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Emerging Animal Disease Is Recognized Too Late When Surveillance Systems Wait for Diagnostic Certainty: A Signal-to-Action Architecture for Syndromic Detection, Laboratory Uncertainty, Spatial Clustering, and Veterinary Outbreak Preparedness

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ABSTRACT

Emerging animal diseases may become epidemiologically consequential before conventional surveillance reaches diagnostic certainty. Clinical deterioration, production losses, behavioral change, unusual mortality, laboratory ambiguity, spatial concentration, temporal aberration, wildlife events, and movement-linked exposure can each provide incomplete but potentially actionable information. This original non-empirical surveillance architecture examines how such signals can be interpreted without converting uncertainty into premature diagnosis. The analysis distinguishes observation from confirmation, signal convergence from etiologic proof, statistical aberration from biological specificity, and preparedness action from definitive control action. Across the reviewed evidence, early-warning value is repeatedly conditioned by species, production system, sampling design, baseline stability, search effort, network completeness, and false-alarm burden. The article therefore proposes a signal-to-action architecture in which heterogeneous evidence streams remain analytically separate until an explicit interpretation boundary is crossed; confidence is updated through corroboration, discordance checking, contextual modifiers, and laboratory reassessment; and veterinary response is scaled to urgency, reversibility, and the cost of being wrong. The architecture is intended to support earlier verification, focused sampling, risk-based surveillance, and cross-sector notification without implying that weak signals establish infection. It is designed for heterogeneous veterinary systems in which waiting carries costs but acting prematurely can also cause harm. Its principal limitation is that the proposed states, transitions, and escalation logic have not been prospectively validated across diseases, species, or jurisdictions. Their value must therefore be tested against real outbreak timelines, false-alarm costs, surveillance drift, implementation constraints, and external performance before operational adoption.

Keywords: Animal health surveillance, Syndromic surveillance, Diagnostic uncertainty, Spatial clustering, Outbreak preparedness, One Health

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Introduction

Animal-health surveillance often acquires its strongest evidentiary label only after a chain of prior observations has already occurred. Contemporary syndromic surveillance research shows that non-specific animal-health indicators can be assembled for earlier warning, yet much of the published field remains at proof-of-concept rather than routine operational maturity [1]. This creates a practical distinction between information being available and information being sufficiently interpreted to change action. One Health surveillance scholarship adds a second problem: relevant animal, wildlife, environmental, and public-health signals may remain institutionally separated even when they describe the same emerging hazard [2]. Qualitative evidence from Australia further indicates that communication, shared governance, and professional silos can obstruct integration independently of technical surveillance capacity [3].

Laboratory confirmation is also not an instantaneous event. Rapid-response preparedness depends on access to appropriate samples, protocols, and coordinated screening capacity before a confirmatory result can be produced [4]. The central argument developed here is therefore not that diagnosis should be bypassed, but that veterinary systems should distinguish evidence sufficient to justify verification or preparedness from evidence sufficient to establish etiology. The article develops this distinction across clinical, production, mortality, laboratory, spatial, temporal, wildlife, and movement signals, then proposes a signal-to-action architecture in which uncertainty is carried forward rather than hidden. The intended contribution is architectural: to organize how heterogeneous pre-confirmation evidence could be reconciled, escalated, reassessed, and bounded without claiming validated predictive performance or universal applicability.

Why confirmed cases are late surveillance signals

A confirmed case is often late only in a relational sense: it appears downstream of earlier events such as abnormal behavior, production change, mortality, clinician recognition, sample collection, transport, testing, and interpretation. Syndromic surveillance demonstrates that non-specific indicators can exist before etiologic attribution [1]. Rapid-screening preparedness likewise shows that confirmation depends on upstream access to suitable samples and coordinated procedures [4]. The relevant surveillance question is therefore not whether confirmation is unnecessary, but whether all meaningful action should be deferred until confirmation is complete.

