Monitoring	Cattle/Livestock (I)	**5 H**
B2-A05	Precision veterinary epidemiology (Big Data)	10.2460/javma.25.01.0026	**O**	HIC	Traditional ML	Predictive Surveillance	Multi-species (D)	**4 M**
B2-A06	Visual analytics for animal diseases	10.1109/PacificVis56936.2023.00015	**O**	HIC	Traditional ML (Visual Analytics)	Event-based	Multi-species (D)	**3 M**
B2-A07	GIS expert elicitation (surveillance indicators)	10.17582/journal.aavs/2020/8.11.1147.1153	**E**	HIC	Traditional ML (GIS)	Predictive Surveillance	Multi-species (D)	**5 H**
B3-A01	Rodent surveillance using ML	10.1002/ece3.72382	**E**	LMIC	Traditional ML	Predictive Surveillance	Zoonotic vectors (D)	**6 H**
B3-A02	SPR + SOM diagnostics	10.1039/C9RA01466G	**E**	HIC	Deep Learning / CNN (SOM)	Disease Detection	Multi-species (I)	**5 H**

Article ID	Short title	DOI	Type	Setting	AI method	Surv. category	Species (zoonotic)	Q
B3-A03	Digital One Health Cameroon	10.3389/fdgth.2025.1507391	**O**	LMIC	NLP / Text Mining	Event-based	Multi-species (D)	**4 M**
B3-A04	GAN-based image enhancement	10.1007/s00521-023-09100-z	**O**	HIC	Deep Learning / CNN (GAN)	Disease Detection	Multi-species (I)	**3 M**
B4-A01	Multimodal poultry disease identification	10.1109/ICCPCT65132.2025.11176642	**E**	LMIC	Deep Learning / CNN	Disease Detection	Poultry (I)	**5 H**
B4-A02	Early broiler diagnosis (RF + Swarm)	10.1590/1806-9061-2024-2046	**E**	LMIC	Traditional ML	Disease Detection	Poultry (I)	**5 H**
B4-A03	IoT–ML water quality (Tilapia)	10.1016/j.rechem.2025.102456	**E**	LMIC	IoT + ML Hybrid	Predictive Surveillance	Aquaculture (I)	**5 H**
B4-A04	Hybrid attention livestock monitoring	10.1109/FIT60620.2023.00021	**E**	LMIC	Deep Learning / CNN	Automated Monitoring	Cattle/Livestock (I)	**5 H**
B4-A05	Sheep face recognition (lightweight)	10.1016/j.atech.2025.101362	**O**	HIC	Edge AI / TinyML	Automated Monitoring	Cattle/Livestock (I)	**3 M**
B4-A06	Aquaculture predictive modelling	10.1016/j.scitotenv.2025.180965	**E**	HIC	Traditional ML	Predictive Surveillance	Aquaculture (I)	**5 H**
B5-A01	Rabies epidemiology using ML	10.1038/s41598-024-76089-3	**E**	LMIC	Traditional ML (XGBoost)	Predictive Surveillance	Multi-species (D)	**6 H**
B5-A02	Blood parasite identification (SSL)	10.14202/vetworld.2024.2619-2634	**E**	LMIC	Deep Learning / CNN (SSL)	Disease Detection	Zoonotic vectors (D)	**5 H**
B5-A03	Edge-AI chicken health detection	10.1016/j.compag.2024.109432	**E**	LMIC	Edge AI / TinyML	Disease Detection	Poultry (I)	**5 H**
B5-A04	YOLOv8 cattle body segmentation	10.1109/ISCS61804.2024.10581048	**O**	HIC	Deep Learning / CNN (YOLO)	Automated Monitoring	Cattle/Livestock (I)	**3 M**
B6-A01	Kyasanur Forest Disease prediction (TL)	10.1038/s41598-023-38074-0	**E**	LMIC	Transfer Learning	Event-based	Zoonotic vectors (D)	**6 H**
B6-A02	Fish stress recognition (KD)	10.32604/cmes.2022.019378	**E**	LMIC	Edge AI / TinyML	Automated Monitoring	Aquaculture (I)	**5 H**
B6-A03	Dengue wave dynamics	10.1038/s41467-022-28231-w	**O**	LMIC	Traditional ML (Spatial)	Predictive Surveillance	Zoonotic vectors (D)	**3 M**
B6-A04	Artificial intelligence and avian influenza	10.1111/tbed.13318	E	HIC	Traditional ML (Gradient Boosted Trees)	Predictive Surveillance	Wild birds (D)	5 H
B6-A05	Poultry farm distribution models	10.1371/journal.pcbi.1011980	**O**	HIC	Traditional ML (Spatial)	Predictive Surveillance	Poultry (I)	**3 M**

