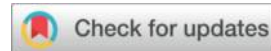




THE ROLE OF ARTIFICIAL INTELLIGENCE IN SMALL ANIMAL VETERINARY
MEDICINE: CURRENT APPLICATIONS AND FUTURE PERSPECTIVES



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THE ROLE OF ARTIFICIAL INTELLIGENCE IN SMALL ANIMAL VETERINARY MEDICINE: CURRENT APPLICATIONS AND FUTURE PERSPECTIVES

Abstract

Artificial Intelligence (AI) is increasingly being investigated as a tool to support diagnostics, clinical decision-making, and workflow optimization in small animal veterinary medicine. This narrative review critically summarizes current evidence on AI applications in companion animal healthcare, with a particular focus on diagnostic imaging, clinical pathology, predictive analytics, and aclinical workflow optimization. Recent studies have demonstrated promising performance of deep learning models in diagnostic imaging, including automated vertebral heart scale assessment, while predictive models trained on electronic health records have identified cats at risk of chronic kidney disease up to two years before clinical diagnosis. Machine learning algorithms have also shown high diagnostic performance for canine hypoadrenocorticism, with reported sensitivity and specificity of 96.3% and 97.2%, respectively. In addition, AI-assisted clinical documentation using natural language processing and wearable sensor technologies has demonstrated potential to improve workflow efficiency and continuous patient monitoring, with selected validation studies reporting accuracies exceeding 99% for quantifying specific behaviours such as scratching. Despite these advances, current evidence remains limited by challenges related to algorithm interpretability, automation bias, heterogeneous datasets, and the absence of standardized regulatory frameworks for veterinary AI. Overall, available evidence suggests that AI represents a valuable adjunct to veterinary practice; however, its safe clinical implementation requires rigorous validation, appropriate regulatory oversight, and continued human supervision.

Introduction

Artificial intelligence (AI) is increasingly being explored as a tool to support data-driven diagnostics and clinical decision-making in veterinary medicine (1). Broadly defined, AI refers to computational systems designed to perform tasks that typically require human intelligence, such as visual perception, speech recognition, and complex decision-making (2,3). In the current veterinary landscape, AI has been proposed as one approach to help address modern challenges such as veterinary workforce burnout, the global shortage of diagnostic specialists, and the rising demand for high-throughput precision healthcare (3,4). To ensure scientific clarity, it is essential to distinguish between the various modalities of AI. Machine Learning (ML) is a subset of AI that employs statistical methods to enable computers to identify patterns and make decisions based on data without being explicitly programmed for specific tasks (2). Deep Learning (DL) represents a more advanced subset of ML that uses multilayer artificial neural networks to learn complex patterns from data; a prominent example in veterinary medicine is the use of Convolutional Neural Networks (CNNs) for diagnostic imaging to identify spatial hierarchies and extract features from medical images (5). Furthermore, Generative AI, such as Large Language Models (LLMs), focuses on creating new content based on trained datasets, though its clinical application requires caution due to the potential for "hallucinations" the generation of plausible but fabricated information (6,7). Similar structural vulnerabilities, including algorithm opacity and data fragmentation, have been highlighted as major integration barriers across broader food safety systems (8).

AI applications in the veterinary field are generally categorized into clinical practice, biomedical research, public health, and administration (1). Within the clinical domain, published studies have demonstrated promising performance in diagnostic imaging,

where DL models analyze radiographs, CT scans, and MRIs to detect abnormalities like fractures or cardiac enlargement (9). Additionally, AI-driven tools have been investigated for automated cell counting and parasite identification in veterinary clinical pathology (10,11). Beyond reactive diagnostics, predictive models are increasingly being investigated in internal medicine to forecast the risk of chronic conditions, such as feline chronic kidney disease or canine hypoadrenocorticism, before the onset of clinical symptoms (2,12).

This review focuses specifically on the application of AI within small animal veterinary medicine. In many contemporary societies, the increasing "humanization" of companion animals has driven a demand for advanced digital health services that mirror human medical standards (13,14). Because companion animals cannot directly communicate subjective symptoms, AI-powered tools such as behavioral analysis and predictive risk modeling have the potential to provide objective data to improve patient outcomes (14,15). The objective of this narrative review is to critically summarize the current evidence regarding AI's role in supporting diagnostics, patient care, and clinical workflow optimization in small animal practice while addressing the ethical and regulatory barriers to its adoption.