This article proposes two evidentiary states that should not be conflated. The first is evidence sufficient for low-regret preparedness: intensified observation, targeted sampling, verification of data quality, temporary movement scrutiny, or expert review. The second is evidence sufficient for etiologic attribution and consequential disease-specific control. Integrated One Health surveillance supports the need to connect information across sectors [2], while rapid-response work shows why pre-arranged verification pathways matter [4]. The boundary remains essential: premature action may impose welfare, trade, logistical, or credibility costs. Accordingly, “late” does not mean diagnostically unnecessary; it means that confirmation may occur after earlier observable information has already become relevant to preparedness.

Clinical and syndromic signals

Clinical and syndromic signals occupy the earliest interpretive layer because they describe abnormal health states without requiring a known cause. In Irish dairy cattle, routinely collected milk-recording data were developed into syndromic indicators for herd-health surveillance [5]. Such signals are valuable because they can be generated repeatedly from existing systems, but they remain etiologically nonspecific. A decline in production, reproductive performance, or other routinely recorded measures may reflect infection, nutrition, management, seasonality, or recording error.

The interpretive value increases when multiple signals deviate together, provided their shared confounders are considered. In breeding swine herds, combined productivity and electronic sow-feeding data produced PRRSV-associated statistical alerts, although performance varied by farm and method [6]. This supports convergence as a reason to intensify verification, not as a substitute for diagnosis. This article therefore proposes keeping clinical signs, production measures, and sensor-derived behavior as separate evidence channels even when they move in parallel. Their surveillance value lies in detecting departure from an expected state, whereas their weakness lies in ambiguity about cause. A signal-to-action system must preserve both properties simultaneously: sensitivity to change and restraint about etiology.

Production and behavioral anomalies

Production and behavioral anomalies deserve a separate surveillance lane because their measurement process differs from a clinical encounter. Milk yield, fertility, feed intake, movement, or other routinely captured variables may be generated continuously or at high frequency, creating a longitudinal picture of herd state that is unavailable from episodic examination. Dairy syndromic surveillance demonstrates the feasibility of extracting health-relevant signals from routine production data [5]. Yet these data are inseparable from husbandry context. Nutrition, weather, housing, lactation stage, equipment failure, staffing changes, or altered recording practices can produce deviations that resemble disease.

Behavioral data create the same opportunity and hazard. Electronic sow-feeding records contributed to outbreak-related statistical alerts in monitored breeding herds [6], but off-feed behavior cannot itself identify infection. The proposed architecture therefore treats production and behavior as distinct measurement channels whose credibility depends on baseline quality, sensor integrity, persistence, and corroboration. Their strongest role is not to trigger disease-specific control in isolation, but to move a herd from ordinary monitoring toward verification when the deviation is unusual, sustained, or concordant with other evidence. This distinction prevents continuously measured data from acquiring unwarranted diagnostic authority merely because they are timely or numerically precise.

Mortality and morbidity deviations

Mortality is intuitively compelling because death is unambiguous, but mortality surveillance is not. Wild-boar carcass surveillance for African swine fever has shown that search effort can be deliberately targeted toward settings where infected carcasses are more likely to be found [7]. Consequently, observed mortality reflects both the underlying event and the surveillance process used to observe it. Spatial analysis of Latvian ASF surveillance further showed that landscape and search context influence carcass-detection locations [8]. A cluster of carcasses can therefore contain biological information, observation-process information, or both.

Routine livestock data add another layer. Evaluation of excess-mortality notification in Dutch cattle supports mortality deviation as a passive-surveillance trigger while also showing that expected mortality differs among production categories [9]. The relevant unit is therefore not "death present versus absent," but deviation from a defensible baseline within the appropriate animal and production context. Morbidity should be interpreted similarly: increases in illness, treatment, reproductive failure, or nonspecific clinical reporting gain meaning only relative to expected frequency and ascertainment. Before translating these patterns into action, surveillance should separate severity, persistence, denominator stability, detection effort, and corroboration.

Table 1 presents how baseline deviation, search effort, and biological severity distinguish mortality and morbidity signals.