Type column: E = primary empirical evaluation (n=20, blue fill); O = descriptive operational evaluation (n=10, orange fill). Q column: numeric score (max 6) followed by category letter (H = High, M = Moderate, L = Low). Species column suffix: (D) = Direct zoonotic relevance, (I) = Indirect zoonotic relevance. All 30 studies meet the empirical eligibility criterion specified in Supplementary eligibility framework of the main manuscript.

S3 — Summary distribution table (n = 30)

Characteristic	n	%
Evidence type		
Primary empirical evaluation (E)	20	66.7
Descriptive operational evaluation (O)	10	33.3
Income setting		
High-Income Countries (HIC)	15	50.0
Low/Middle-Income Countries (LMIC)	15	50.0
Surveillance application category		
Predictive Surveillance	9	30.0
Event-based Surveillance	7	23.3
Automated Monitoring	7	23.3
Disease Detection & Diagnosis	7	23.3
AI methodological category		
Traditional ML (incl. spatial, GIS, syndromic, visual analytics)	12	40.0
Deep Learning / CNN (incl. SSL, SOM, GAN, attention)	9	30.0
NLP / Text Mining / Integration	3	10.0
Edge AI / TinyML	3	10.0
IoT + ML Hybrid	2	6.7
Transfer Learning	1	3.3
Target population		
Multi-species	11	36.7
Poultry	7	23.3
Zoonotic vectors	4	13.3
Wild birds	1	3.3
Cattle / Livestock	4	13.3
Aquaculture	3	10.0
Zoonotic relevance		
Direct	14	46.7
Indirect (via documented spillover pathway)	16	53.3
Quality rating		
High	21	70.0
Moderate	9	30.0
Low	0	0.0

Note: All percentages reflect the synthesis of n = 30 empirical and operational studies. The balanced HIC–LMIC distribution (15 of 30 studies in each setting) supports substantial LMIC representation in the AI veterinary surveillance literature.

Supplementary Material S4: Articles reclassified as ineligible during revision (n = 9)

Following application of the predefined empirical eligibility criterion (Supplementary eligibility framework in the main manuscript), nine articles previously retained from the original screening were reclassified as ineligible for the quantitative synthesis. These articles were identified as conceptual reviews, perspective articles, narrative reviews, or bibliometric analyses that did not report primary empirical evaluation outcomes. These studies were excluded from the formal evidence synthesis (quantitative and structured narrative synthesis) but were retained only as contextual references where appropriate.

#	Article ID	Short title	DOI	Reason for reclassification	Retained as context?
1	**B1-A05**	Decision-support epidemiology	N/A	Conceptual framework; no empirical evaluation	Yes (Section 4.3)
2	**B2-A08**	AMR One Health review	10.1016/j.tibtech.2023.05.004	Narrative review (not primary empirical)	Yes (Section 4.2)
3	**B2-A09**	Blockchain + AI food safety	10.1016/j.jclepro.2024.140102	Conceptual / opinion paper	No
4	**B3-A05**	Big Data epidemiology review	10.1016/j.epidem.2023.100687	Narrative review	No
5	**B4-A07**	IoT-aquaculture bibliometric	10.3390/agriculture14040532	Bibliometric analysis (not empirical evaluation)	No
6	**B4-A08**	Optical sensor technologies review	10.1016/j.tifs.2023.01.006	Narrative review of enabling technologies	No
7	**B5-A05**	DL in neglected vector-borne diseases (SLR)	10.1016/j.actatropica.2024.107105	Systematic literature review (overlapping scope)	No
8	**B5-A06**	Modern technologies for zoonotic surveillance	10.1016/j.onehlt.2024.100627	Conceptual / perspective article	Yes (Section 4.2)
9	**B5-A07**	AMR genomic revolution	10.1016/j.tim.2023.101051	Conceptual / opinion paper	No

This reclassification directly addresses Reviewer 2's comment that 'if only primary empirical studies were intended to be eligible, then the authors should re-evaluate the included studies and exclude articles that do not meet this criterion'. The revised synthesis is now methodologically consistent with the empirical eligibility criterion stated in Supplementary eligibility framework.

