Artificial Intelligence–Assisted Interpretation of Veterinary Radiographs

Opportunities, Risks, and Best Practices for Clinicians

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KEYWORDS

• Artificial intelligence • Veterinary radiology • Deep learning • Diagnostic imaging • Clinical decision support • Professional accountability

KEY POINTS

- Artificial intelligence serves as an assistive tool in veterinary practice, not a replacement for licensed veterinarian judgment and accountability.
- Veterinarians remain fully responsible for AI-assisted decision, even without formal regulations governing AI use in veterinary medicine.
- Practioners must understand AI systems well enough to explain their function to clients before incorporating them into patient care decisions.
- Responsible AI adoption requires understanding training data, disclosing AI use to clients, following best practices, and maintaining professional accountability.
- AI cost-effectiveness remains unclear, depending on acquisition costs, clinical outsome improvements, and potential expenses from false-positives and unnecessary follow-up testing.

INTRODUCTION

Diagnostic radiography remains one of the most widely used imaging modalities in veterinary clinical practice, routinely deployed across species, practice types, and resource settings. Veterinary radiology, in particular, faces critical challenges due to

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Abbreviations	
AI	artificial intelligence
HIPAA	Health Insurance Portability and Accountability Act

increasing clinical workload, uneven access to board-certified radiologists, and growing expectations for rapid diagnostic turnaround, prompting the expansion of teleradiology and, more recently, artificial intelligence (AI) in the profession.[1,2] Unsurprisingly, such challenges have driven interest in AI–based tools designed to assist with radiographic interpretation.

In recent years, AI systems—largely based on deep learning and convolutional neural networks—have been introduced for a range of veterinary radiography tasks, including abnormality detection, pattern classification, quantitative measurements, and report generation.[3] Commercial availability of these tools has expanded rapidly, outpacing the development of formal guidance for their clinical use. Unlike human medical imaging, where software intended for diagnostic support is subject to defined regulatory pathways, veterinary AI tools are currently deployed with limited external oversight. As a result, responsibility for the appropriate selection, validation, and use of these systems rests largely with the practicing veterinarian.

When used appropriately, AI-assisted radiograph interpretation can provide meaningful benefits, including workflow triage, improvements in measurement consistency, and decision support in settings with limited radiology access. However, these systems also introduce new risks: Performance may vary across species, breeds, image acquisition protocols, and disease prevalence. Errors may be subtle, systematic, or difficult to detect, particularly when clinicians place undue confidence in automated outputs. Without a clear understanding of a system's intended use, training data, and limitations, there is a risk that AI tools may be misapplied, over-relied on, or inappropriately used in clinical decision-making.

The purpose of this article is to provide practicing veterinarians with a practical overview of AI-assisted radiograph interpretation, focusing on tools currently available or emerging in veterinary medicine. Rather than offering a technical review of algorithm development, this article emphasizes clinical relevance: how these tools function, where they may add value, and their limitations. Drawing on guidance from veterinary professional organizations and established medical imaging frameworks, we outline core principles for responsible implementation, including local evaluation, human oversight, transparency, and ongoing performance monitoring.

OVERVIEW OF ARTIFICIAL INTELLIGENCE–BASED RADIOLOGY TOOLS

Research literature on AI-assisted radiographic tools is proliferating rapidly, and a meaningful synthesis of the state-of-the-art is a formidable task. Moreover, keeping pace with the simultaneous acceleration of commercial AI deployment in clinical settings, along with critical reviews of its use, is becoming a significant challenge. Today, there are numerous review articles, narratives, and publications not only on radiology and AI, but also directed to the veterinary radiologist.[4–9] Diagnostic radiology tools may be broadly categorized into detection and triage, classification and decision support, quantitative measurement, and reporting and workflow tools.

