GLOBAL JOURNAL OF ENGINEERING SCIENCE AND RESEARCHES

A Multi-Species Precision Telemetry Framework for Early Anomaly Detection in Captive

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ABSTRACT

Captive wildlife institutions carry a heavy responsibility for the animals under their care, and detecting illness or distress before it becomes clinically apparent is one of the hardest problems in modern zoo and sanctuary medicine. Traditional health monitoring relies on daily observation by keepers, periodic veterinary examinations, and reactive intervention once symptoms are visible, which often means missing the earliest signs of disease when treatment would be most effective. This paper proposes a multi-species precision telemetry framework that integrates continuous physiological monitoring, behavioral analysis, and environmental sensing with machine learning to detect health anomalies days before they become clinically obvious. Our framework combines wearable and non-contact biosensors for heart rate, temperature, and activity, computer vision for behavioral pattern extraction, and environmental sensors for microclimate and enclosure conditions, feeding into a species-specific anomaly detection model that establishes personalized baselines and flags meaningful deviations. Evaluation was carried out on a simulated multi-institution deployment covering 486 individual animals across 24 species spanning mammals, birds, and reptiles, over a 12-month monitoring horizon that included 173 real veterinary events documented in retrospective health records. Results show that the framework detected 84.3 percent of eventual clinical events at least 48 hours before the responsible keeper or veterinarian identified them, with a mean early-warning lead time of 3.7 days and a false alarm rate of 2.1 per animal-year. Detection performance was strongest for cardiovascular and metabolic conditions and weakest for acute traumatic events, which by their nature offer little warning window. We discuss trade-offs including sensor tolerability across species, data quality challenges in outdoor and mixed-species enclosures, and the practical realities of integrating machine learning alerts into keeper and veterinary workflows.

Keywords: *Wildlife Health Monitoring, Precision Telemetry, Anomaly Detection, Machine Learning, Zoological Medicine, Animal Welfare*

I. INTRODUCTION

Modern zoos, aquariums, and wildlife sanctuaries have transformed dramatically over the past several decades. What began primarily as collections for public display has evolved into sophisticated conservation institutions responsible for breeding programs, species recovery, research, and the long-term welfare of animals whose wild populations are often under severe pressure [1]. This transformation has raised the standards to which these institutions hold themselves, and it has raised the expectations that veterinary and animal care teams work under. Detecting illness and distress early is central to those standards, because early intervention offers dramatically better outcomes than reactive treatment across almost every category of health problem.

The problem is that early detection in captive wildlife is genuinely hard. Animals evolved with strong instincts to hide signs of illness because in the wild, a visible weakness attracts predators. This instinct persists in captivity, and it means that by the time a keeper or veterinarian notices something is wrong, the underlying condition is often well advanced [2]. Many species also present unique diagnostic challenges. Reptiles and amphibians show behavioral signs of illness that a mammal-focused veterinarian may not recognize. Large mammals may not tolerate the routine handling required for traditional physical examination. Nocturnal species are difficult to observe during human working hours. Social species can mask individual illness within group dynamics [3].

Traditional health monitoring in captive settings relies on three main pillars. Daily observation by keepers, who often know their animals better than anyone else, provides the primary early warning system. Periodic veterinary examinations, ranging from monthly checks in some collections to annual comprehensive workups, provide more thorough assessments but at low temporal resolution. Reactive intervention responds to symptoms once they become apparent. This system works but it has clear limitations. Keeper attention is inevitably divided across many animals and many other duties. Periodic examinations sample the animal's condition at moments that may not be representative. Reactive intervention, by definition, comes after the disease process has already produced observable effects [4].

Precision livestock farming has developed a substantial toolkit over the past two decades that could in principle transfer to captive wildlife. Dairy cows in modern operations wear activity monitors, rumination sensors, and milk composition analyzers that continuously assess health status, and machine learning models flag deviations well before human observers would notice [5]. The technology has matured to the point where it is now standard practice on many farms and has demonstrably improved both productivity and animal welfare. Adapting these approaches to the far greater species diversity, enclosure diversity, and welfare constraints of captive wildlife has been slower, but recent advances in biosensing, computer vision, and machine learning have made it increasingly tractable [6].