Supplementary Table S5: AI application categories with detailed study allocation

This table presents the four AI application categories identified in the revised synthesis (n = 30), with detailed allocation of studies. The categories were derived inductively from study objectives and are mutually exclusive.

Category	n	%	Description	Article IDs
Predictive Surveillance	**9**	30.0	Outbreak prediction, spatial risk mapping, early-warning system development; predominantly ML-based methods including XGBoost, Random Forest, and spatial modelling approaches	*B2-A05*, *B2-A07*, *B3-A01*, *B4-A03*, *B4-A06*, *B5-A01*, *B6-A03*, *B6-A04*, *B6-A05*
Disease Detection & Diagnosis	**7**	23.3	Case identification, outbreak confirmation, animal health assessment; predominantly CV/CNN-based architectures and self-supervised approaches	*B2-A02*, *B3-A02*, *B3-A04*, *B4-A01*, *B4-A02*, *B5-A02*, *B5-A03*
Automated Monitoring	**7**	23.3	Continuous monitoring, behaviour analysis, IoT and sensor-based health surveillance; real-time analytics including Edge AI	*B1-A04*, *B2-A03*, *B2-A04*, *B4-A04*, *B4-A05*, *B5-A04*, *B6-A02*
Event-based Surveillance	**7**	23.3	Web/text-based event detection, syndromic classification, transfer-learning-enhanced event prediction, digital One Health platform integration	*B1-A01*, *B1-A02*, *B1-A03*, *B2-A01*, *B2-A06*, *B3-A03*, *B6-A01*
TOTAL	**30**	**100.0**		

Supplementary Table S6: Surveillance performance indicators by AI approach

Performance metrics are presented as reported ranges rather than pooled estimates because of substantial heterogeneity in study design, data sources, and outcome definitions. Direct comparisons between AI approaches were not performed.

Indicator	Studies (n)	Reported range	Most-frequently reported in	Consistency	Evidence base
Detection sensitivity / accuracy	11	85–98.8%	Deep Learning / CNN	Consistent	Retrospective
Case-detection increase	3	>3-fold	Traditional ML (XGBoost)	Consistent	Field validation
F1-score	7	0.87–0.9995	NLP / Text Mining	Consistent	Retrospective
Reporting timeliness	4	Near real-time	Edge AI / TinyML	Emerging	Proof-of-concept
Early detection (vs. conventional)	5	1–3 days earlier	Event-based / NLP	Emerging	Mixed
Inference latency (Edge AI)	3	< 80–200 ms	Edge AI / TinyML	Consistent	Proof-of-concept

'Consistent' = ≥ 3 independent studies report convergent ranges; 'Emerging' = ≤ 2 studies or substantial heterogeneity. Principal exemplars referenced in the main manuscript: B5-A01 (rabies XGBoost; ~3-fold case-detection increase in low-surveillance LMIC field setting) and B1-A01 (PADI-web; retrospective F1-macro = 0.9995; prospective performance not yet validated).

Supplementary Table S7: Item-level critical appraisal scores (n = 30)

Methodological quality was assessed independently by two reviewers. The quality appraisal applied a standardised 6-item evaluation framework integrating elements from the JBI critical appraisal checklists for analytical/descriptive studies and PROBAST for prediction model studies, adapted for the evaluation of AI-based surveillance research. Items scored as Yes (Y) = 1 or No/Unclear (N) = 0, with maximum total = 6.

Items assessed:

QA1. Were the inclusion/sample criteria clearly defined?
QA2. Were the study setting and data sources described in detail?
QA3. Was the AI/ML method clearly specified and reproducibly described?
QA4. Were outcome measures defined using standard, objective criteria?
QA5. Was the analysis appropriate and statistically valid?
QA6. Was the surveillance/operational context adequately contextualised?