Table 1. How baseline deviation, search effort, and biological severity distinguish mortality and morbidity signals

	Signal seen		Interpretive controls		Surveillance work	
Signal form	Population departure	Recorded pattern	Baseline or search control	Alternative explanation	Verification response	Comparison that resolves priority
Isolated severe event	No sustained excess	Single death/severe case	Susceptibility; herd size	Sentinel event or unrelated cause	Verify context and samples	Escalate if corroborated
Baseline-adjusted excess mortality	Illness may rise or remain hidden	Deaths exceed local expectation	Production category; season	Etiology remains nonspecific	Intensify investigation	Recheck baseline and alternatives
Spatially concentrated mortality	Morbidity incompletely observed	Localized carcass concentration	Landscape; search intensity	Detection effort shapes cluster	Focus search and sampling	Compare effort with plausibility
Persistent morbidity	Recurrent illness/performance loss	Repeated cases or disruption	Phenotype; reporting practice	Management may mimic disease	Seek cross-stream corroboration	Update as other streams evolve

Laboratory signals under diagnostic uncertainty

Laboratory evidence is often treated as the boundary between suspicion and certainty, yet its meaning depends on the test, reference standard, population, specimen, and timing. In ASF diagnostics, Bayesian latent-class analysis has been used to estimate PCR and ELISA accuracy without assuming that any single test is a perfect gold standard [10]. This matters conceptually because the laboratory result is an observation of an underlying infection state, not the state itself.

Performance may also vary across populations. Modeling of leptospirosis testing in beef cattle indicated that sensitivity could differ among herds rather than remain constant [11]. A surveillance architecture should therefore avoid carrying one sensitivity estimate unchanged across epidemiological contexts. Specimen choice and timing create further instability. Experimental ASFV work showed that diagnostic sensitivity differed among porcine biological samples following exposure [12]. A negative result obtained early, from a less informative specimen, or in a different population context should not automatically erase otherwise credible surveillance evidence. Conversely, uncertainty must not become an excuse to dismiss negative testing indefinitely. The appropriate function of laboratory uncertainty is to shape confidence, resampling strategy, and interpretation—not to convert every discordant result into presumptive infection.

Spatial clustering

Spatial clustering is informative only when "more events in one place" is defined relative to where events could have been observed. Latvian wild-boar surveillance demonstrates that landscape and search conditions can influence where carcasses are detected [8]. A raw map of cases, deaths, or carcasses therefore mixes epidemiological concentration with the observation process. Surveillance should, where feasible, consider animal population distribution, search intensity, accessibility, reporting opportunity, and denominator stability before interpreting a hotspot as biological concentration.

Targeted carcass-search strategies make this distinction explicit: surveillance may intentionally look harder in places expected to yield higher detection [7]. That can improve efficiency, but it also means later clustering cannot be interpreted as if effort were geographically uniform. Routine excess-mortality systems add a complementary lesson because expected mortality itself differs across cattle production categories [9]. The same principle applies spatially: expected event density is rarely uniform across species, farms, habitats, or management systems. The proposed architecture therefore treats spatial clustering as contextual corroboration rather than automatic escalation. A spatial signal becomes stronger when concentration persists after accounting for observation intensity, aligns with plausible animal distribution or contact pathways, and converges with independent temporal, clinical, laboratory, or movement evidence.

Temporal clustering

Temporal clustering converts the surveillance question from "did an event occur?" to "did its timing depart from expectation?" Statistical process-control approaches applied to swine production data have demonstrated how repeated observations can generate graded alerts when trends cross detection limits, although simulated outbreak performance does not establish validated operational thresholds [13]. The important design principle is that magnitude and persistence can strengthen evidence, but only relative to a stable and context-appropriate baseline. Real-world aquaculture surveillance illustrates the operating trade-off. In Norwegian salmon farms, mortality-based syndromic models achieved substantial sensitivity while also producing high false-alarm rates, and alarms were often close in time to conventional surveillance rather than uniformly earlier [14]. Temporal abnormality is therefore not synonymous with useful lead time. Species heterogeneity adds another constraint: during the Dutch BTV-3 outbreak, mortality effects differed markedly between sheep and goats [15]. A temporal signal that is prominent in one host may be weak in another.

Table 2 presents temporal signal shapes and the baseline checks required before surveillance escalation.