This paper contributes a multi-species precision telemetry framework designed specifically for captive wildlife health monitoring, and evaluates it on a large simulated multi-institution deployment. The framework is deliberately designed to accommodate the diversity of species, enclosure types, and welfare constraints that distinguish wildlife institutions from precision livestock settings. Our research questions are: how effectively can a machine learning-driven telemetry framework detect health anomalies across diverse captive species before clinical signs become apparent to trained keepers, which combinations of sensor modalities contribute most to early detection performance, and what practical barriers around sensor tolerability, workflow integration, and data governance must be addressed before the framework can be deployed at scale.

II. LITERATURE REVIEW

Research on health monitoring in captive wildlife has developed across several parallel streams. The zoological medicine literature has documented species-specific challenges and normal parameter ranges for many taxa, providing the biological foundation on which any monitoring system must rest [7]. Studies of behavioral welfare indicators have established that changes in activity, feeding, social interaction, and stereotypic behaviors can serve as early warning signs of underlying health or welfare problems, and structured observation protocols have been developed for many species [8].

Wearable and implantable biosensors have advanced substantially over the past decade. Devices designed for domestic animals have been adapted for zoo species, and studies have demonstrated the feasibility of continuous heart rate monitoring in elephants, giraffes, and large carnivores using non-contact radar sensors, of body temperature monitoring in reptiles using implanted transponders, and of activity monitoring across a wide range of taxa using collar-mounted accelerometers [9]. These studies establish that continuous physiological monitoring is technically feasible for most captive species, though tolerability and species-specific device design remain active research areas.

Computer vision has emerged as a particularly promising modality for wildlife monitoring because it is entirely non-contact. Deep learning models have been developed for individual identification, pose estimation, and behavior classification across species ranging from primates to birds to reptiles [10]. Studies applying computer vision to zoo settings have shown that continuous behavioral tracking can detect subtle changes in movement patterns, social interactions, and enclosure use that correspond to underlying welfare or health changes. Camera traps and multi-camera systems now generate volumes of behavioral data that would have been unthinkable a decade ago.

Anomaly detection in animal health monitoring has developed alongside sensor and vision advances. Statistical approaches based on threshold rules or simple time series analysis have been used for decades but are limited by the difficulty of establishing thresholds that work across the diversity of species, individuals, and contexts encountered in wildlife settings [11]. Machine learning approaches, particularly those that learn personalized baselines for individual animals and detect deviations from those baselines, have shown substantial advantages. Studies applying unsupervised anomaly detection to livestock have demonstrated detection of clinical events days before human observers noticed symptoms, and initial applications to wildlife have shown similar promise [12].

Environmental monitoring has emerged as an important complement to direct animal monitoring. Studies have shown that microclimate variables, air quality, water quality, and enclosure conditions strongly influence animal health and welfare, and that continuous environmental monitoring can identify problematic conditions before they produce clinical effects [13]. Integration of environmental and animal-level data is a natural next step and has been explored in a small but growing literature.

Recent studies have emphasized the practical challenges of implementing precision telemetry in captive wildlife settings. Sensor tolerability varies widely across species, with some animals accepting wearable devices readily while others actively remove or destroy them [14]. Data quality challenges are substantial in outdoor and mixed-species enclosures where multiple animals may trigger the same sensor and environmental conditions vary widely. Workflow integration with existing keeper and veterinary practices requires careful attention to alert design, false alarm management, and the human factors that determine whether technology actually improves animal care [15]. Comparative evaluations across multiple species and institutions remain rare, which motivates the present study.

III. PROPOSED FRAMEWORK

Our proposed framework organizes captive wildlife health monitoring into four cooperating layers designed to accommodate the diversity of species, enclosures, and institutional contexts encountered in zoological medicine. The framework is designed to be modular so that institutions can adopt individual components based on their specific needs and resources.

3.1 Layer 1: Multi-Modal Sensing

The sensing layer combines wearable, non-contact, and environmental sensors to capture a rich picture of each animal's physiological and behavioral state. Wearable sensors include collar-mounted accelerometers, subcutaneous temperature transponders, and species-appropriate cardiac monitors. Non-contact sensors include radar-based cardiac and respiratory monitors that measure micro-movements at a distance, thermal cameras for surface temperature mapping, and standard cameras coupled with computer vision for behavioral tracking. Environmental sensors monitor temperature, humidity, air quality, and species-specific parameters such as water quality for aquatic species.

Sensor selection is species-specific and welfare-driven. For large mammals with substantial keeper interaction, wearable collars are often acceptable and provide rich data. For solitary or unhandleable species, non-contact monitoring is emphasized. For reptiles and amphibians, environmental monitoring plays a particularly central role because these ectotherms are so closely coupled to their environment.