Search Strategy and Selection Criteria

This narrative review examines the current evidence regarding artificial intelligence (AI) applications in companion animal healthcare. To identify relevant literature, a structured literature search was conducted across major electronic databases, including PubMed, Google Scholar, and Web of Science, for studies published between 2016 and 2026. The search strategy utilized combinations of keywords including "artificial intelligence,"

"machine learning," "deep learning," "small animal medicine," "canine," "feline," "diagnostic imaging," "predictive modeling," and "veterinary ethics." Selection criteria focused on original research, including retrospective studies and proof-of-concept investigations, to provide a critical appraisal of diagnostic performance and clinical utility. Priority was given to peer-reviewed original studies over secondary review articles to ensure the reliability of the synthesized evidence. Each cited study was critically evaluated based on its study design, sample size, reported diagnostic performance (including sensitivity and specificity where applicable), and methodological limitations.

Current Evidence in Small Animal Diagnostics

The application of artificial intelligence (AI) and machine learning (ML) is being investigated as a tool to support diagnostic accuracy and reduce the subjectivity inherent in human clinical interpretation (14,15). While published studies have demonstrated that these systems can identify patterns in large datasets, it is important to note that much of the current evidence is based on retrospective investigations or proof-of-concept studies (9).

- Diagnostic Imaging and Cardiology

In veterinary imaging, deep learning (DL) models, particularly Convolutional Neural Networks (CNNs), are used to extract features from complex images (5). These systems have been explored for detecting abnormalities such as thoracic lesions, primary tumors, and fractures, with some studies reporting accuracy levels comparable to board-certified radiologists (9,16).

A prominent area of investigation is the automated measurement of the Vertebral Heart Scale (VHS) to mitigate interobserver variability (16). Algorithms have been reported to

provide consistent results for long-term monitoring of cardiac enlargement (16,17). Furthermore, DL models have been investigated for grading intervertebral disc degeneration in MRI scans and identifying tracheal collapse from radiographs (18,19). Additional studies have utilized AI-driven systems to estimate kidney volume from CT scans (20). Multi-stage AI systems are also being developed for the automated estimation of right atrial pressure during echocardiography to reduce variability in manual analysis (21).

- *Clinical Pathology*

In clinical pathology, AI is being explored to automate repetitive tasks like cell counting and classification (22). Platforms such as VETSCAN IMAGYST utilize DL algorithms to identify fecal parasites, with performance metrics that align with expert parasitologists (23,24). Moreover, models have demonstrated the ability to classify lymphocytes in canine lymph node aspirates, which may support the diagnosis of lymphoma (25,26). Despite these promising results, the clinical implementation of these tools must account for the high degree of inter-species anatomical variation (27,28).

- *Predictive Modeling and Internal Medicine*

The integration of predictive modeling is being investigated for early disease detection via Early Disease Warning Systems (EWS) (12). Recurrent Neural Networks (RNNs) have been developed to forecast the risk of Chronic Kidney Disease (CKD) in cats up to two years before clinical diagnosis (12,29). Similarly, ML algorithms have been trained to diagnose canine hypoadrenocorticism from routine blood panels, reporting a sensitivity of 96.3% and a specificity of 97.2% (30). Furthermore, machine learning models have been applied to the early detection of canine leptospirosis (31). While these models can identify correlations invisible to the human eye, their successful adoption remains

contingent upon the availability of high-quality, standardized data (4). The real challenge lies in bridging the gap between successful laboratory prototypes and daily clinical use. While these studies show that AI can match specialist performance, they often rely on perfectly curated data that doesn't reflect the messy, non-standardized records found in most clinics. Additionally, because many deep learning models operate as 'black boxes,' veterinarians face the difficult task of trusting a result they cannot fully trace. To make these tools truly useful, they must be implemented as supportive assistants that help the clinician without overriding their final diagnostic authority.

Transforming Patient Care through Predictive Modeling

The integration of artificial intelligence (AI) is being investigated for its potential to support a shift from reactive treatment toward proactive, personalized medicine (15). Historically, veterinary medicine has relied on the identification of clinical signs followed by generalized treatment protocols; however, the emergence of Early Disease Warning Systems (EWS) aims to provide a more nuanced approach that accounts for individual physiological differences (1,32). One of the most impactful developments in this domain is predictive modeling for chronic diseases, which leverages datasets from electronic health records (EHRs) to forecast potential health risks (12,33).

