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Review Article

The Avian Digital Twin Intelligence: A Multimodal AI, Bioacoustic and Precision-Phenotyping Framework for Predictive Health, Disease Forecasting and Welfare Optimization in Companion Parrots

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Abstract:

Companion parrots present an unusually complex challenge for preventive veterinary medicine because clinically meaningful changes may initially manifest as subtle alterations in behaviour, vocal activity, posture, locomotion, feeding, social interaction, plumage condition or daily activity patterns. Conventional clinical assessment generally provides a snapshot of an animal at a particular point in time, whereas companion parrots continuously generate behavioural and environmental information that could potentially be transformed into longitudinal health indicators. Recent advances in artificial intelligence (AI), multimodal sensing, computer vision, bioacoustics, self-supervised learning and time-series modelling create an opportunity to develop a fundamentally different paradigm: **the individualized avian digital twin**.

An avian digital twin can be conceptualized as a continuously updated computational representation of an individual bird that integrates heterogeneous observations—including video, vocalizations, activity, environmental conditions, feeding behaviour, physiological measurements and veterinary records—with biological and statistical models. Rather than relying exclusively on population-level thresholds, such a system could establish an individualized baseline and detect deviations in multimodal trajectories. Computer vision could quantify posture, locomotion, plumage appearance and activity; bioacoustic models could characterize vocal repertoire, temporal structure and acoustic features; environmental sensors could contextualize behavioural changes; and longitudinal machine-learning models could integrate these signals into probabilistic health and welfare trajectories.

This framework is particularly relevant to parrots because vocal learning, social complexity and individual behavioural variation make simplistic interpretation of single behavioural signals problematic. Recent literature also demonstrates both the promise and the limitations of automated animal bioacoustics and AI-based welfare monitoring. Importantly, a 2024 systematic review identified substantial gaps in validated parrot-specific welfare indicators, while a 2026 expert-developed tool, PsittaWel, provides a structured framework encompassing physical health, activity, enrichment, nutrition, social behaviour, human–animal interactions and maladaptive behaviours.

This article proposes a **Multimodal Avian Intelligence Architecture (MAIA)** integrating individual digital twins, foundation-model representations, explainable AI, uncertainty quantification, causal inference, federated learning and edge computing. The objective is not to replace veterinary diagnosis but to establish a continuous decision-support layer capable of identifying clinically relevant deviations earlier, prioritizing veterinary assessment and supporting individualized welfare optimization. Major challenges include dataset scarcity, species and individual variability, annotation quality, confounding environmental factors, algorithmic bias, interpretability, validation, privacy and the risk of overinterpreting behavioural correlates as disease-specific biomarkers. A clinically credible avian digital twin therefore requires prospective validation against veterinary ground truth, calibrated uncertainty and human oversight.

Keywords: companion parrots; avian medicine; digital twin; artificial intelligence; multimodal AI; bioacoustics; computer vision; precision veterinary medicine; animal welfare; digital phenotyping; foundation models; explainable AI; uncertainty quantification; predictive health.

1. Introduction:

Parrots occupy a distinctive position within companion-animal medicine. Their behavioural repertoire is highly developed, their social interactions can be complex, and many species possess

sophisticated vocal-learning abilities. Companion parrots may therefore generate a rich stream of behavioural information that is potentially relevant to health and welfare. At the same time, interpreting this information is difficult because an identical observable behaviour can have different meanings depending on context, individual history, species, social environment and environmental conditions.

The challenge is compounded by the fact that many welfare-relevant variables in parrots remain insufficiently validated. A systematic review published in *Animal Welfare* identified 1,848 retrieved studies, of which 98 met the review criteria, and evaluated 1,512 potential outcomes associated with parrot welfare. The authors highlighted substantial taxonomic and methodological limitations and noted the underrepresentation of companion parrots.