CURRENT APPLICATIONS AND POTENTIAL BENEFITS

Based on the current state in the literature, AI research in conventional veterinary radiography spans 4 main areas: orthopedics (detection of hips, hip dysplasia, and stifle

joints), thoracic imaging (detecting pulmonary abnormalities, pleural effusion, and various thoracic lesions), cardiac silhouette evaluation (including automated vertebral heart score measurements and cardiomegaly classification), and image quality assessment.[10–13] The largest deployment involved training a commercial deep learning model on more than 2.5 million canine and feline radiographs, demonstrating improved generalizability through semisupervised learning, using natural language processing to extract labels from radiological reports.[14] Overall performance varies considerably across tasks and studies, with some commercial AI tools showing high negative predictive values but lower positive predictive values, suggesting these tools may be most useful for confirming normal cases rather than definitive diagnosis of abnormalities. Comparative studies between AI and veterinary radiologists produced mixed results. In some cases, AI outperformed radiologists for specific lesions, while in others, radiologists maintained equal or superior performance, highlighting that current AI tools function best as decision support aids rather than autonomous diagnostic systems.[15–21] Studies using generative active learning approaches with variational autoencoders could address the fundamental challenge of limited labeled veterinary radiographic datasets, though data scarcity remains a significant constraint to AI development and validation.

With respect to supporting general versus referral practices, there are little data on overall adoption by practice size; hence, no generalizations about the suitability of commercial systems based on practice size, patient volume, geographic location, or other potential covariates can be safely drawn. Of note, commercial solutions are largely aimed at general practitioners, who may, in turn, hire radiologists to oversee AI model outputs.

LIMITATIONS, RISK, AND FAILURE MODES

AI systems in veterinary radiography face multiple failure modes that practicing clinicians must recognize. First, AI models are fundamentally limited by their lack of contextual understanding: commercially available AI systems may, or may not, analyze images in isolation without integrating patient history, physical examination findings, or other diagnostic tests. Uncertainty or lack of transparency in how AI models arrive at decision-making creates risk when complex cases require nuanced clinical reasoning that extends beyond pixel-level pattern recognition. An example is loss of serosal contrast in young animals, which is physiologically normal but cannot be distinguished from pathology through image evaluation alone. In this instance, the clinician must integrate skeletal maturity markers visible on the radiograph with patient signalment, a multistep reasoning process that current AI systems may not replicate. Second, technical failure modes include sensitivity to differences between training and clinic-specific images, and performance degradation when AI encounters imaging equipment, patient populations, or technical protocols that differ from those in the training data, often occurring silently without obvious warning signs.[14] Third, human–AI interaction failures pose substantial clinical risk, particularly automation bias. Automation bias is the tendency of humans to trust the outputs of an automated system over their own judgment or that of other experts. The extent of this bias appears to be related to trust in the automated system, task difficulty, self-confidence, cognitive load, and time pressure.[22] An alarming finding in human medicine is that, broadly, automated clinical decision support systems can induce automation bias.[23] In their findings, Kücking and colleagues (2024) suggests nonspecialists (like, eg, a general practice veterinarian) using AI are more susceptible to automation bias than specialists (eg, a veterinary radiologist). Fourth, the absence of independent

ground-truth validation in many veterinary AI studies means that performance claims may not reflect real-world clinical accuracy when compared with surgical, pathologic, or long-term outcome data. Moreover, claims of performance, particularly for less common conditions, should be balanced with prevalence data and bias.[24,25] Fundamentally, this is a data problem; the limited availability of well-labeled veterinary datasets constrains both AI development and validation, resulting in a lag in AI development, deployment, and adoption in veterinary medicine compared to human medicine.[26] These limitations underscore that AI's value in radiology lies in its role as a decision support tool that requires radiologist oversight, rather than autonomous diagnostic authority.

REGULATORY, ETHICAL, AND PROFESSIONAL CONSIDERATIONS

Currently, the Food and Drug Administration does not regulate AI in veterinary products as done in human medicine, creating a regulatory vacuum for veterinary-specific AI tools. Software as a Medical Device for human medicine AI products requires clinical validation studies and regulatory clearance before deployment through defined pathways.[27] Conversely, veterinary AI products face no mandatory independent testing, standardized performance benchmarks, or postmarket surveillance requirements.[28] This absence of validation results in veterinary AI tools reaching the market with little oversight, shifting the burden of quality assurance and risk assessment onto practicing veterinarians and their clinics or institutions.