In feline medicine, the application of Recurrent Neural Networks (RNNs) has been explored for managing Chronic Kidney Disease (CKD) (12). By analyzing longitudinal data specifically creatinine, blood urea nitrogen (BUN), urine specific gravity (USG), and age these models have demonstrated the ability to predict the onset of CKD up to two years before clinical diagnosis (12,29). This early detection is significant because cats often mask symptoms of renal impairment, and identifying the disease at an earlier IRIS stage may improve outcomes (34). Proactive interventions, such as tailored diets and the

avoidance of nephrotoxic drugs, can thus be investigated long before the patient reaches a critical state (12).

Similar predictive capabilities are being studied for the diagnosis of difficult-to-detect internal conditions in canines, such as hypoadrenocorticism (Addison's disease) (30). AI algorithms trained on routine blood panels complete blood counts and serum chemistry can identify subtle patterns indicative of the disease, with reported sensitivity of 96.3% and specificity of 97.2% (30). Furthermore, machine learning models have been investigated for the early detection of canine leptospirosis, showing performance that may supplement traditional serological screening methods (31).

In the realm of cardiology, AI applications are being investigated to support the diagnosis and management of cardiovascular diseases in companion animals, although current evidence remains limited and further clinical validation is required (5). Additionally, AI-driven tools have been investigated to assess the risk of future congestive heart failure by analyzing radiographic markers like the Vertebral Heart Scale (VHS) (16,17).

Beyond disease detection, AI is being evaluated for its role in creating personalized treatment plans based on an animal's unique genetic makeup and medical history (14,15).

In oncology, platforms such as ImpriMed aim to map mutations in canine cancers to help develop precision therapeutics (2,35). By comparing a patient's tumor profile to clinical databases, AI models are investigated for their ability to predict individual responses to specific chemotherapy agents (36). This approach aims to optimize drug dosages and ensure protocols are effective for the specific patient (2,37).

Predictive modeling also extends to orthopedics and injury prevention. Random Forest classifiers have been utilized to assess bone fracture risk in canines by analyzing variables such as age, weight, breed, and gender (38). These models may identify vulnerabilities in

specific subgroups, allowing for preventative safety measures (38). Similarly, algorithms are being developed to forecast seizures in epileptic dogs based on intracranial EEG recordings (39,40).

The success of these predictive systems relies heavily on the integration of multi-omics data (28,33). These systems allow for the development of "digital twins" virtual replicas used to simulate potential outcomes of management decisions (33,41). However, the adoption of these models remains contingent upon the availability of standardized EHR data and collaboration between data scientists and veterinary specialists (4). Ultimately, predictive modeling aims to augment rather than replace the expertise of the veterinarian (3,6). Clinical judgment remains essential for interpreting AI findings (4,7). As these technologies evolve, they may provide a more objective basis for decision-making, aiming for a proactive healthcare system (4,9,42).

Critically, while these predictive models demonstrate impressive statistical performance in research settings, their real-world clinical utility depends on the veterinarian's ability to interpret algorithmic outputs without succumbing to automation bias. The transition toward proactive healthcare requires not only technical accuracy but also the development of clear clinical protocols for managing asymptomatic patients identified as 'high-risk.' Ultimately, the success of predictive modeling rests on maintaining a human-in-the-loop approach, ensuring that technology serves as a tool to expand clinical dialogue rather than providing a final, unquestioned verdict.

Optimizing Clinical Workflows and Real-Time Monitoring

The application of artificial intelligence (AI) is being explored for its potential to streamline clinical operations in small animal practice by automating administrative tasks (4,14). Veterinary professionals frequently face significant time constraints, with standard

consultations often exceeding allocated time slots, which has been proposed as a contributing factor to workforce burnout (14). Natural Language Processing (NLP) is investigated as a tool to mitigate these pressures by analyzing and attributing meaning to unstructured text within medical records (3,43). Published models have demonstrated the ability to automatically extract critical diagnostic codes from clinician notes, a task that traditionally requires manual entry (6,44).

