What’s in the box? A toolbox for safe deployment of artificial intelligence in veterinary medicine

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ABSTRACT
This report describes a comprehensive framework for applying artificial intelligence (AI) in veterinary medicine. Our framework draws on existing research on AI implementation in human medicine and addresses the challenges of limited technology expertise and the need for scalability. The critical components of this framework include assembling a diverse team of experts in AI, promoting a foundational understanding of AI among veterinary professionals, identifying relevant use cases and objectives, ensuring data quality and availability, creating an effective implementation plan, providing team training, fostering collaboration, considering ethical and legal obligations, integrating AI into existing workflows, monitoring and evaluating performance, managing change effectively, and staying up-to-date with technological advancements. Incorporating AI into veterinary medicine requires addressing unique ethical and legal considerations, including data privacy, owner consent, and the impact of AI outputs on decision-making. Effective change management principles aid in avoiding disruptions and building trust in AI technology. Furthermore, continuous evaluation of AI’s relevance in veterinary practice ensures that the benefits of AI translate into meaningful improvements in patient care.

Keywords: artificial intelligence, data management, data quality, implementation, ethics

Introduction
The evolution of artificial intelligence (AI) in daily activities is relentless and rapid. Learners, educators, businesses, and healthcare communities are facing critical challenges in how to use these AI technologies safely and responsibly. This is especially true in veterinary medicine, where AI can profoundly impact workflow, patient care, and outcomes. Despite a lack of regulatory framework for AI, striving for responsible and practical uses of AI in our professional activities remains of utmost importance. Establishing a framework to derive reliable benefits from the technology before and during this transition will benefit veterinary professionals.

Over the last 10 years, there has been a near-exponential increase in research publications involving veterinary medicine and artificial intelligence (Figure 1). Significant historical events, such as the release of the first image-based convolutional neural network (AlexNet) coupled with open-source codes compiled on high-performance computers, have enabled a rapid ascent in AI technologies and potential applications in veterinary medicine. Associated with this ascent is the availability of commercial AI solutions dedicated to veterinary medicine.1 Commercial solutions for veterinarians are enticing, as they can economize their work throughout a patient’s care path. While yet to be proven, they can improve patient health outcomes. However, to effectively deploy AI in veterinary practice, one must understand and address the challenges associated with AI in the veterinary landscape. A significant challenge faced by veterinary professionals is inherent to AI but exacerbated by a lack of regulatory framework in veterinary medicine; it is challenging to understand how AI algorithms arrive at a response. This is the so-called “black-box” nature of AI. The learning curve for understanding the underpinnings of AI can be steep, and industries may need to be more open to revealing details of their AI architecture. Research on interpretable or explainable AI (XAI) is rightly entered into the conversation where efforts are directed toward understanding the rationale behind an AI model’s prediction that is understandable to humans.2 In the context of AI, “interpretable” refers to “the degree to which a person can understand the cause of a decision.”3 In other words, it identifies the rules, features, or explanations for how the AI arrives at a decision. Explainable AI extends the concept of interpretability to render explanations that humans can effectively understand.4 For example, when an AI...

Received January 15, 2024
Accepted March 5, 2024
doi.org/10.2460/javma.24.01.0027
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is building the knowledge and skills to reach a basic level of competency and proficiency in AI technologies. Second, there is the task of determining how to introduce these technologies into practice safely and effectively. Whether AI technologies are developed internally or purchased as a service or software, a reasonable question veterinarians must face is how they can and should deploy AI within their practices.

This Viewpoint article describes some important considerations for veterinarians when adopting AI in their practices, clinics, and communities. The first task of achieving basic proficiency and competency in AI is not the focus of this work; the reader is instead pointed to several excellent articles that introduce these concepts aimed at the veterinarian, including recent reports that appeared in JAVMA, AJVR, and a special issue in a publication dedicated to AI for the radiology and radiation oncology community.7–9 Instead, current best practices, significant lessons learned in implementing AI in healthcare, and a strategy for implementing AI safely in veterinary practice are proposed. We aim to provide some essential considerations to safely “build” AI in your community. While we believe these considerations are broad enough to apply to most veterinary circumstances, some steps may or may not be necessary or require an entirely different strategy. As such, this submission is a template for adopting AI in veterinary medicine to identify the skills, processes, or provisions (or “tools”) that should be considered.