The regulatory gap requires veterinarians to serve simultaneously as purchasers, validators, and de facto regulators of complex AI technologies. In diagnostic radiology, the American College of Veterinary Radiology and the European College of Veterinary Diagnostic Imaging have published a joint position statement which "*... outlines the guiding principles for the ethical development and integration of AI technologies to ensure patient safety and clinical effectiveness.*[2]*"* Recommendations include that users and developers adopt *Good Machine Learning Practices,* ensuring a veterinary professional (ideally a radiologist) is the *human in the loop* while using AI, supporting research and peer-reviewed publications evaluating clinical platforms, establishing a framework for unbiased and independent evaluations of AI products, and finally acknowledging legal responsibility when using AI.[28]

Veterinarians using AI tools have an ethical obligation to disclose this use to clients, explain the role of AI in the diagnostic process, and clarify that AI outputs represent decision support rather than independent diagnosis (**Table 1**).[29–32] This transparency is essential for informed consent and maintains trust within the veterinarian-client-patient relationship. Clients making financial decisions about their animals' care—particularly those that may influence euthanasia or expensive treatment plans—should understand which expertise (human, algorithmic, or combined) underlies their pets' diagnostic recommendations. The principle of transparency extends beyond simple disclosure to meaningful explanation: *if a veterinarian cannot explain how an AI tool functions and what its limitations are in terms a client can understand, this raises serious questions about whether that tool should be used in clinical practice.* Professional standards require that, as might be the case with AI, standard-of-care techniques be documented in the patient's medical records, with a clear understanding of how AI-generated information was integrated into clinical decision-making (see **Table 1**).

An important consideration in the ethical and professional evaluation of AI tools is the relationship between cost and clinical value, particularly as the cost of care becomes a challenging principle to navigate in veterinary practice. While AI-assisted

Table 1
Examples of disclosure of artificial intelligence use to clients

Before use (example)	*"I'm going to use an AI-assisted software tool to help analyze your dog's chest radiographs. This computer system has been trained to identify common abnormalities and can help flag areas that need closer attention. However, I want to be clear that I will personally review all the images and the AI suggestions, and I am responsible for the final diagnosis and treatment recommendations. The AI is a support tool, not a replacement for my professional judgment."*
Documenting AI use in Clinical Decision-Making	Example medical record entries: *"Thoracic radiographs (LL and VD views) obtained and evaluated. AI-assisted interpretation software (Vendor AI Tool V1.0) flagged possible interstitial pattern in caudal lung fields with 85% confidence. Upon personal review, confirmed mild interstitial pattern present, consistent with early bronchitis. AI did not flag hilar lymphadenopathy also present on images. Final diagnosis based on combination of radiographic findings, clinical presentation, and physical examination..."* Or for a case where AI and clinician disagree: *"Abdominal radiographs reviewed with AI assistance (Vendor AI Tool V1.0). AI suggested possible intestinal obstruction. Personal examination of radiographs reveals normal gas pattern with no evidence of obstruction; AI likely misinterpreted fecal material in descending colon. Diagnosis: normal study. Plan: symptomatic treatment for mild gastroenteritis."*

interpretations are typically less expensive than consultations with board-certified radiologists, cost must be evaluated in relation to demonstrated clinical outcomes and patient benefit rather than the acquisition price alone. The value proposition of AI is compelling when it enables general practitioners to retain cases in-house rather than refer radiographs to specialists, offering rapid diagnostic responses to clients while reducing costs. However, rigorous research is required to determine whether AI-based systems produce clinical outcomes comparable to those achieved by veterinarians working alone or with radiologist oversight. Such comparative effectiveness studies are challenging and costly to design and implement, yet they remain essential for evidence-based adoption of these technologies.