Art. ID	Short title	DOI	QA1	QA2	QA3	QA4	QA5	QA6	Total	Rating
B1-A01	PADI-web 3.0	10.1016/j.onehlt.2021.100357	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**6/6**	**High**
B1-A02	Kenya Animal Health Surveillance System	10.1371/journal.pone.0244119	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**6/6**	**High**
B1-A03	Automated syndromic ML (Lab data)	10.1371/journal.pone.0057334	**Y**	**Y**	**Y**	**Y**	**Y**	**N**	**5/6**	**High**
B1-A04	ACMSPT Poultry Monitoring	N/A	**Y**	**Y**	**Y**	**Y**	**N**	**N**	**4/6**	**Moderate**
B2-A01	Text mining veterinary clinical data (Part II)	10.1016/j.prevetmed.2014.01.017	**Y**	**Y**	**Y**	**Y**	**Y**	**N**	**5/6**	**High**
B2-A02	Automated dead chicken detection (ViT)	10.3390/app15010136	**Y**	**Y**	**Y**	**Y**	**Y**	**N**	**5/6**	**High**
B2-A03	AI-based laying hen behavior monitoring	10.3390/agriculture15181963	**Y**	**Y**	**Y**	**Y**	**Y**	**N**	**5/6**	**High**
B2-A04	IoT-driven hybrid AI for cows	10.1007/s44163-025-00610-4	**Y**	**Y**	**Y**	**Y**	**Y**	**N**	**5/6**	**High**
B2-A05	Precision veterinary epidemiology (Big Data)	10.2460/javma.25.01.0026	**Y**	**Y**	**Y**	**Y**	**N**	**N**	**4/6**	**Moderate**
B2-A06	Visual analytics for animal diseases	10.1109/PacificVis56936. 2023.00015	**Y**	**Y**	**Y**	**N**	**N**	**N**	**3/6**	**Moderate**

Art. ID	Short title	DOI	QA1	QA2	QA3	QA4	QA5	QA6	Total	Rating
B2-A07	GIS expert elicitation (surveillance indicators)	10.17582/journal.aavs/2020/ 8.11.1147.1153	Y	Y	Y	Y	Y	N	5/6	High
B3-A01	Rodent surveillance using ML	10.1002/ece3.72382	Y	Y	Y	Y	Y	Y	6/6	High
B3-A02	SPR + SOM diagnostics	10.1039/C9RA01466G	Y	Y	Y	Y	Y	N	5/6	High
B3-A03	Digital One Health Cameroon	10.3389/fdgth.2025.1507391	Y	Y	Y	Y	N	N	4/6	Moderate
B3-A04	GAN-based image enhancement	10.1007/s00521-023-09100-z	Y	Y	Y	N	N	N	3/6	Moderate
B4-A01	Multimodal poultry disease identification	10.1109/ICCPCT65132.2025.11176642	Y	Y	Y	Y	Y	N	5/6	High
B4-A02	Early broiler diagnosis (RF + Swarm)	10.1590/1806-9061-2024-2046	Y	Y	Y	Y	Y	N	5/6	High
B4-A03	IoT–ML water quality (Tilapia)	10.1016/j.rechem.2025.102456	Y	Y	Y	Y	Y	N	5/6	High
B4-A04	Hybrid attention livestock monitoring	10.1109/FIT60620.2023.00021	Y	Y	Y	Y	Y	N	5/6	High
B4-A05	Sheep face recognition (lightweight)	10.1016/j.atech.2025.101362	Y	Y	Y	N	N	N	3/6	Moderate
B4-A06	Aquaculture predictive modelling	10.1016/j.scitotenv.2025.180965	Y	Y	Y	Y	Y	N	5/6	High
B5-A01	Rabies epidemiology using ML	10.1038/s41598-024-76089-3	Y	Y	Y	Y	Y	Y	6/6	High
B5-A02	Blood parasite identification (SSL)	10.14202/vetworld.2024.2619-2634	Y	Y	Y	Y	Y	N	5/6	High
B5-A03	Edge-AI chicken health detection	10.1016/j.compag.2024.109432	Y	Y	Y	Y	Y	N	5/6	High
B5-A04	YOLOv8 cattle body segmentation	10.1109/ISCS61804.2024.10581048	Y	Y	Y	N	N	N	3/6	Moderate
B6-A01	Kyasanur Forest Disease prediction (TL)	10.1038/s41598-023-38074-0	Y	Y	Y	Y	Y	Y	6/6	High
B6-A02	Fish stress recognition (KD)	10.32604/cmes.2022.019378	Y	Y	Y	Y	Y	N	5/6	High