**Current Best Practices in AI Adoption**

An emerging field of research focuses on machine learning operations, often referred to as ML-Ops, which provides an analogy to the common phrases of business operations (Bus-Ops), development operations (Dev-Ops), Financial Operations (Fin-Ops), and such, all of which focus on activities, processes, and practice considerations with an emphasis on efficacy and efficiency in a particular field.10 There has been a rapid increase in publications focusing on best practices in ML-Ops in human healthcare, some of which are summarized here.11–13

In October 2021, the US FDA, Health Canada, and the UK’s Medicines and Health Products Regulatory Agency outlined 10 good machine learning practice (GMLP) principles.14 These consist of (1) leveraging multidisciplinary expertise throughout the AI software life cycle; (2) implementing sound software engineering and security practices; (3) patients and datasets representative of the intended patient population; (4) independence in the training and testing datasets; (5) using the best available methods for developing reference datasets; (6) designing models tailored to the data and intended use; (7) ensuring there is a “human in the loop” that considers human factors and interpretability; (8) testing the performance of the AI under clinically relevant conditions; (9) clear, essential information on how to safely use the technology; and (10) monitoring the performance of models and ensuring risks associated with retrained models are
managed. These practices are vital to promote internal transparency and allow effective and safe adoption of AI. To date, these practices are underestablished in veterinary AI.

Sendak et al. recently published vital best practices for AI software development and integration in human healthcare. They invited 7 research teams to examine “Surfacing Best Practices for AI Software and Integration in Healthcare.” They focused on institutions with frameworks for internally designed AI software instead of “off-the-shelf” commercialized AI products. They observed 2 key similarities among all the teams. First, there was a focus on the life cycle of the software itself, consisting of 4 major stages: problem definition and solution procurement, development and adaption of the software, technical and clinical integration, and life cycle management. A second key theme was the need for interdisciplinarity, often supported by academics and graduate students. Some institutions adopted sophisticated engineering principles and process control methods when integrating machine learning into their environments. They reported consensus on 3 AI integration practices. First, they described the importance of initial testing or simulating AI performance before clinical use: this can help identify patient safety risks, biases, and other integration concerns. A second practice was the importance of sound software and data-management principles, attributing accountability throughout the AI software’s life cycle and encouraging a quality management approach to the AI system. Finally, there was a common practice of continuous monitoring and auditing of the software. These align with the GMLP and identify similar themes in AI adoption. It is essential to recognize that these teams were large institutions with access to data scientists and provisions to support in-house AI solutions, which may not be the case generally for veterinarians.

In addition to GMLP and the Sendak et al. report, the “5 pillars” of translational machine learning in the human healthcare environment described by Harris et al. outline similar themes for AI. These pillars included (a) real-world development that uses real-world data, (b) platforms that are robust and adaptable, (c) design and oversight by experts in AI safety, (d) characterizing how algorithms influence patients and clinicians, and (e) continuous evaluation that reduces the potential for bias.

Wilson et al. also described 10 practical tips for introducing AI in a human clinical environment, loosely organized into 3 phases. The first phase is conceptualizing the use cases and establishing a framework. These steps include assembling a multidisciplinary team before undertaking any significant decisions, carefully considering the end user’s use cases for AI to identify where AI technologies might be leveraged, establishing a framework for any collaborative agreements within the team, seeking out guidance on ethics and review boards before making any significant decisions on deploying the AI solution, and training and education of fundamental data sciences to improve communication between team members. In phase 2, they recommend engagement with data science experts to help identify data-extraction pitfalls, address (human) patient privacy concerns, and address quality and reliability. The third phase is devoted to designing trustable AI algorithms, and the final fourth phase considers the regulatory framework for medical devices, such as those described by the FDA.

While these guidelines are valuable, they may need to capture issues relevant to veterinary medicine. Wilson et al. described AI workflows in the context of veterinary radiology. They suggested introducing quality control steps in training data and pointing to 3 critical steps for successful AI integration in radiology workflows: research, production, and feedback. Others have reported the need for consistent data curation and model transparency in veterinary AI models.