In addition to data extraction, NLP-driven assistants are being investigated for the real-time generation of Subjective-Objective-Assessment-Plan (SOAP) notes and discharge instructions (6,45). By processing physical examination findings and clinical histories, these systems aim to allow clinicians to prioritize direct patient interaction over documentation (2,4). Furthermore, such automation may improve the consistency of medical records through the use of standardized terminology (46,47). AI-driven chatbots are also being utilized for initial client triage and managing expectations regarding disease types and potential costs (48).

The use of AI-integrated wearables, such as smart collars and harnesses, has introduced methods for continuous data collection and patient monitoring. These devices utilize sensors like triaxial accelerometers and gyroscopes to capture high-resolution data on animal movement and physiological parameters (42,49). In companion animals, this technology has been successfully validated to quantify specific pruritic behaviors, such as scratching and head shaking, with accuracies exceeding 99% (50,51). Objective data from these sensors provide clinicians with insights into a patient's status that might be missed during brief clinic visits where animals may hide signs of pain or distress (49). Real-time surveillance is also being investigated for monitoring sleep patterns, water intake, and general activity, which may serve as early indicators for chronic conditions or

acute deterioration (2,51). For example, AI-based behavioral recognition can detect subtle changes in gait or posture, potentially aiding in the early diagnosis of lameness or neurological disorders (42,52). These systems are often integrated with cloud-based platforms to trigger alerts when health indicators deviate from an individual's normal baseline (49,53). Such proactive monitoring is considered particularly vital for at-risk patients or those in post-operative recovery (2,12).

The combination of wearables and telemedicine platforms is being explored to increase the accessibility of veterinary care (45,54). Smartphone-based ECG devices allow owners to record heart rate and rhythm at home for direct transmission to a veterinarian (55). This approach is investigated for its ability to evaluate dogs with arrhythmias in a natural environment, potentially providing high-quality diagnostic data while reducing the stress associated with clinic visits (56).

In animal nutrition, AI is being investigated for the creation of individualized feeding plans (42). Algorithms aim to calculate precise portion sizes based on metabolic profiles and activity data from wearables to address pet obesity (57). Furthermore, these systems may identify unnoticed dietary intolerances by correlating historical health data with feeding patterns (42). Automated feeding systems can then adjust rations dynamically based on caloric expenditure (42,58).

Finally, AI tools are being studied for their contribution to the One Health framework by monitoring pet populations for zoonotic threats, antimicrobial resistance (AMR) patterns, and ensuring food safety through proactive monitoring of contaminants across the supply chain (2,8,28). NLP models have been investigated for tracking antimicrobial usage in medical records to identify inappropriate patterns (2,59). By integrating clinical and

environmental data, AI aims to support a holistic approach to disease prevention (28,60). Integrating these technologies into a busy clinical setting is about more than just speed; it is about shifting the practitioner's focus back to the patient. However, there is a delicate balance to maintain, as the influx of constant data from wearables and automated notes can easily lead to information overload. If a veterinarian begins to rely solely on these digital summaries, there is a danger that their own diagnostic sharp-sightedness might diminish over time. These systems are most powerful when they function as a 'smart agency' handling the repetitive data processing while leaving the complex, empathetic, and final decision-making where it belongs: with the veterinary clinician.

Ethical, Regulatory, and Practical Challenges

While the potential of artificial intelligence (AI) in companion animal medicine is significant, its integration is currently constrained by complex ethical and regulatory hurdles (7). A primary technical concern identified in the literature is the 'black box' problem, where the decision-making processes of advanced deep learning models lack transparency, a challenge that also hinders regulatory acceptance in broader sectors like food safety (8,27). This opacity has been identified as a factor that can impede clinician trust, as veterinarians may be unable to verify the rationale behind a machine-generated diagnosis or treatment plan (3,7).

The regulatory landscape remains fragmented. In North America, there is currently a lack of a federal premarket approval framework specifically designed for veterinary AI tools (45). Unlike human medicine, where Software as a Medical Device (SaMD) is subject to rigorous review, manufacturers of veterinary AI are not consistently required to report validity or performance data before market entry (7,9). Consequently, the burden of

validation and legal liability often rests on the individual veterinarian holding the Veterinarian-Client-Patient Relationship (VCPR) (3,45). Conversely, the European Union AI Act (Regulation (EU) 2024/1689) has introduced a stricter framework by classifying certain AI-driven medical devices as high-risk, mandating compliance with specific security and transparency standards (61,62). This regulatory shift emphasizes the necessity for human oversight and accountability as prerequisites for professional adoption (7,62).