The practical question is not simply whether AI is less expensive, but whether it adds value to clinical decision-making. For example, if an AI system costs $X per interpretation but generates uncertainty by flagging nonspecific findings such as *gastric content*, and thus triggering additional diagnostics (ultrasound examination, escalated radiologist consultation), the net cost-benefit becomes unclear. Similarly, if AI interpretations produce equivocal results for conditions that experienced human interpreters would confidently diagnose (such as linear foreign bodies), leading to downstream testing that would otherwise be unnecessary, the appropriateness of such systems in routine clinical practice warrants scrutiny. Until outcome-based studies demonstrate improved patient care or equivalent diagnostic accuracy at reduced total cost, the clinical and economic value of AI tools remains uncharacterized.

AI systems in veterinary practice rely on large amounts of sensitive data, including patient medical records and client personal information, raising critical questions about data security, privacy, and ownership.[33] Veterinary practices must ensure that all data used by AI systems are encrypted and stored securely, with clear policies governing who has access to this information. Unlike in US human health care, where the Health Insurance Portability and Accountability Act (HIPAA) provides a regulatory framework for data protection, these responsibilities lie with the veterinarian and the clinic. Questions of data ownership can become convoluted when patient image data are ingested into AI vendors to train or improve their algorithms. Practices should clarify whether client data is shared with third parties, how it will be used, and whether clients retain ownership rights over their animals' medical information. The absence of regulatory guidance on veterinary data privacy means practices must proactively develop policies that protect client confidentiality while enabling beneficial AI applications.

PRACTICAL GUIDANCE FOR RESPONSIBLE CLINICAL IMPLEMENTATION

Whenever new technology is introduced into clinical practice, sound change-management principles should be applied. The Non-Adoption, Abandonment, Scale-up, Spread, and Sustainability framework, frequently used in human medicine (see Shin and colleagues 2025 for a scoping review), suggests careful planning before purchasing and deploying any new technology.[34] Best practices for deploying AI in human medicine also apply to adopting AI in clinical workflows.[35–37] Implementation begins with assembling a multidisciplinary team, building foundational AI literacy, defining clear clinical objectives, and validating data quality before developing or procuring AI models. A critical step is also addressing ethical and legal considerations upfront, followed by team training and engagement to ensure buy-in across the practice. Integration requires continuous improvement through ongoing monitoring and evaluation of AI performance, proactive management of system changes and potential disruptors (such as equipment updates or workflow modifications), and commitment to staying current with evolving AI capabilities and limitations. A cyclical framework recognizes that AI deployment is an iterative process where performance metrics, workflow compatibility, and alignment with clinical goals can be measured and tracked. Finally, AI systems evolve, patterns of care change, and clinical needs change, emphasizing adaptability as a principle of responsible AI adoption in veterinary medicine. **Table 2** summarizes considerations that, although likely impractical for individual clinics to undertake, are important for the broader veterinary community to address collectively through collaborative research and knowledge sharing.

FUTURE DIRECTIONS AND OPEN QUESTIONS

The future of AI in veterinary radiography will likely be shaped by advances in multimodal AI systems that integrate diverse data sources, including radiographic images, clinical pathology results, electronic health records, and patient history.[38] AI in automated report generation and clinical communication represents both an opportunity and a significant risk area in diagnostic radiology.[39] While generative AI models show potential to reduce documentation burden and help standardize reporting, the risk of hallucinations raises medicolegal concerns when AI-drafted text enters medical records without rigorous verification. The recent veterinary radiology consensus statement on imaging report foundations provides structure and interpretability in an unambiguous way and could be readily generated with simple prompts using commonly accessible large language models.[40]