A Framework for AI Deployment in a Veterinary Healthcare Setting

On the basis of these findings, we find common themes for safely integrating AI into practice (Figure 2). A key consideration in this summary is that the institution is not expected to have a wealth of information technology and data science expertise in its environment. The approach we describe is scalable and agnostic of an institution’s size and local expertise but not meant to be prescriptive.

A helpful analogy to use when adopting new and untested technology, such as AI, in a clinic is the steps typically undertaken when introducing regulated devices, such as a new x-ray imaging device in the clinic, or managing other potentially disruptive changes, such as migrating from a paper to an electronic medical record (EMR); as such, essential change management principles would be conducted with a focus on the stakeholders, provisions for managing the new technology, ensuring there are appropriate safeguards in place when using that technology, and a quality management system. To help provide context for the steps described here, we will frequently refer to analogous situations of implementing an x-ray imaging device or EMR and the people and skills associated with implementing such changes.

Assembling an AI team

Basic knowledge and competency in AI are essential before a decision is made to purchase or develop an AI technology. Veterinarians are not data scientists; they are the “end users” of the technology in question and should not be expected to have an in-depth knowledge of AI. However, as is the case for implementing any new technology (eg, x-ray device or new EMR), it is crucial to identify a veterinarian or clinical expert who will be responsible for the safe use and implementation of the technology and has the power to make decisions related to the AI’s safe use. This person should have a basic understanding of AI, speak confidently with vendors, and be able to steward the implementation of the AI technology.
Akin to a “radiation safety officer” for an x-ray imaging system, there should be a responsible agent or steward of the AI technology. This person may need to gain an in-depth understanding of a data scientist (e.g., a health or radiation physicist in x-ray imaging). Still, they understand how the technology will be safely used for their patients and maintain responsibility for its safe use.

Best practices in AI adoption highlight the importance of establishing a multidisciplinary team. This may include local information technology support representation, the end users of the technology (veterinarians or technicians), support teams, and those empowered to make purchasing and management decisions. Access to individuals with data science expertise is highly beneficial, but this may be challenging to achieve in smaller facilities. Having different disciplines that might touch AI technology has been reported to reduce barriers to implementation. The analogous team necessary when introducing an x-ray imaging system is the “radiation safety committee.” This team has several vital functions: establishing, adhering, and monitoring policy; compliance with regulatory agents; risk assessment, mitigation, and management; training and education; equipment selection, management, and quality assurance; and communication with stakeholders. Except for regulatory oversight for an x-ray imaging system, this team should be empowered to execute those functions in the context of AI technology. The team size can vary: Sendak et al. reported sizes of teams ranging from 3 to 27. The team size may also depend on the invasiveness of the AI technology in practice. For example, one would not establish a team if deploying an AI-driven grammar-checking algorithm within a word-processing software; however, one can imagine that if an AI system provides a decision support tool that diagnoses benign from malignant conditions, the implications are much more complex, as they involve the support staff, veterinarian, patient, and the owner. These 4 stakeholders can provide the context for the level of complexity in the AI technology. If all stakeholders can be affected by an AI’s output, it is reasonable to have a larger team to ensure that all stakeholders’ interests are accounted for. Conversely, the team may not need to be large if the technology touches only support staff or veterinarians.

Fundamentals of AI

The team should be reasonably conversational on AI. This should include a basic understanding of how AI models are developed, tested, and evaluated; the role and importance of data in the context of bias and fairness; and essential diagnostic accuracy and...
performance metrics and how they might be improved. Understanding the basics of AI allows all team members to adopt consistent language, minimize the risk of misunderstandings, and clearly define use cases and strategies for implementing changes in workflow. A recent AI supplement provides an excellent overview of AI fundamentals, which can be a starting point for AI education.³

**Defining purpose and use cases**

In veterinary practice, the end user of an AI product can vary by role, and a single product can impact numerous end users. To effectively and safely implement AI in practice, the purpose of the proposed solution of the use case to which it will be applied should be clearly established by the AI implementation team. By clearly setting use cases and achieving buy-in from the end user, AI systems will be more likely to be successfully adopted in veterinary healthcare. Defining the problem will likely take significant effort, and a one-size-fits-all or off-the-shelf solution may need to be significantly adapted to be relevant, practical, or valuable to a specific practice. End users are embedded in existing workflows and are able to identify opportunities to leverage AI. For example, as with adopting an EMR, the AI’s purpose should be clearly stated. In the case of an EMR, the goal may be to replace paper record systems completely to improve efficiency. Specific use cases may vary for different members of the team. Veterinarians may want an EMR to speed up writing medical records, whereas reception team members may need such a system to improve efficiency in retrieving records. The use cases of an AI system should meet the needs of the veterinary healthcare team and not be used solely for the purpose of technological adoption for the sake of technological innovation itself. Examples of categories of use cases may include challenges associated with improving medical care, client communication or interactions, medical record-keeping, billing, finances, and overall hospital management.