This creates an important opportunity for precision veterinary medicine. Instead of evaluating a bird exclusively against a generalized reference population, technology could establish a **personalized longitudinal baseline**. The question would consequently change from:

“Is this behaviour abnormal for parrots?”

to:

“Has this individual bird undergone a statistically and biologically meaningful deviation from its own established baseline?”

This distinction is fundamental.

A digital twin does not simply mean a camera connected to an artificial-intelligence model. Contemporary animal digital-twin architectures combine sensor observations, records and computational models into continuously updated representations of biological state. A 2026 perspective in *npj Veterinary Sciences* describes animal digital twins as architectures coupling sensor observations and animal/farm records with process-based, data-driven or hybrid models, while emphasizing ground-truth calibration and uncertainty-aware verification.

For companion parrots, this concept can be translated from the population or production-animal level to an **individualized veterinary digital phenotype**.

2. Why Parrots Are an Ideal Testbed for Multimodal Veterinary AI?

2.1 Behaviour is biologically informative—but context dependent:

Parrot welfare encompasses physical health, activity, social interactions, exploration, environmental enrichment, nutrition, human–animal interaction and abnormal behaviours. A recent systematic review identified changes in activity, social interaction, exploration, body weight, plumage condition and abnormal behaviours among potentially useful welfare outcomes.

However, behaviour should not be treated as a one-to-one diagnostic code.

For example:

- reduced activity may reflect illness, sleep disruption, environmental change or temperature;

- increased vocalization may represent social engagement, frustration, territorial behaviour or distress;
- feather changes may reflect normal moult, environmental factors, nutritional problems or feather-damaging behaviour;
- altered feeding may reflect food preference, enrichment, social context or disease.

AI therefore needs to model **contextual relationships**, rather than simply classify isolated behaviours.

3. The Avian Digital Twin Concept:

The proposed **Avian Digital Twin** is an individualized computational model containing five interconnected layers:

Layer 1 — Biological Identity:

- species
- age
- sex where known
- individual phenotype
- medical history
- vaccination/health records where relevant
- previous disease episodes
- nutritional history
- behavioural baseline

Layer 2 — Continuous Sensing:

- RGB/video cameras
- microphones
- environmental sensors
- activity sensors
- body-weight measurements
- feeding and drinking observations
- optional physiological measurements

Layer 3 — Multimodal Representation:

AI converts raw observations into structured representations:

Video → posture → movement → behaviour

Audio → acoustic embedding → vocalization pattern

Environment → temperature/humidity/light/noise

Clinical records → longitudinal health representation

Layer 4 — Individual State Model:

The system estimates:

- behavioural state
- welfare trajectory
- anomaly probability
- health-risk trajectory
- uncertainty
- change-point probability

Layer 5 — Veterinary Decision Support:

The output is not simply: **“Disease detected.”**

Instead: **“The probability of a clinically meaningful deviation has increased relative to this bird's**

baseline; the primary contributing signals are reduced activity, altered vocal structure and decreased feeding behaviour. Confidence: moderate. Veterinary assessment recommended."

This distinction is critical for responsible veterinary AI.

4. Multimodal Digital Phenotyping:

4.1 Computer Vision:

Computer vision could provide continuous, non-contact monitoring of:

- locomotion
- perching
- wing movement
- posture
- head orientation
- grooming
- feeding
- drinking
- exploration
- social interaction
- abnormal repetitive behaviour
- plumage condition
- facial/body displays

Modern computer-vision systems could employ object detection, pose estimation, temporal action recognition and vision transformers.

A future system could construct a **Parrot Behavioural State Space**, where each time interval is represented as a multidimensional behavioural vector rather than a single categorical label.

For example:

$$B_t = [A_t, P_t, F_t, G_t, S_t, E_t, V_t]$$

where:

- A_t = activity
- P_t = posture
- F_t = feeding
- G_t = grooming
- S_t = social interaction
- E_t = exploration
- V_t = vocal activity.

The importance lies not in one value but in the **trajectory of the vector over time**.