Art. ID	Short title	DOI	QA1	QA2	QA3	QA4	QA5	QA6	Total	Rating
B6-A03	Dengue wave dynamics	10.1038/s41467-022-28231-w	**Y**	**Y**	**Y**	**N**	**N**	**N**	**3/6**	**Moderate**
B6-A04	Artificial intelligence and avian influenza	10.1111/tbed.13318	Y	Y	Y	Y	Y	N	5/6	High
B6-A05	Poultry farm distribution models	10.1371/journal.pcbi.1011980	**Y**	**Y**	**Y**	**N**	**N**	**N**	**3/6**	**Moderate**

Y = Yes (criterion met); N = No or Unclear (criterion not met). Rating: High = 5–6/6; Moderate = 3–4/6; Low = ≤ 2/6. The articles originally rated as low quality during preliminary screening were among the 9 conceptual articles subsequently excluded during the revision-stage eligibility re-evaluation (Supplementary S4). The revised synthesis of n = 30 therefore contains no low-quality studies; 21 (70.0%) are rated High and 9 (30.0%) Moderate.

Supplementary Table S8: Identified research gaps in AI-enabled zoonotic disease surveillance

Domain	Current evidence	Remaining gap / research priority
Disease detection	High detection sensitivity (85–98.8%) reported under controlled experimental conditions, predominantly deep-learning architectures.	Transferability across species, regions, equipment, and real-world surveillance contexts not established. Priority: external validation across multiple settings with operationally-relevant datasets.
Predictive surveillance	Improved outbreak prediction and zoonotic risk mapping in proof-of-concept settings, including ~3-fold increase in rabies surveillance data.	Few prospective operational studies. Cost-effectiveness not rigorously evaluated. Priority: prospective field-implementation with health-economic evaluation.
Automated monitoring	IoT + ML hybrid and Edge AI/TinyML systems demonstrate feasibility under resource-constrained settings.	Limited evidence on scalability, maintenance, workforce capacity, long-term sustainability. Priority: longitudinal implementation studies with sustainability metrics.
Event-based surveillance	High classification accuracy under retrospective validation (e.g., F1-macro = 0.9995 for PADI-web).	Limited operational validation in routine surveillance workflows; false-positive burden under operational conditions not characterised. Priority: prospective operational evaluations with operator-relevant metrics.
Edge AI / TinyML	Feasibility demonstrated in resource-constrained settings (inference latency < 80 ms; deployment on low-cost devices).	Limited evidence on scalability across deployment sites, maintenance under field conditions, performance drift. Priority: multi-site deployment studies with prospective monitoring.
Transfer learning	Effective adaptation to local veterinary contexts with reduced labelled-data requirements (e.g., Kyasanur Forest Disease prediction).	Generalisation across species, pathologies, and imaging modalities not systematically evaluated. Priority: cross-domain transfer studies with standardised reporting.
One Health integration	Emerging digital platforms integrating animal and human health data (Cameroon, Kenya operational examples).	Weak interoperability standards; underdeveloped cross-sectoral governance frameworks. Priority: standardised data-sharing protocols and governance frameworks for AI-enabled One Health.
LMIC implementation	Strong LMIC representation in the revised synthesis (50.0%); methodological approaches with reduced infrastructure dependencies align with LMIC constraints.	LMIC feasibility largely inferred from technical characteristics rather than demonstrated through routine operational deployments. Priority: implementation research within national veterinary surveillance systems of LMICs.
Governance and ethics	Limited explicit discussion across included studies; ethical/governance frameworks generally not addressed.	Critical evidence gap: accountability frameworks, data ownership, algorithmic transparency, human oversight in AI-assisted decision-making. Priority: governance frameworks specific to AI in veterinary and One Health surveillance.