A significant challenge reported by Watson et al²⁷ was associated with the cultural challenges in implementing AI technology, resulting from a lack of consensus among stakeholders and attitudes toward AI technologies. They found clinicians were central in identifying the clinical need, guiding model development, and determining where to introduce these technologies while minimizing workflow disruptions. Veterinarians are critical stakeholders in ensuring the adoption of AI technologies and identifying the use cases with the most significant impact.

In addition to identifying suitable use cases, ensuring the outputs from the system meet the needs of the veterinary team requires input from stakeholders.²⁸ Finding the right balance between over- and underalerting can be challenging. In a summary of 19 academic human healthcare centers that adopted AI, 1 interviewee reported a challenge with AI-based alerting: “one of the biggest challenges in implementation is figuring out what signals you should send and who to send them to, when and how.”²⁸ This challenge must be considered in the veterinary setting, where resources may not be as ample as those found in human healthcare, and where technicians and veterinarians may take on various tasks usually assigned to nurses, technicians, and other human healthcare professionals.

Another common theme reported in several reports from human healthcare adoption of AI is the value of “starting small and simple.” Pinch points in the healthcare delivery chain can be addressed through introductions of small but effective changes in practice or the application of low-cost technologies. Artificial intelligence has great potential to short-circuit such pinch points or bottlenecks in workflow and increase productivity. For example, the time taken to report pathology findings could be dramatically reduced, thus increasing throughput and providing critical information to the attending veterinarian and clients more quickly. An overarching framework that teams can use to guide the responsible development of AI is described by Badal et al,²⁹ who note some key principles in human healthcare. These principles include alleviating existing health disparities, clinically meaningful outcomes from the technology, reduction of overdiagnosis and overtreatment, high value while diverting resources from other priority health areas, consideration of biographical drivers of health, customizability of the technology to local populations, promotion of a learning healthcare system, and the facilitation of shared decision-making. These are helpful dimensions to characterize the use case and value of AI technology.

**Determining data needs, availability, and quality**

While much of this section deals with data availability and quality, it is essential to make the distinction on whether the AI technology is developed in-house, the technology is developed in partnership with a commercial party, or the entire platform—including data management—is contracted to a commercial party. Creating the in-house technology requires the most significant level of resources. If veterinary clinics or groups develop in-house technologies, the implementation team must ensure the correct dataset is available to create the model. Accessing commercially available systems requires less data at the outset but requires data considerations for ongoing use and quality control. The considerations raised in this section should be taken when deploying the technology.

When developing an AI technology, the number of datasets needed to create robust AI models depends on many factors, such as the dimensionality of the data, complexity of the problem the AI model tackles, and type of AI algorithm used. Datasets with diverse and representative instances or classes are more generalizable and useable than datasets with small cohorts or instances of diseases. For example, dogs can have different types of oral cancers (eg, osteosarcoma, squamous cell carcinoma, melanoma) and abnormalities presented on a CT scan may be malignant, benign, neoplastic, or reactive. A center’s dataset may have only a handful of plasmacytoma cases on file compared to osteosarcomas. Thus, there may need to be more datasets to “learn” patterns
from plasmacytoma diagnoses. Alternatively, it may be reasonable to use different or more pragmatic classification methods (eg, benign vs malignant or neoplastic vs reactive) when developing a model. It may be possible to use datasets from other institutions to bolster training datasets, but this can give rise to additional challenges such as technical and confidentiality limitations in sharing data as well as “batch” effects where, in the case of CT images and classifying oral cancers, could arise from using different imaging protocols, reconstruction algorithms, or patient positioning.10,31

Training models from “scratch” often requires several hundred to thousands of data points. This is highly challenging to obtain in veterinary medicine since, apart from the availability of DICOM imaging formats from imaging systems, there are no requirements for data harmonization among clinics for health records information or other biomarker data. A common approach is thus to train models with smaller datasets, but the range of usefulness of these models (ie, classifying all the types of oral cancers in dogs) becomes reduced. Some of these challenges can be addressed via data augmentation (ie, generating synthetic data as opposed to real patient data) or retraining existing AI algorithms initially designed for a similar problem in humans (ie, transfer learning).