5. Bioacoustic Intelligence:

Parrot vocalizations represent one of the most technologically interesting modalities.

Parrots are among the taxa capable of lifelong vocal learning, and vocal behaviour varies considerably among and within species. A survey involving 877 companion parrots found substantial interspecific variation in vocal mimicry, with African grey parrots exhibiting particularly large mimicry repertoires in that dataset.

This creates both an opportunity and a warning.

Opportunity:

AI can potentially learn:

- individual vocal signatures
- call-type distributions

- temporal patterns
- vocal repertoire changes
- unusual acoustic events
- social-context associations
- longitudinal deviations.

Warning:

A vocalization should **not automatically be labelled as an emotion or disease biomarker** merely because an algorithm can classify it.

Animal bioacoustic research emphasizes the importance of automatic detection, appropriate annotation and biologically meaningful interpretation.

A 2026 veterinary review specifically proposed integrating sound, vision and other data streams for animal-health monitoring while emphasizing the developmental nature of quantitative acoustic health indicators.

6. From Acoustic Features to Avian Foundation Models:

Traditional acoustic pipelines may extract:

- Mel-frequency cepstral coefficients (MFCCs)
- spectral centroid
- spectral bandwidth
- spectral entropy
- fundamental frequency
- duration
- amplitude modulation
- harmonic structure.

The next generation can move toward **self-supervised acoustic representation learning**.

Instead of requiring every vocalization to be manually labelled, a foundation model could learn general acoustic representations from large quantities of unlabeled parrot recordings.

A conceptual pipeline is:

Audio → *Spectrogram/Waveform* → *Self – Supervised Encoder* → *Acoustic Embedding*
→ *Temporal Transformer* → *Individual Vocal Phenotype*

Recent reviews of AI-driven animal vocalization analysis describe the transition from handcrafted acoustic features toward CNNs, recurrent architectures, attention mechanisms and self-supervised models such as wav2vec-style approaches.

For parrots, the goal should not initially be to create an artificial “parrot language translator.”

A scientifically stronger objective is:

learning robust representations of individual vocal behaviour and identifying reproducible deviations associated with clinically relevant states.

7. Multimodal Fusion: The Core of the Digital Twin

The most important innovation is **sensor fusion**.

Suppose a parrot produces fewer vocalizations. Audio alone cannot determine why.

However:

Audio + activity + feeding + posture + environmental conditions + longitudinal history

can provide substantially richer context. A multimodal model can be represented as:

$$Z_t = f(A_t, V_t, E_t, P_t, C_t, H_t)$$

where:

- A_t = acoustic representation
- V_t = visual representation
- E_t = environmental state
- P_t = physiological/physical observations
- C_t = contextual variables
- H_t = historical health state.

The resulting latent state Z_t becomes the computational representation of the bird at time t .

Sensor-fusion approaches in animal monitoring have already been investigated across raw-data, feature-level and decision-level fusion architectures.

8. Individual Baseline Modelling:

This is arguably the most important scientific component. Instead of defining a universal threshold such as:

$$Activity < X$$

the system could learn:

$$P(X_t | X_{1:t-1} IndividualEnvironment)$$

The model therefore asks whether the present observation is improbable given the bird's own historical state.

A **Bayesian state-space model**, recurrent neural network, temporal transformer or Gaussian-process model could estimate expected trajectories.

For example:

$$D_t = \|Z_t - \hat{Z}_t\|$$

where:

- Z_t = observed multimodal state
- $\hat{Z}_t$ = predicted state.

A large deviation does not mean “disease.”

It means: **anomaly requiring contextual interpretation.**

This distinction prevents a major failure mode of automated veterinary systems: confusing statistical abnormality with clinical diagnosis.

9. The Avian Health Risk Engine:

The digital twin could generate several parallel outputs.