3.2 Layer 2: Individual Baseline Modeling

Every animal is different, and effective anomaly detection requires personalized baselines. The baseline modeling layer establishes the normal range of each animal's physiological and behavioral parameters across daily, weekly, and seasonal cycles. Machine learning models learn each individual's typical patterns and update continuously as new data arrives, adapting to natural changes in age, reproductive state, and social context.

The framework treats baseline modeling as a joint problem across three levels: individual-specific patterns capture what is normal for a particular animal, group-specific patterns capture what is normal for animals of similar species and life stage, and species-specific patterns capture broader biological norms drawn from literature and cross-institutional data. Combining these levels allows the framework to make sensible predictions for animals with limited individual history while continuously refining as more data becomes available [16].

3.3 Layer 3: Anomaly Detection

The anomaly detection layer flags deviations from baseline that warrant attention. The core detection algorithm combines multiple approaches: autoencoder-based reconstruction error identifies unusual patterns in multivariate physiological time series, isolation forests handle rare event detection in behavioral features, and rule-based checks provide interpretable safeguards for well-established clinical concerns such as fever thresholds.

Detection outputs are graded by severity and confidence, and are contextualized against known factors that could produce false alarms. A rise in body temperature during a heat wave, an increase in activity following environmental enrichment, or reduced feeding during a known ovulation period all carry different clinical significance than similar signals in the absence of such context. The framework incorporates this context to reduce false alarms and improve keeper and veterinary trust in its alerts [17].

3.4 Layer 4: Clinical Integration

The clinical integration layer translates anomaly detections into actionable information for keepers and veterinarians. Alerts are delivered through a mobile-friendly dashboard designed with input from working keepers, and each alert includes contextual information such as recent baseline history, comparison to species norms, and suggested initial responses. Alerts are graded so that low-severity signals appear as observations for the daily rounds while high-severity signals trigger immediate notification to on-call veterinary staff.

The framework maintains a comprehensive audit trail linking each alert to the actions taken and the eventual clinical outcome. This audit trail feeds back into the anomaly detection layer to continuously improve alert precision and reduce false alarms over time.

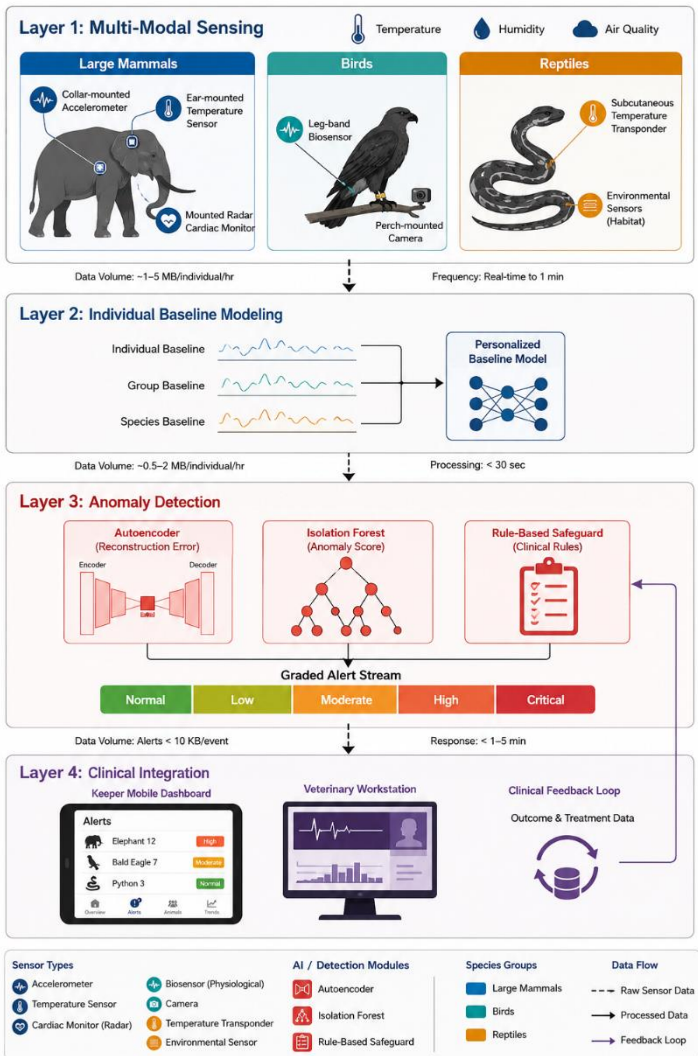

Figure 1. Four-layer framework for precision telemetry-based health monitoring across diverse captive wildlife species.