Another consideration is ensuring the datasets are of high quality, meaning that all datasets are correctly labeled without errors and do not suffer from noise, contamination, or other data inconsistencies, and that data are representative of the population on which the AI algorithm will be used (real-world data). The data-curation process itself is not trivial and often requires many steps: collection, cleaning, transformation, annotation, and often an initial exploration. The data-cleaning step usually requires more effort than building the AI itself.11,32 Once a model is deployed in practice, there remain ongoing data-management requirements to facilitate quality control and monitoring of the model.

Finally, as discussed in the “Consider ethical and legal obligations” section, the challenge remains of what data should or should not be considered private.

Model development or procurement
Once an appropriately trained AI implementation team has defined a use case and determined data needs, availability, and quality, a model must be developed or procured. The process of building an AI model is outside the scope of this manuscript. However, an appropriate implementation team adhering to GMLP guidelines and engaging stakeholders across disciplines will likely be able to develop various AI models across the veterinary industry should the relevant data be available. Data science and engineering expertise may be limited in many veterinary institutions, and therefore engaging commercial entities to procure a system is a likely path for many institutions.13

To assess the appropriateness of an AI model for implementation, an AI implementation team must consider many factors, including those related to the internal transparency of the product and how well the solution aligns with the stated use case.

Joslynn and Alexander13 have described a series of questions to evaluate AI products for veterinary radiology, broadly applicable across the industry regardless of the use case. Veterinary implementation teams should consider the clinical task, clinical relevance and impact, model type, dataset, performance metrics, AI retraining, and error management, sources of bias, compatibility and useability, financial considerations, and legal/ethical considerations. A thorough evaluation of each product is recommended before adoption, and software is unlikely to be safely deployed if it is selected because of limited options and a desire to implement technology rather than pass a thorough evaluation.

Creating an implementation plan
Implementing AI in practice will likely succeed when the prior steps are met and a strategic plan is implemented. Technology implementation should involve change management strategies like any other policy or process. Workflow systems should be adjusted following the needs of the stakeholders. Of particular note for AI implementation plans is considering the technology and infrastructure required. Depending on the point of application, implementation will require different computing resources and a plan for ongoing management. Algorithms are not drugs, so how healthcare professionals, support staff, and owners view of them differs.10 The AI technology can act either passively, such as generating a dataset for interpretation by the veterinarian for assessment or review in their decision-making processes, or actively, such as triggering an alarm, alert, or patient flag in the electronic chart; each approach has different human-computer interactions and, as such, affects behaviors of the operator.34 For these and other reasons, Harris et al33 urge the need for multidisciplinary teams and avoiding implementation offline and in isolation.

Training and engagement—The rapid uptake and deployment of data sciences in modern society have led to shortages of healthcare-focused data scientists, statisticians, and computer scientists.13 Up-skilling team members from other disciplines in the implementation team is necessary to help shorten the knowledge gaps in data scientists, veterinarians, and other support team members and to help ensure consistency in semantics, definitions, and data science approaches. Once the AI technology is ready for clinical testing, the “train-the-trainer” approach can be used to deploy the technology.35 Some of the advantages of the train-the-trainer approach include reaching a broader audience and leveraging the skills of exceptional educators to increase the knowledge and engagement of end users. Furthermore, having trainers with vocational expertise closest to the AI technology’s end users provides a means of better identifying potential challenges in deploying the AI technology. It provides a mechanism for reliable and robust feedback on that technology.

Monitor and evaluate performance—Rapid evaluation and refinement of the technology can engender trust and both evaluate and demonstrate efficacy and
efficiency among multidisciplinary teams. Depending on the technology, this evaluation may be sequential or comprehensive, including algorithm performance, user feedback on the implementation, and clinical practice modifications. The latter two are particularly important for AI technologies that provide clinical decision support through alerts and patient flags since alert fatigue from false alarms can introduce risks in patient care. Alerts can be well described or explained to the user (as is the trend in XAI), which can further engender trust in AI technologies.