9.1 Anomaly score:

$$A_t = P(\text{state deviation} | X_{1:t})$$

9.2 Welfare Trajectory:

$$W_t = f(\text{behaviour, environment, social interaction, physical indicators})$$

9.3 Health-risk Trajectory:

$$R_t = P(\text{clinically relevant deterioration} \mid Z_{1:t})$$

9.4 Uncertainty:

$$U_t = H[P(Y_t \mid X_{1:t})]$$

where H represents predictive entropy.

This allows the system to distinguish: **High risk + high confidence** from **High risk + high uncertainty**.

The latter should trigger additional observation or veterinary evaluation rather than an automated intervention.

10. Explainable AI for Veterinary Use:

A black-box prediction such as: “**Risk = 83%.**” is insufficient for clinical decision support.

An explainable system should instead report contributing evidence:

Example:

Observed deviation-

- activity ↓ 28%
- feeding-event frequency ↓ 19%
- vocal repertoire diversity ↓
- nocturnal rest fragmentation ↑
- environmental temperature stable
- body weight mildly decreased

Model interpretation-

“The current state is inconsistent with the individual's established baseline. The strongest contributors are reduced activity and feeding behaviour. Acoustic changes provide secondary evidence. Environmental confounding is currently low.”

This allows the veterinarian to interrogate the model rather than simply accept it.

11. Uncertainty-Aware Veterinary AI:

Uncertainty should be treated as a **first-class output**.

Potential uncertainty sources include:

- poor microphone quality
- occluded video
- insufficient baseline data
- unusual environmental conditions
- species differences
- age effects
- individual behavioural variation
- incomplete clinical records
- domain shift between households.

A robust system should therefore implement:

Selective Prediction:

When confidence is inadequate: “**Insufficient evidence—human review required.**”

This is preferable to forcing a classification.

The importance of uncertainty-aware verification is also emphasized in contemporary animal digital-twin architecture.

12. Precision Welfare Intelligence:

The digital twin should not become exclusively a disease-detection system. Its second major function should be **welfare optimization**.

A 2024 systematic review found that social behaviour, environmental enrichment, housing, human interaction and abnormal behaviours are important components of companion-parrot welfare assessment. A 2026 study introduced **PsittaWel**, a structured companion-parrot welfare tool containing 75 questions covering 145 welfare indicators across eight domains, including physical health, housing and activity, enrichment, nutrition, social/reproductive behaviour, human–parrot interactions and maladaptive/fear-related behaviours.

This creates an opportunity to combine expert-developed welfare constructs with continuous digital phenotyping.

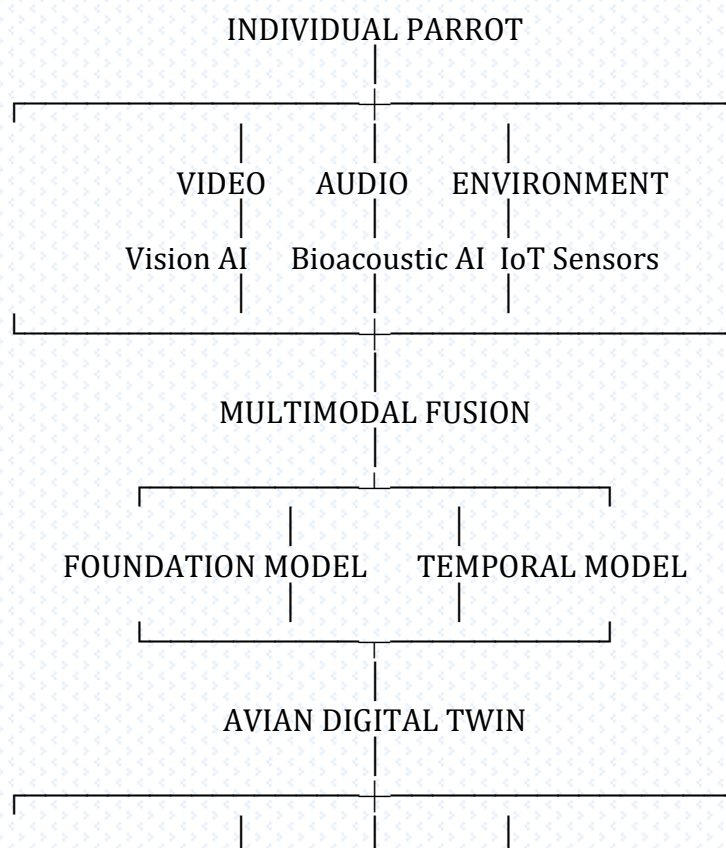
For example:

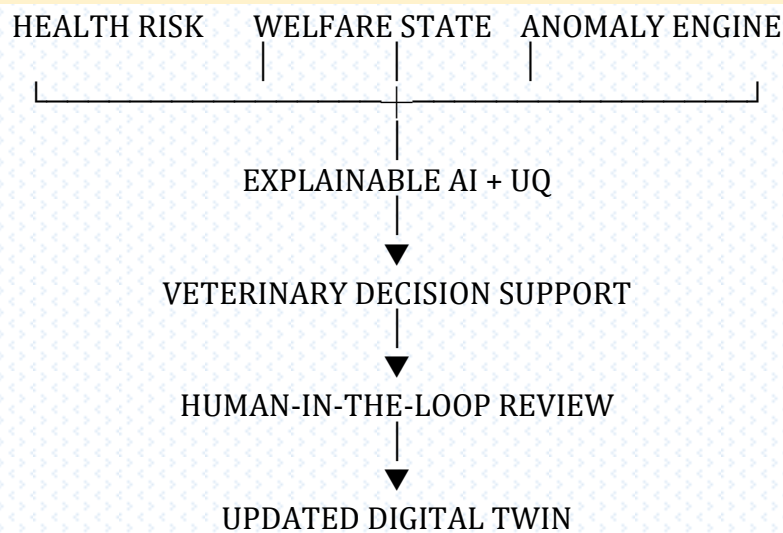
$$Welfare_t = w_1H_t + w_2A_t + w_3S_t + w_4E_t + w_5N_t + w_6B_t$$

where the weights would require empirical validation rather than being arbitrarily assigned.

13. The Proposed MAIA Architecture:

Multimodal Avian Intelligence Architecture:





The system becomes a **closed-loop learning architecture**, but the learning loop should be governed by clinical validation rather than unrestricted autonomous model updating.

14. Edge AI and Real-Time Monitoring:

A practical deployment would not necessarily transmit every video or audio recording to a cloud server.

Instead:

Sensor → Edge device → Local inference → Feature extraction → Secure cloud synchronization could reduce bandwidth requirements and improve privacy.

Edge AI could perform:

- real-time activity detection
- acoustic event detection
- posture classification
- abnormal-event screening
- data compression.

Only clinically relevant embeddings, alerts or anonymized summaries could be transmitted.

This is particularly important for household companion animals, where continuous audiovisual monitoring creates legitimate privacy concerns.

15. Federated Learning:

A major obstacle is the lack of large, diverse, well-labelled parrot datasets. One solution is **federated learning**.

Instead of transferring raw recordings from multiple households:

$$Local\ Data_i \rightarrow Local\ Model_i$$

model updates can be aggregated:

$$Global\ Model = Aggregate(M_1, \dots, Model_1, Model_2, \dots, Model_n)$$

This could theoretically allow models to learn from geographically and demographically diverse populations while reducing the need to centralize raw household recordings.

However, federated learning does not automatically solve privacy, bias or data-quality problems.

These would still require explicit governance.

16. Causal AI: Moving Beyond Correlation

A sophisticated digital twin should eventually distinguish:

Correlation from causal influence.

For example:

Reduced vocalization → disease? is an oversimplification.