Table 2. Temporal signal shapes and the baseline checks required before surveillance escalation

Temporal question	Single-point aberration	Persistent moderate deviation	Abrupt severe cluster	Recurrent low-yield alarms
Clinical meaning of the time pattern	Noise or abrupt event	Changed population state increasingly plausible	Potential high-consequence event	Operating point may be over-sensitive
Dependence on baseline or host context	Reporting interval; denominator	Seasonality; production cycle	Host susceptibility	Reporting frequency; calibration
Observed temporal signature	One unexpected excursion	Consecutive abnormal observations	Rapid morbidity/mortality rise	Frequent unconfirmed alerts
Surveillance response	Verify data integrity	Intensify verification	Accelerate preparedness and testing	Review thresholds and context
False-positive route	Recording/management artifact	Baseline drift may mimic persistence	Etiology unresolved	Fewer alerts may reduce sensitivity

Condition for reclassification	Return to baseline if isolated	Recalculate expectation; corroborate	Update rapidly with new evidence	Recalibrate against missed-event risk

Wildlife and environmental Signals

Wildlife surveillance can reveal change outside domestic-animal reporting systems, but interpretation is constrained by detectability, ecology, and uncertain linkage to livestock or people. Integrated One Health surveillance explicitly includes wildlife and environmental information because hazards may emerge or circulate across sectoral boundaries [2]. Targeted wild-boar carcass surveillance also shows that wildlife evidence is partly shaped by where and how search effort is deployed [7]. The proposed architecture treats wildlife observations as a parallel evidence stream rather than indirect confirmation in domestic animals.

Environmental context has a similarly dual role. Access to environmental and animal sample collections can strengthen preparedness for emerging-pathogen screening [4], while landscape influences where wildlife mortality is observed [8]. Environmental information may function as direct evidence when a validated assay detects a hazard, or as context changing another signal's plausibility or observability. Those roles should remain separate. Wildlife mortality, vector activity, water or habitat conditions, and interface events should raise surveillance priority only to the extent that their ecological pathway, measurement process, and connection to the population at risk are credible.

Movement and contact-network signals

Movement data add a different form of evidence: opportunity for contact. Analysis of U.S. swine shipments demonstrates substantial heterogeneity in premises and interstate connectivity, allowing surveillance to identify structurally important pathways without establishing infection at those nodes [16]. Network centrality should modify surveillance priority, not become a surrogate diagnostic result.

Networks are also unstable. In East African pastoral and agropastoral systems, livestock connectivity changed with season and husbandry context, including shifts in communal-resource and trading contacts [17]. A network-derived alert therefore requires sufficiently recent movement information and interpretation within the production system that generated it. Static maps can become misleading when animal flows, markets, weather, or resource access change.

Biological observations along a movement pathway can strengthen the interpretation. A controlled field experiment in Bangladeshi poultry marketing chains found no intervention-control difference in avian-influenza detection at market arrival but lower detection odds in the intervention group 12 hours later, consistent with infection opportunities arising during transport, trade, or market processes [18]. This does not mean every recorded edge transmits infection. It supports separating structural connectivity from evidence that a particular pathway is biologically consequential.

Signal integration before diagnostic confirmation

Integration should not erase why each signal is uncertain. Syndromic systems differ in indicator construction and operational maturity [1], while even laboratory results can represent an imperfect observation of latent infection status [10]. Combining those streams into one undifferentiated score would conceal differences in denominator, measurement frequency, specificity, and level of analysis. The proposed approach retains source identity while asking whether independent streams converge on the same abnormal state.

Convergence can justify stronger verification without establishing etiology. Routine dairy and swine indicators can reveal abnormal herd states, while diagnostic evidence may remain probabilistic under imperfect reference conditions [5, 6, 10]. The proposed rule is therefore additive in interpretation but noncompensatory in meaning: several nonspecific signals cannot manufacture diagnostic certainty, and one uncertain laboratory result should not automatically erase coherent epidemiological evidence.