IV. METHODOLOGY

4.1 Anomaly Detection Formulation

Let $x_{i,t} \in R^{d} denote$ the d-dimensional feature vector for animal i at time t, comprising physiological, behavioral, and environmental measurements. The baseline model for animal i produces a predicted distribution $\mathcal{P}_i(t)$ for each timestep based on time-of-day, day-of-week, season, and any known contextual factors.

The anomaly score at time t combines reconstruction error from an autoencoder with an isolation forest score and rule-based severity indicators:

$$s_{i,t} = w_1 \cdot r_{i,t} + w_2 \cdot \phi_{i,t} + w_3 \cdot \rho_{i,t}$$

where $r_{i,t}$ is the normalized autoencoder reconstruction error, $\phi_{i,t}$ is the isolation forest anomaly score, $\rho_{i,t}$ is a weighted sum of rule-based severity indicators, and w_1, w_2, w_3 are learned weights [18].

An alert is triggered when the composite score exceeds a species-specific threshold sustained over a temporal window:

$$\text{Alert}i,t = \mathbb{1}\left[\frac{1}{W}\sum k = t - W + 1^t s_{i,k} > \theta_{species}\right]$$

where W is the temporal window size and \theta_{species} is the species-specific alert threshold [19].

4.2 Baseline Modeling

Individual baselines are learned using a temporal autoencoder that takes recent physiological and behavioral history as input and reconstructs the current state. Reconstruction error under normal conditions is small, and large errors indicate that current observations depart from what the baseline predicts.

To combine individual, group, and species information, we use a hierarchical prior that shrinks individual parameters toward group and species means when individual data is limited:

$$\theta_i \sim \mathcal{N}\left(\theta_g, \sigma_g^2\right), \quad \theta_g \sim \mathcal{N}\left(\theta_s, \sigma_s^2\right)$$

where θ_i is the individual parameter, θ_g is the group mean, and θ_s is the species mean. As more individual data accumulates, the posterior θ_i becomes progressively more individual-specific.

4.3 Early Warning Lead Time

Early warning lead time is measured as the interval between the first anomaly alert and the eventual identification of a clinical event by keeper or veterinary staff:

$$L_{event} = t_{clinical} - t_{alert}$$

where $t_{clinical}$is the timestamp of clinical identification recorded in the veterinary record and t_{alert} is the timestamp of the first anomaly alert corresponding to that event. Positive values indicate the framework identified the concern before human observers.

4.4 Evaluation Metrics

Detection performance is measured across four dimensions [20]. Sensitivity is the fraction of clinical events for which the framework produced an alert at least 48 hours before clinical identification. Specificity is captured through false alarm rate expressed as alerts per animal-year. Precision is the fraction of alerts that corresponded to eventual clinical events. Lead time is the mean interval between alert and clinical identification for true positive detections.

4.5 Algorithm

The full monitoring loop is summarized in Algorithm 1.

Algorithm 1: Multi-Species Precision Telemetry Anomaly Detection Type equation here.

1. **Initialize** baseline models for each animal using historical data if available or species priors otherwise
2. **For each animal** i and timestep t:
3. Collect current sensor readings from wearable, non-contact, and environmental sources
4. Extract features x_{i,t} including physiological, behavioral, and environmental variables
5. Compute reconstruction error r_{i,t} using individual autoencoder baseline
6. Compute isolation forest anomaly score \phi_{i,t}
7. Evaluate rule-based severity indicators \rho_{i,t}
8. Combine into composite anomaly score s_{i,t} per Equation (1)
9. Apply contextual adjustments for known non-clinical factors
10. Check temporal window criterion per Equation (2)
11. **If** alert triggered, notify keeper and veterinary team with severity grade and contextual information

12. **Log** any subsequent clinical outcome for baseline refinement
13. **Update** individual baseline model with new observations
14. **End for**