Table 2
Responsible-use checklist for veterinary clinics

Before you buy	☐ Clear intended use: species, anatomy, indication, image types ☐ Evidence beyond marketing: validation data, not just accuracy claims ☐ Training data disclosure: who labeled the images and how ☐ Known failure modes stated (positioning, exposure, implants, rare breeds) ☐ Update policy: what changes, how often, and whether performance is retested ☐ Training, education, and support needs well identified
Before you use	☐ Build up AI literacy in your team and engage all stakeholders ☐ Local testing on your own radiographs (small retrospective sample) ☐ Written internal policy: when AI is used and when it is ignored ☐ Staff warned about automation bias (AI misses things; AI hallucinates) ☐ Address disclosure of use for owners
During routine use	☐ AI output treated as advisory only, not a diagnosis ☐ Discordant cases tracked (AI vs clinician disagreement) ☐ No *silent upgrades* without re-evaluation and communication ☐ Reassessment after software updates or equipment changes ☐ Willingness to turn it off if performance degrades ☐ Staying relevant, continuous education ☐ Addressing impacts of new imaging technology
Consent and Transparency	☐ Clinic can clearly explain if and how AI is used to clients ☐ AI use does not replace professional judgment ☐ Data handling and privacy are documented

Perhaps most critically, the widest gaps between human and veterinary AI-assisted radiology are (the lack of) validation frameworks and performance benchmarks. While regulatory oversight of veterinary AI platforms has not yet emerged as a priority in most jurisdictions, the field urgently needs veterinary-specific standards for AI validation that account for species diversity, variable disease prevalence across practice types, and the unique technical constraints of veterinary imaging. The development of such frameworks will require collaboration among veterinary domain experts, AI developers, professional organizations, and regulatory bodies. Research gaps persist across multiple dimensions: comparative effectiveness studies evaluating AI performance against board-certified specialists across diverse practice settings, investigations of automation bias and human–AI interaction patterns in veterinary contexts, longitudinal studies assessing the real-world clinical impact and patient outcomes, and the development of methods for detecting and mitigating data drift in deployed systems. Until these questions are addressed through rigorous, peer-reviewed research, the responsible, safe, and effective integration of AI in radiography resides solely with the practicing veterinarian.

SUMMARY

AI tools in veterinary radiography are being increasingly used to address workforce shortages and workflow pressures, with applications spanning orthopedics, thoracic imaging, cardiac evaluation, and image quality assessment. The largest deployment to date trained on more than 2.5 million radiographs, and several large commercial

AI solutions are currently on the market.[5] Currently, the FDA does not regulate AI in veterinary products as it does in human medicine, creating a regulatory vacuum where veterinarians must serve as purchasers, validators, and de facto regulators of these technologies.

AI systems face critical limitations: they lack contextual understanding of patient history and clinical findings and are vulnerable to silent performance degradation when encountering different equipment or populations and induce automation bias. Automation bias is particularly problematic because nonspecialists are more likely to over-rely on automated outputs. The limited availability of labeled veterinary datasets further constrains validation.

Responsible implementation requires veterinarians to demand vendor transparency about intended use, training data, and known failure modes; conduct local validation testing on their own radiographs; maintain human-in-the-loop oversight; track discordant cases; and be willing to disable tools if performance degrades. Veterinarians have ethical obligations to disclose the use of AI to clients, ensure data security in the absence of HIPAA-equivalent protections, and document AI's role in clinical decision-making (see **Table 1**).

The field would greatly benefit from veterinary-specific validation frameworks, standardized performance benchmarks based on well-labeled, species- and breed-diverse radiographs, and collaborative efforts among domain experts, developers, and professional organizations. Until these gaps are addressed, the burden of ensuring safe and effective AI integration rests entirely with practicing veterinarians.

CLINICS CARE POINTS

- Appreciate that artificial intelligence (AI) is a tool, not a clinician.
- The licensed veterinarian is always accountable.
- Lack of regulation does not mean lack of responsibility.
- If you cannot explain the AI to a client, you probably should not be using it.
- Follow best practices when adopting AI technologies into clinical practice.

DECLARATION OF ARTIFICIAL INTELLIGENCE AND ARTIFICIAL INTELLIGENCE–ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the authors used generative AI tools were used primarily for spell-checking and grammatical suggestions to improve readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

DISCLOSURE

P.S. Basran is a consultant for PrimVeterinary. Ryan Appleby is the cofounder of 2 companies related to the subject matter. Cygnus Veterinary Imaging Group: teleradiology group, impacted by radiology artificial intelligence (AI) services and Kairos Veterinary Technologies: AI-based copilot for radiologists. The other author discloses no conflicts.

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