Context further changes priority. False-alarm burden and timing vary across surveillance systems [14], and livestock connectivity can change seasonally [17]. Thus identical raw observations may merit different responses depending on persistence, host susceptibility, observation intensity, current network structure, and competing explanations. **Table 3** presents how independent, discordant, and context-amplified evidence streams alter pre-confirmation inference.

Table 3. How independent, discordant, and context-amplified evidence streams alter pre-confirmation inference

Evidence-stream configuration	Source identity and dependency	Pre-confirmation meaning	Escalation opened	Etiology still unavailable	Discriminating corroboration
Single-stream anomaly	**Context:** Baseline quality **Pattern:** One credible deviation	Possible abnormal state	Verify source and context	Cause unresolved	Seek independent stream
Cross-stream convergence	**Context:** Shared confounders **Pattern:** Independent signals align	Abnormal state more credible	Intensify sampling/review	Convergence is not etiology	Test competing explanations
Discordant laboratory context	**Context:** Specimen, timing, population **Pattern:** Epidemiology and test disagree	Evidence remains unresolved	Repeat or redirect verification	Neither stream automatically dominates	Update with better specimen/context
Context-amplified signal	**Context:** Spatial, temporal, network plausibility **Pattern:** Signal aligns with current risk context	Priority may rise without certainty	Accelerate low-regret preparedness	Context modifies plausibility only	Reassess as context changes

A proposed signal-to-action architecture

Operational surveillance requires more than an anomaly detector. A recent Jordanian syndromic-surveillance roadmap illustrates the practical need to coordinate heterogeneous data streams, analytic methods, governance, and communication when constructing a national pilot [19]. Semantic interoperability is a separate requirement: the Animal Health Surveillance Ontology was developed because heterogeneous surveillance records cannot be meaningfully integrated if equivalent concepts are represented inconsistently [20]. Multisectoral collaboration likewise has organizational, implementation, and functional dimensions that can be evaluated independently of technical detection performance [21].

On that foundation, this article proposes a reversible signal-to-action architecture. Signals remain in source-specific lanes until they reach an interpretation boundary where data validity, baseline deviation, corroboration, plausible exposure, laboratory context, and competing explanations are reconciled. The resulting confidence state does not diagnose disease; it determines the next proportional action, from continued observation to intensified verification, focused sampling, notification, or disease-specific procedures once evidentiary and legal requirements are met. Discordant evidence is routed through an alternative-explanation channel rather than averaged away. Every action state feeds back into surveillance through new observations, testing, or contextual information.

Figure 1 is needed because the contribution lies in these relationships: evidence streams remain distinct, uncertainty can constrain escalation, and confidence can rise or fall recursively rather than progressing through a one-way pipeline.

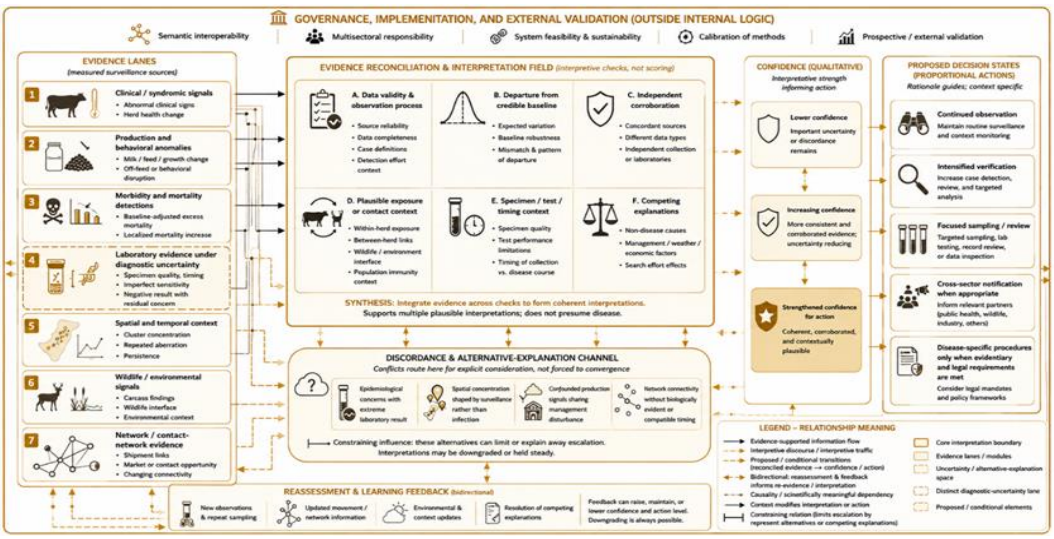

Figure 1. Discordant veterinary surveillance signals cross an explicit interpretation boundary before confidence can justify stronger action