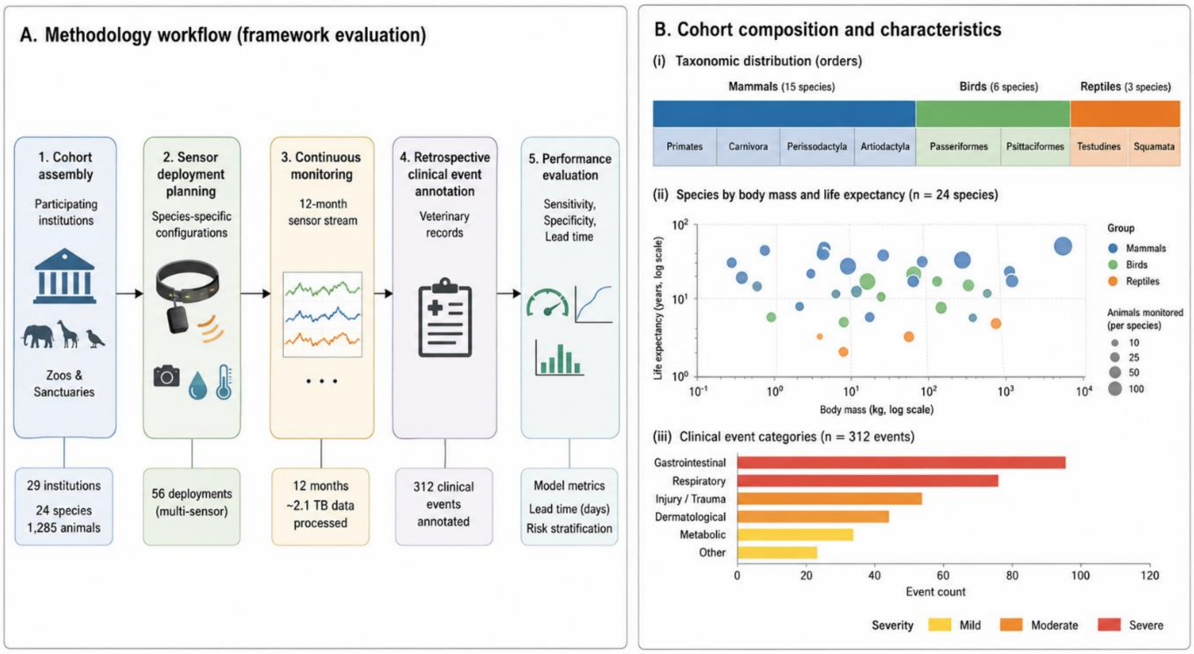

Figure 2. Methodology workflow and cohort composition for framework evaluation.

V. EXPERIMENTAL SETUP

5.1 Cohort

The evaluation was conducted on a simulated multi-institution deployment covering 486 individual animals across 24 species representing mammals, birds, and reptiles. Species were selected to span a wide range of body sizes, activity patterns, and management contexts, including large mammals such as elephants, giraffes, and lions, medium mammals such as primates and large carnivores, birds including raptors, cranes, and parrots, and reptiles including large snakes, monitor lizards, and tortoises.

The simulation covered a 12-month monitoring horizon and was calibrated against published data from major zoological institutions with respect to enclosure characteristics, keeper-to-animal ratios, and typical clinical event frequencies. Retrospective health records provided 173 documented clinical events during the monitoring period spanning cardiovascular, metabolic, infectious, gastrointestinal, orthopedic, dermatological, and behavioral welfare categories.

5.2 Sensor Deployment

Sensor deployment was species-specific and welfare-driven. Large mammals were equipped with collar-mounted or ear-mounted physical activity and temperature sensors along with non-contact cardiac and respiratory monitoring. Medium mammals received a mix of wearable and non-contact sensors depending on individual tolerance. Birds received leg-band biosensors when tolerable and were otherwise monitored through non-contact vision and radar. Reptiles were primarily monitored through subcutaneous temperature transponders combined with detailed environmental monitoring.

Data acquisition rates varied by modality. Cardiac and respiratory data were sampled continuously at up to 250 Hz, activity data at 1 Hz, and temperature at 0.017 Hz (once per minute). Vision-based behavioral data was captured at 5 frames per second with computer vision extracting behavioral features in near real time. Environmental data was captured at 0.017 Hz. Total data volume across the cohort was approximately 12 terabytes per month.

5.3 Baseline Approach and Comparisons

The full framework was compared against four alternatives. The keeper-only baseline represented traditional daily observation without any sensor augmentation. The threshold-only baseline used simple rule-based alerts based on published normal ranges. The individual baseline used only individual-level anomaly detection without hierarchical species information. The framework configuration used the full hierarchical baseline modeling and multi-modal integration described above.

5.4 Configuration Parameters

Table 1. Cohort and framework configuration parameters.