A causal framework might instead model:

Environment → Stress/Behaviour

Disease → Behaviour

Socialisolation → Vocalbehaviour

Noise → Vocalbehaviour

Sleepdisruption → Activity

This matters because veterinary interventions should target causes rather than merely observable correlations.

17. Digital Phenotype of a Companion Parrot:

The long-term objective could be a continuously updated **Parrot Digital Phenotype** containing:

Behavioural Phenotype:

- activity rhythm
- locomotion
- exploration
- grooming
- social behaviour
- stereotypic behaviour.

Acoustic Phenotype:

- repertoire
- call frequency
- temporal structure
- acoustic embeddings
- individual vocal signature.

Physical Phenotype:

- body weight
- posture
- plumage
- movement symmetry
- feeding behaviour.

Environmental Phenotype:

- temperature
- humidity
- photoperiod
- noise
- enclosure characteristics
- enrichment exposure.

Clinical Phenotype:

- previous diseases
- medications

- laboratory data
- veterinary examinations.

Together these data could form a longitudinal representation:

$$DP_i(t) = \{B, A, P, E, C\}_t$$

where $DP_i(t)$ is the digital phenotype of individual i at time t .

18. Clinical Applications:

Potential applications include:

- **Early Deviation Detection:** Identifying persistent behavioural changes that warrant clinical assessment.
- **Chronic Disease Monitoring:** Tracking longitudinal changes after diagnosis or treatment.
- **Postoperative Monitoring:** Detecting changes in activity, feeding or behaviour following procedures.
- **Welfare Surveillance:** Monitoring enrichment, social interaction and abnormal behaviour.
- **Environmental Optimization:** Identifying associations between environmental conditions and behavioural changes.
- **Preventive Veterinary Medicine:** Creating individualized risk trajectories rather than relying solely on episodic clinical visits.

Importantly, these applications should initially be considered **decision-support objectives**, not autonomous diagnostic capabilities.

19. Major Scientific Challenges:

- **Dataset Scarcity:** High-quality parrot datasets containing synchronized:
 - audio
 - video
 - environmental data
 - clinical information
 - expert annotations are currently limited.
- **Species Heterogeneity:** A macaw, cockatoo, African grey and budgerigar cannot automatically be treated as interchangeable data points.
- **Individuality:** Parrots exhibit strong individual behavioural and vocal differences.
- **Ground Truth:** The central challenge is linking AI outputs to reliable veterinary ground truth.
- **Confounding:** Environmental change can mimic health-related behavioural changes.
- **Annotation Burden:** Expert annotation of thousands of hours of video and audio is expensive and time consuming.
- **Domain Shift:** A model trained in one household may perform differently in another.
- **False Positives:** Excessive alerts could produce caregiver fatigue and unnecessary veterinary consultations.
- **False Negatives:** Failure to detect meaningful deterioration could be more consequential than an

occasional false alarm.

20. Ethical and Welfare Considerations:

AI for animals must remain **animal-centred**.

A technically sophisticated system could still be harmful if it encourages:

- excessive surveillance
- unnecessary handling
- inappropriate automated interventions
- behavioural labelling without biological validation
- substitution of AI for veterinary expertise.

The objective should therefore be:

AI ≠ Veterinary Replacement

but:

AI + Veterinarian + Longitudinal Data → Better Decision Support

The system should also avoid anthropomorphic interpretations. A model identifying a change in vocalization does not automatically establish that the bird is “sad,” “anxious” or “happy.” Biological interpretation requires validated behavioural and physiological evidence.

21. Validation Framework:

Before clinical deployment, the proposed architecture should undergo staged validation.

Phase I — Technical Validation:

Measure:

- | | |
|---------------|--------------------------------------|
| • sensitivity | • AUROC |
| • specificity | • calibration |
| • precision | • latency |
| • recall | • robustness to noise and occlusion. |
| • F1 score | |

Phase II — Biological Validation:

Compare model outputs against:

- expert behavioural assessment
- veterinary examination
- validated welfare measures
- physiological measurements where appropriate.