Supplementary Figure S1: Conceptual framework for AI approach selection

Four-step inductive synthesis derived from recurring implementation themes across the 30 included studies, illustrating the alignment between surveillance objectives, resource constraints, AI methodological approaches, and implementation considerations. The framework is presented as a heuristic synthesis; individual implementation decisions should be guided by context-specific feasibility assessment.

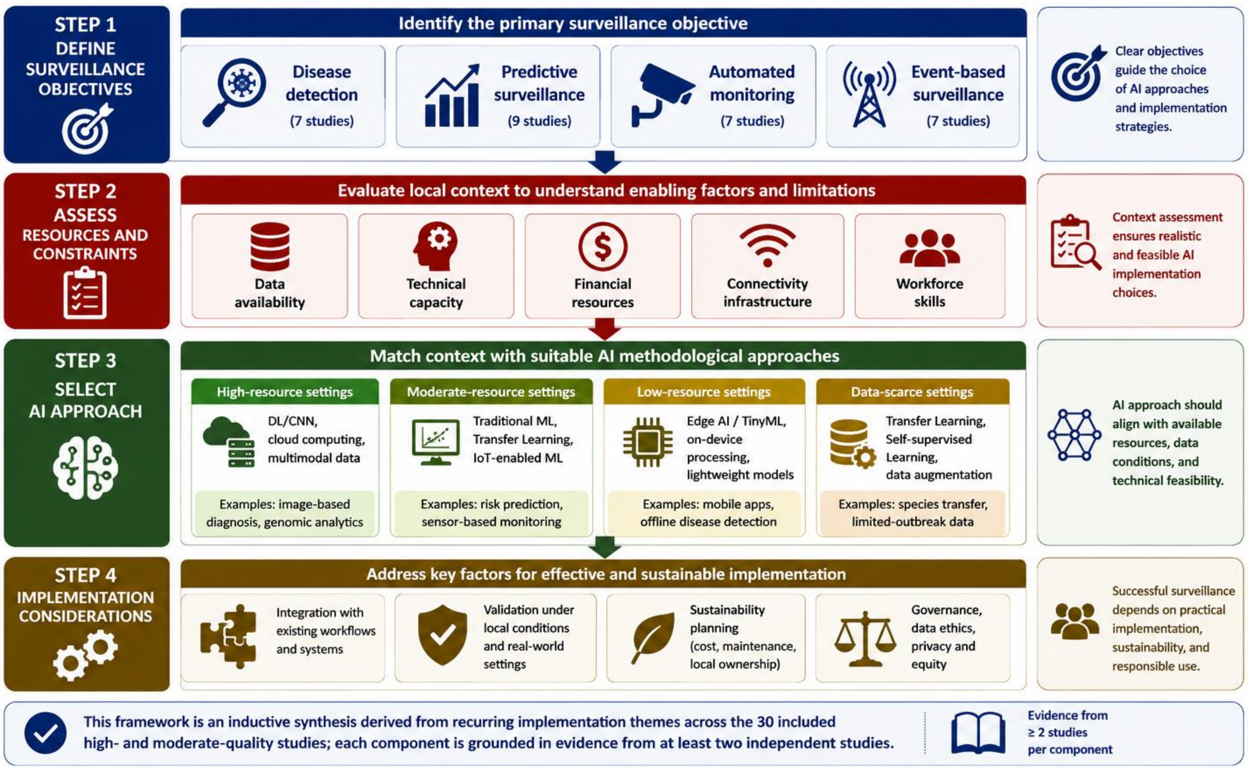

Figure S1 caption: Conceptual decision-support framework for selecting and implementing AI approaches in veterinary and zoonotic disease surveillance. Derived inductively from recurring implementation themes across the 30 included high- and moderate-quality studies; each component is grounded in evidence from at least two independent studies.

Notes on data availability and reproducibility

In accordance with the Data Availability Statement of the main manuscript, all data supporting the findings of this systematic review are available within the article, these Supplementary Materials, and the accompanying Master Extraction File (Excel format). The Master Extraction File contains the complete per-study extraction variables for all 30 included studies plus full documentation of the 9 articles reclassified as ineligible during revision.

For this final supplementary version, the current manuscript is the controlling reference source; bibliographic DOI entries were synchronized to its 51-reference list where a direct correspondence exists.

— END OF SUPPLEMENTARY MATERIALS —