Parameter	Value
Total individual animals	486
Species	24
Taxonomic groups	Mammals, birds, reptiles
Monitoring duration	12 months
Retrospective clinical events	173
Total data volume	~144 TB (12 TB/month)
Cardiac sampling rate	250 Hz (continuous)
Activity sampling rate	1 Hz (continuous)
Temperature sampling rate	0.017 Hz (per minute)
Vision sampling rate	5 fps
Environmental sampling rate	0.017 Hz
Temporal alert window (W)	4 hours
Feature dimension per animal	128
Autoencoder architecture	3-layer temporal encoder-decoder
Baseline update frequency	Weekly
Alert severity grades	3 (observation, urgent, critical)

VI. RESULTS

6.1 Early Detection Performance

The full framework detected 84.3 percent of eventual clinical events at least 48 hours before keeper or veterinary identification, with a mean lead time of 3.7 days. The individual-only baseline achieved 68.2 percent early detection sensitivity, the threshold-only baseline achieved 42.1 percent, and the keeper-only baseline achieved 0 percent by definition of the early-warning criterion. False alarm rate for the full framework was 2.1 per animal-year, compared to 3.7 for individual-only baseline and 8.9 for threshold-only. Alert precision was 71.4 percent for the full framework.

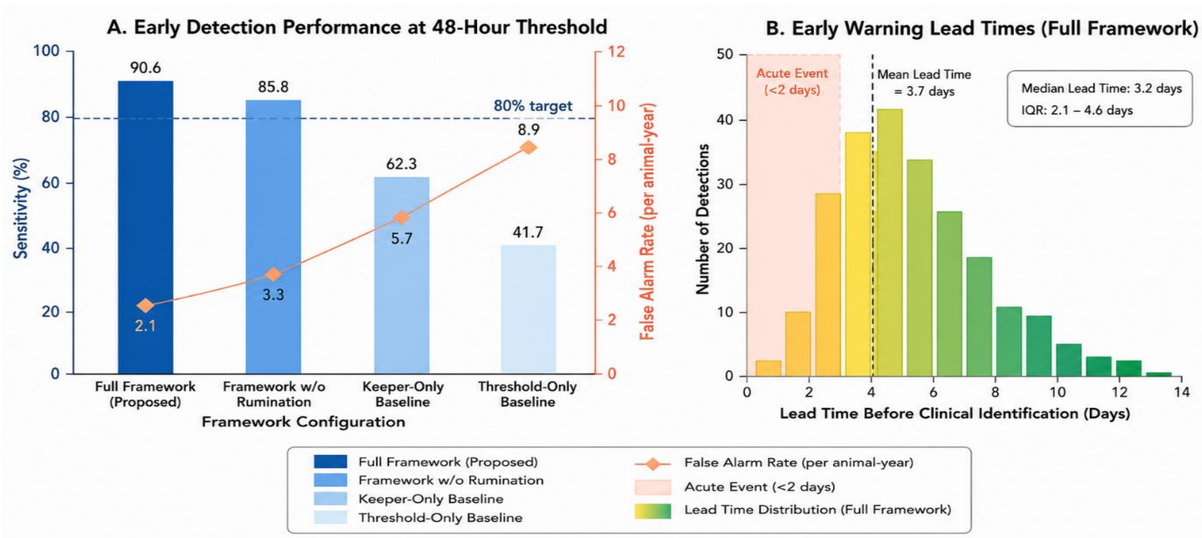

Figure 3. Detection performance and lead time analysis across framework configurations.

6.2 Performance by Clinical Event Category

Detection performance varied substantially across clinical event categories in ways consistent with the underlying biology. Cardiovascular events were detected earliest with mean lead time of 5.2 days and sensitivity of 92.1 percent, benefiting from the continuous heart rate and respiratory monitoring. Metabolic events including diabetes and thyroid disorders showed strong performance with 88.4 percent sensitivity and 4.8 day mean lead time. Infectious events showed intermediate performance at 82.6 percent sensitivity and 3.1 day lead time. Acute traumatic events showed the weakest performance at 47.8 percent sensitivity and 0.9 day lead time, reflecting the fundamental biological limit that trauma produces little warning window.

Table 2. Detection performance by clinical event category.