Practitioners must also account for psychological and data-related limitations. Automation bias the tendency to trust automated outputs even when they contradict clinical intuition or physical findings remains a documented risk (7,45). Furthermore, the reliability of AI is fundamentally limited by the quality of training data; models trained on skewed or non-standardized datasets may produce biased results that lead to misdiagnosis (9,63). The "garbage in, garbage out" principle is particularly relevant in veterinary medicine due to data fragmentation and high inter-species anatomical variation (27,28).

The rise of generative AI and Large Language Models (LLMs) introduces additional practical risks, such as "artificial hallucinations" where models generate plausible but fabricated scientific or diagnostic information (6,64). This can mislead both clinicians and owners who seek rapid advice from AI chatbots, potentially delaying necessary professional intervention (48,64). Additionally, data security and client confidentiality represent critical frontiers, as open AI systems may absorb sensitive patient information into public databases if not properly de-identified (6,42).

To mitigate these risks, current evidence suggests that the veterinary community must prioritize a 'human-in-the-loop' approach, ensuring that AI functions as a 'smart agency' subordinated to human intelligence to avoid professional de-skilling (8,9,45). This necessity for a human-in-the-loop architecture is strongly reinforced in food safety and quality frameworks to safeguard legal liability and protect public health (8). Ongoing professional education and the establishment of clear standards for informed consent are essential to ensure that technology is implemented responsibly and transparently (7,45). Ultimately, maintaining the "human touch" including empathy and social intelligence remains an irreplaceable component of veterinary practice (4). The shift toward an AI-integrated practice is not merely a technical upgrade but a fundamental challenge to professional oversight. Currently, a significant 'regulatory ambiguity' exists, where the lack of standardized validation protocols for veterinary software can create a 'safer-not-to-know' mentality, potentially slowing the adoption of beneficial tools. To move forward responsibly, AI must be viewed as a 'smart agency' that remains strictly subordinated to the intelligence of the veterinary clinician. Practitioners must maintain 'meta-autonomy' the conscious ability to decide when to delegate a task to an algorithm and when to take manual control to prevent professional de-skilling and the erosion of clinical judgment. Ultimately, achieving transparency through Explainable AI (XAI) is essential for building the trust required to ensure that the final accountability for patient care remains firmly in human hands.

Conclusion

The integration of artificial intelligence (AI) in small animal veterinary medicine represents a transition toward data-defined precision and proactive healthcare management. Evidence from current research suggests that AI is evolving from a

theoretical concept into a functional tool that supports various facets of companion animal practice, from initial diagnostic screening to long-term chronic disease management.

The advancements in diagnostics, particularly in imaging and pathology, demonstrate that automated systems can support general practitioners by providing repeatable, standardized measurements. By identifying complex patterns in radiographs and cytological slides, these tools aim to reduce the subjectivity and inter-observer variability inherent in manual interpretation. Furthermore, the development of predictive models for conditions such as chronic kidney disease and hypoadrenocorticism suggests a shift toward early intervention strategies that may extend the quality of life for feline and canine patients.

Beyond clinical outcomes, AI-driven applications like Natural Language Processing and wearable sensors are being explored for their ability to optimize clinical workflows and address professional burnout. These technologies provide objective behavioral and physiological data, potentially bridging the communication gap between non-verbal patients and their caregivers.

However, the clinical adoption of these technologies remains contingent on addressing significant ethical, regulatory, and methodological limitations. The lack of transparency in "black box" models and the absence of a standardized regulatory framework for veterinary software necessitate a "human-in-the-loop" approach, where the veterinarian remains the final authority in clinical decision-making. Ensuring data privacy, mitigating algorithmic bias, and maintaining the irreplaceable human elements of empathy and social intelligence are essential prerequisites for the responsible integration of AI.

In conclusion, the future of small animal medicine depends on a balanced synergy between human expertise and computational tools. AI should be viewed as an adjunct that augments rather than replaces the clinician's judgment. Practitioners who embrace these tools with ethical diligence and a commitment to evidence-based validation will be best positioned to provide precise and compassionate care for their animal companions.

Conflict of Interest

The authors declare that they have no financial remuneration, personal relationships, or competing interests that could inappropriately influence or bias the content or conclusions of this manuscript.

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