Phase III — Prospective Validation:

Evaluate performance on **future unseen individuals**, rather than only retrospective datasets.

Phase IV — External Validation:

Test across:

- species
- age groups
- households
- geographic regions
- husbandry environments.

Phase V — Clinical Utility:

Determine whether AI-assisted monitoring actually improves:

- time to veterinary assessment
- welfare outcomes
- diagnostic workflow
- caregiver adherence
- clinical decision quality.

High classification accuracy alone should not be regarded as proof of clinical usefulness.

22. Future Research: Toward an Avian Foundation Model

The ultimate evolution could be an **Avian Foundation Model** trained across multiple modalities:

Audio + Video + Environment + Clinical Data + Behaviour

Such a model could generate a shared latent representation of avian behavioural and physiological states.

A future research ecosystem could include:

Parrot-Foundation Model:

- species adaptation
- individual adaptation
- digital twin
- continuous monitoring
- uncertainty estimation
- veterinary decision support.

However, foundation models should be evaluated carefully for dataset bias, spurious correlations and lack of biological interpretability.

23. The Concept of “Predictive Welfare”

Traditional welfare assessment is often periodic.

The proposed framework shifts toward: **Predictive welfare**

Instead of asking: “Is this bird currently experiencing a welfare problem?”

the system could ask: “Is the bird's current trajectory moving away from its established behavioural and environmental optimum?”

This introduces the possibility of **trajectory-based welfare management**.

The distinction is important because welfare deterioration may be gradual rather than abrupt.

24. Proposed Research Roadmap:

- **Stage 1 — Digital Phenotyping:** Create standardized multimodal datasets.
- **Stage 2 — Behavioural Foundation Model:** Learn general representations of parrot behaviour.
- **Stage 3 — Bioacoustic Foundation Model:** Develop species and individual aware acoustic representations.
- **Stage 4 — Multimodal Fusion:** Combine audio, video and environmental streams.
- **Stage 5 — Individual Digital Twins:** Construct longitudinal models for individual birds.
- **Stage 6 — Veterinary Validation:** Associate deviations with independently verified clinical outcomes.
- **Stage 7 — Explainability and Uncertainty:** Introduce calibrated risk estimates and interpretable evidence.
- **Stage 8 — Prospective Deployment:** Evaluate real-world veterinary utility.

25. Conclusion:

The convergence of artificial intelligence, computational bioacoustics, computer vision, sensor fusion and precision veterinary medicine provides an opportunity to fundamentally reconsider how companion-parrot health and welfare are monitored. Parrots are particularly compelling subjects for this development because their complex behavioural and vocal repertoires provide a potentially information-rich but biologically challenging monitoring environment. Existing research supports the feasibility of automated animal bioacoustic analysis and multimodal monitoring, while recent parrot-specific welfare research demonstrates both the importance of individualized indicators and the current limitations in validation.

The proposed **Avian Digital Twin** should therefore be viewed not as a speculative replacement for veterinary medicine, but as a computational infrastructure for longitudinal observation. Its central innovation is the integration of **individual baseline modelling, multimodal representation learning, bioacoustic phenotyping, computer vision, uncertainty quantification and explainable veterinary decision support**.

The most important conceptual shift is from **snapshot-based assessment to trajectory-based precision monitoring**.

A future companion-parrot health system could continuously learn what is normal for an individual bird, identify meaningful deviations, contextualize those deviations using environmental and behavioural information, quantify uncertainty and present interpretable evidence to a veterinarian or caregiver.

The final objective is not an algorithm that claims to “understand” a parrot. It is a scientifically validated system that can say, with appropriate uncertainty:

“This individual has changed. Here is what changed, how unusual the change is, what evidence contributes to the signal, and why professional assessment may be warranted.”

That distinction could form the foundation of a new generation of **precision avian medicine and welfare science**.

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