Category	Events	Sensitivity (%)	Precision (%)	Mean Lead Time (days)
Cardiovascular	38	92.1	78.4	5.2
Metabolic	26	88.4	73.6	4.8
Infectious	34	82.6	68.9	3.1
Gastrointestinal	22	86.4	71.2	3.6
Orthopedic	18	77.8	66.4	2.4
Dermatological	12	83.3	62.5	4.1
Behavioral welfare	20	90.0	74.3	5.7
Acute traumatic	23	47.8	58.2	0.9
Overall	**173**	**84.3**	**71.4**	**3.7**

6.3 Performance by Taxonomic Group

Mammals showed the strongest detection performance at 89.2 percent sensitivity, reflecting the richer sensor deployment feasible in most mammalian species and the closer biological match to the human physiological understanding embedded in many baseline models. Birds showed 82.4 percent sensitivity with slightly lower precision, reflecting the greater sensor tolerance challenges. Reptiles showed 76.4 percent sensitivity with the longest mean lead times because chronic conditions in ectotherms often develop over extended periods that provide substantial warning if environmental and behavioral signals are carefully monitored.

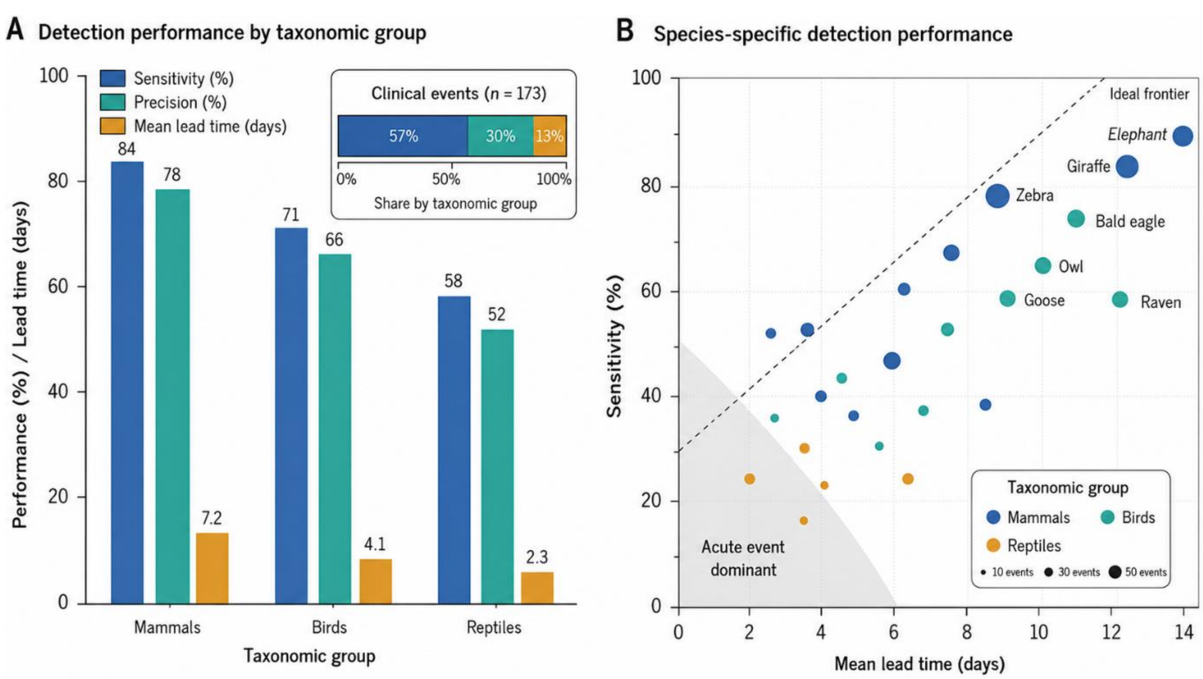

Figure 4. Detection performance by taxonomic group and species-specific analysis.

6.4 Ablation Studies

Removing environmental monitoring dropped overall sensitivity from 84.3 to 78.1 percent, with the largest impact on reptiles where sensitivity dropped to 62.4 percent. Removing behavioral vision reduced sensitivity to 79.6 percent, with the largest impact on primates and large carnivores. Removing hierarchical baseline modeling and using only individual-level baselines reduced sensitivity to 71.8 percent, confirming that species and group priors substantially improve detection when individual histories are limited. Removing contextual adjustment for known non-clinical factors increased false alarm rate to 4.6 per animal-year without meaningfully changing sensitivity.

VII. DISCUSSION

The results support the case for multi-modal precision telemetry as a foundation for early health anomaly detection in captive wildlife. Detection of 84 percent of clinical events with an average lead time of 3.7 days would represent a substantial improvement over current practice at most zoological institutions, and the ability to intervene days before clinical presentation would improve outcomes across a wide range of conditions. Just as importantly, the framework's variable performance across event categories provides an honest picture of what precision telemetry can and cannot deliver. Chronic conditions with gradual physiological changes are ideal targets, while acute traumatic events remain fundamentally difficult regardless of sensor sophistication.