Alert states and escalation thresholds

An alert state should describe what the system is prepared to do, not imply a disease probability. Modeling of higher-sensitivity bovine-tuberculosis testing in England illustrates that increasing sensitivity can also increase false-positive and operational burdens [22]. Escalation should therefore depend on both the cost of missing a consequential event and the cost of being wrong.

Risk can also guide where limited verification resources are used. Computational work on clustered disease surveillance shows that allocating effort according to heterogeneous risk and marginal detection gain can improve system-level efficiency under specified assumptions [23]. This supports risk-weighted escalation, but not a universal algorithm: relative-risk estimates, prevalence, clustering, logistics, and social constraints remain setting dependent.

Output-based surveillance provides an additional guardrail because programs with different operational activities can be evaluated against explicit performance objectives rather than identical procedural thresholds [24]. The proposed alert states are consequently qualitative: observation, verification, heightened preparedness, and disease-specific response represent increasing commitment of resources and authority, but their transition criteria must be calibrated locally. Statutory notification or control requirements may supersede this generic architecture, particularly for regulated or immediately consequential diseases.

Managing false alarms

False alarms are not automatically evidence that an early-warning system has failed. In Norwegian salmon surveillance, appreciable sensitivity coexisted with substantial false-alarm rates, illustrating the cost of operating closer to early detection [14]. The design problem is to make early uncertainty manageable. Low-confidence alerts should preferentially trigger reversible actions such as data-quality checks, targeted observation, confirmatory sampling, or expert review rather than high-burden control measures.

Calibration must jointly consider timeliness, false-positive burden, and the surveillance objective [14, 22, 24]. A system optimized only to suppress false alarms can miss weak emerging signals; one optimized only for sensitivity can exhaust diagnostic capacity and erode trust. This article therefore proposes that false alarms be classified by what generated them—unstable baseline, observation bias, correlated non-disease disturbance, test uncertainty, or context mismatch—because those causes imply different corrections.

Table 4 presents false-alarm mechanisms, diagnostic clues, and cause-specific calibration responses. It does not define numerical thresholds; it distinguishes when to verify the signal, revise the baseline, seek independent corroboration, or reconsider the operating point.

Table 4. False-alarm mechanisms, diagnostic clues, and cause-specific calibration responses

Alarm-generating mechanism	Diagnostic clue	Likely source of distortion	Cause-specific correction	Risk created by correction	Evidence required before retuning
Isolated data anomaly	Implausible single excursion	**Reading:** Low evidential persistence **Driver:** Data integrity	Verify record/sensor	True abrupt event still possible	Restore or escalate after check
Baseline mismatch	Repeated alerts without corroboration	**Reading:** Expected state poorly calibrated **Driver:** Season or production change	Re-estimate baseline	Recalibration can hide true change	Compare missed-event risk
Correlated non-disease disturbance	Several linked streams shift together	**Reading:** Apparent convergence may be shared confounding **Driver:** Management/environment	Seek independent evidence	Multiple signals are not automatically independent	Reassess after disturbance resolves
Persistent unexplained alerts	Recurrent credible alarms	**Reading:** Operating point or emerging hazard unresolved **Driver:** System sensitivity	Intensify review and sampling	Suppression may delay detection	Recalibrate only with outcome evidence

Proportional veterinary response

Response latency can matter economically, but faster action is not automatically better. Economic modeling of foreign-animal-disease scenarios shows that the value of reducing decision time depends on diagnostic accuracy, outbreak assumptions, and the costs created by erroneous action [25]. Proportional response should therefore reflect urgency, potential consequence, reversibility, evidential confidence, animal-welfare implications, legal authority, and resource burden rather than signal intensity alone.