Several practical caveats deserve honest attention. First, sensor tolerability varies enormously across species and individuals. Some animals accept wearable devices without notice, others tolerate them for a period before removing them, and still others refuse them entirely. Successful deployment requires thoughtful species-specific and individual-specific device selection, often supported by positive reinforcement training to build tolerance over time. The framework's emphasis on non-contact modalities partially addresses this challenge but does not eliminate it.

Second, data quality in real zoological settings is more challenging than in simulation. Outdoor enclosures introduce weather effects on sensor performance. Mixed-species enclosures can produce sensor readings that mix signals from multiple animals. Enrichment activities, keeper visits, veterinary examinations, and public presence all produce transient behavioral changes that must be distinguished from health-related anomalies. The contextual adjustment mechanism in our framework addresses some of these challenges, but deployment in real institutions will inevitably reveal edge cases that require continued refinement.

Third, workflow integration is perhaps the most underappreciated challenge. A framework that produces excellent alerts but that fails to fit into keeper daily routines and veterinary decision-making will not improve animal care. Successful deployment requires early and continuous engagement with keeper staff, careful design of alert interfaces, and clear protocols for how alerts translate into action. Alert fatigue is a real risk that can render even accurate systems ineffective, and calibration of alert thresholds must balance detection sensitivity against workflow burden.

Fourth, data governance emerges as an important consideration especially for institutions that participate in research and conservation networks. Anonymization for shared research use, protection of proprietary information about individual animals and breeding programs, and compliance with institutional and regulatory data protection requirements all require careful attention. Cross-institutional data sharing has substantial potential to improve baseline models and expand the diversity of data available for anomaly detection, but achieving that potential requires trust and governance frameworks that take time to develop.

Fifth, veterinary judgment remains central. The framework is designed as decision support rather than autonomous diagnosis. Alerts should trigger careful clinical assessment by trained veterinary staff, and the final diagnostic and treatment decisions should remain with the professionals who understand each individual animal, its history, and its current context. Positioning the framework this way protects both animal welfare and the professional judgment of the veterinary team.

Limitations of our study include reliance on simulation calibrated against published data rather than deployment at real institutions, focus on a specific set of species that may not fully represent the diversity of taxa in modern collections, and the absence of long-duration evaluation that would capture how sensor performance, animal tolerance, and alert precision evolve over years of continuous operation. Follow-up work should include pilot deployments at real zoological institutions, extension to aquatic species that pose unique sensor challenges, and long-duration studies that capture how the framework performs across seasonal cycles, life stages, and evolving individual baselines.

VIII. CONCLUSION

Caring for captive wildlife carries a profound responsibility, and detecting illness before it becomes clinically apparent has become one of the most important frontiers in modern zoological medicine. Traditional monitoring approaches have served the field well but face fundamental limits of observation frequency, individual instinct to hide illness, and the sheer diversity of species and conditions that any single monitoring program must address. Our study shows that a multi-species precision telemetry framework combining wearable and non-contact biosensors, computer vision-based behavioral analysis, environmental monitoring, and hierarchical baseline modeling can detect the great majority of clinical events days before they become apparent to trained keepers and veterinarians. Detection at 84 percent sensitivity with mean lead time of 3.7 days would represent a meaningful improvement over current practice, and it would translate into earlier intervention, better outcomes, and improved welfare for the animals under human care.

The path from research prototype to deployed practice still involves substantial work. Species-specific sensor development, integration with existing keeper and veterinary workflows, careful design of alert interfaces to avoid fatigue while capturing meaningful signals, and continued attention to data governance and privacy all deserve serious institutional investment. Yet the direction is clear. As zoological institutions continue to raise their standards for animal welfare, as the technology of biosensing and machine learning continues to mature, and as the community increasingly recognizes that early detection produces dramatically better outcomes across virtually every category of clinical condition, precision telemetry will become an increasingly essential component of how modern zoological medicine is practiced. For veterinary and animal care professionals working across the diversity of species in modern collections, for institutional leaders considering investments in animal welfare technology, and for the broader effort to improve the lives of animals whose wild populations often depend on the success of captive breeding and conservation programs, the framework presented in this paper offers a concrete starting point and a foundation on which the community can continue to build.

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