Real outbreaks illustrate the need for revision. During Sweden's first ASF outbreak, carcass surveillance and accumulating epidemiological information informed spatial delimitation and iterative control [26]. The evidence supports adaptive refinement of response, not attribution of eradication to any single intervention. Similarly, adaptive risk-based surveillance at wildlife-livestock interfaces has been designed to update priorities as risk information changes [27].

The proposed architecture therefore makes escalation reversible wherever law and biology permit. A heightened surveillance state may be downgraded when alternative explanations become more credible, additional testing remains negative under appropriate sampling conditions, or the original anomaly resolves. Conversely, modest signals may justify rapid escalation when consequences are high and corroboration accumulates. Proportionality is thus a relationship between uncertainty and the burden of the chosen action, not a synonym for minimal intervention.

Cross-sector notification

Cross-sector notification should communicate an evidentiary state, not merely transmit a binary disease label. Integrated One Health surveillance requires coordination across relevant sectors [2], and multisectoral collaboration includes organizational and functional dimensions beyond simple data exchange [21]. This article therefore proposes that an early notification convey the signal source, affected species or system, major uncertainty, relevant spatial-temporal context, current verification status, and the action requested from the receiving sector. The package can remain concise when urgency is high.

Governance determines whether such information becomes actionable. Australian evidence identifies professional silos and communication barriers as practical obstacles to integrated surveillance [3], while the Jordan surveillance roadmap embeds governance and communication within system design [19]. Responsibility transfer should be defined before an emergency: who receives and acknowledges a signal, who can request sampling or movement information, and when statutory notification supersedes discretionary exchange.

No single governance model is appropriate everywhere. Centralized, federal, private-sector, wildlife, laboratory, and public-health structures distribute authority differently. The proposed requirement is narrower: uncertainty should travel with the signal, and accountability for the next verification or response step should not remain implicit.

Implementation and validation

The proposed architecture requires evaluation at more than the level of detection accuracy. RISKSUR EVA was designed to integrate technical, process, and economic evaluation of animal-health surveillance systems [28]. Multisectoral implementation also needs direct examination: assessment of arbovirus surveillance in Serbia, Tunisia, and Georgia showed that integration can differ across governance, data collection and analysis, and dissemination, with early-warning use not uniformly realized [29]. More recent OH-EpiCap applications across 11 European One Health surveillance cases identified recurring leadership, data-sharing, and harmonization challenges, while surveillance impact was often not formally evaluated [30].

Validation should therefore test both whether signals discriminate meaningful events and whether institutions act on them appropriately. Required studies include retrospective challenge datasets, negative-control periods, temporal and external validation, calibration and false-alarm assessment, stream-ablation analyses, and prospective comparison of time to verification or action. Process evaluation should examine notification latency, alert fatigue, data completeness, staffing, interoperability, and governance failure. Economic, animal-welfare, and resource consequences should be measured rather than presumed. Technical, process, economic, and multisectoral evaluation are complementary requirements [28-30]. Failure on any one dimension should be capable of modifying or rejecting the architecture rather than being treated as an implementation inconvenience.

Conclusion

Emerging animal disease surveillance should not confuse absence of diagnostic certainty with absence of actionable information. Clinical, production, mortality, laboratory, spatial-temporal, wildlife, environmental, and movement signals differ in specificity, measurement error, temporal behavior, and level of analysis. Their value therefore lies neither in isolation nor in automatic aggregation. The principal contribution of this article is a proposed signal-to-action architecture that preserves those distinctions, explicitly routes discordance and alternative explanations, and links changing confidence to proportional, revisable veterinary action. Confirmation remains essential for etiologic attribution and for actions that require it; the architecture instead creates a disciplined space for verification and preparedness before that point. Its states, transitions, notification logic, and decision boundaries are hypotheses for surveillance design, not validated operating rules. Their usefulness depends on disease- and species-specific calibration, external validation, governance feasibility, acceptable false-alarm burden, and evidence that earlier action improves decisions without producing disproportionate harms.

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