Like the Consolidated Standards of Reporting Trials (CONSORT) and other standardized reporting publications, there has been a steady evolution in standardized reporting of AI-related works in human healthcare. In relation to CONSORT, CONSORT-AI describes a checklist of details that should be included when reporting on comparative prospective evaluation studies. In preclinical prediction model evaluation, the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD)–AI guidelines run parallel with TRIPOD guidelines for model evaluation. The Standards for Reporting of Diagnostic Accuracy Study (STARD)–AI guidelines run similar to STARD guidelines for preclinical model development, focusing on diagnostic accuracy. The Standard Protocol Items: Recommendations for Interventional Trials (SPIRIT)–AI guidelines run parallel with SPIRIT guidelines for comparative prospective evaluation.

Another critical report stems from Vasey et al. is a guideline for early-stage clinical evaluation of AI-based clinical decision support systems. Unlike CONSORT, TRIPOD, STARD, and SPIRIT, Decision Support Systems Driven by Artificial Intelligence (DECIDE-AI) is a stand-alone guideline that attempts to provide a standardized framework for reporting critical information of the AI. The DECIDE-AI reporting guideline comprises 17 AI-specific reporting items and 10 generic reporting items, ensuring that essential information regarding AI-based decision support systems in healthcare is thoroughly reported in early-stage clinical studies.

**Manage change**

Changes can occur on many levels, from staff AI software versions to hardware and operating system changes. Each of these types of changes can introduce risks in patient care. Managing changes in the context of AI technology requires a multidimensional approach. Artificial intelligence technologies should adopt best practices in routine change management, such as version control, updating standard operating procedures, and training. The extent of information shared with stakeholders must be balanced with the risk of “over messaging.” Still, during significant changes, one should expect scheduled downtimes, expected changes in the software function and operation, and key personnel to be communicated to stakeholders in advance.

Changes to the AI software itself may have unintended consequences. In high-risk medical environments that rely heavily on software and hardware, such as radiation oncology, it is common to have a separate nonclinical test environment to evaluate new versions of software, identify potential pitfalls and changes in procedures, and assess the efficacy of new features. Such test environments are indispensable for helping craft new strategies and provide a safe environment for training the trainers without compromising existing clinical data. Similar approaches could be adopted when introducing changes to AI technologies in the clinic. Establishing sound change management principles ensures safe stewardship of the AI technology throughout its life cycle.

**Consider ethical and legal obligations**

The scope of ethical and legal issues depends significantly on the technology and how it impacts patient care. The recent review article by Cohen and Gordon provides a framework for considering ethical and legal issues in veterinary medicine. In that piece, the authors note that how AI technologies will affect veterinary medicine remains unknown. Cohen and Gordon contend that “... a much different landscape than AI use in human medicine, and necessitate proactive planning to prevent catastrophic outcomes, encourage development and adoption, and protect the profession from unnecessary liability.” Despite these uncertainties, factors such as the lack of a regulatory framework (such as those produced by the FDA) and ethical issues surrounding pet ownership, the rights of the animal and owner, and the practices of euthanasia are key issues that do not contend in human medicine. In contrast, the legal and ethical issues surrounding patient confidentiality are not captured within national (Health Insurance Portability and Accountability Act) or international (GDPR2016/679) legislation. If and when misdiagnoses occur by AI systems, root cause analysis is warranted; however, this becomes challenging to undertake in black-box commercial systems where algorithm details are (often deliberately) hidden from the veterinarian. Nevertheless, worst-case scenarios from AI systems should be considered, mainly if a reasonable outcome from AI technology includes euthanasia. Other considerations, such as cost and convenience, must also be considered.

Another consideration that Cohen and Gordon raise is the rights of the owner and whether they are privy to the findings of the AI system. Consider an AI system suggesting a less expensive course of action when a more expensive one is possible, and the animal suffers complications, misadministration, or another unfortunate fate. The owner’s knowledge of the use of AI by the veterinarian could heavily influence perspectives on the outcome. Whether there should or should not be consent in using AI technologies has not been well described in veterinary medicine, but one may take cues from the human experience thus far. Recently, Perni et al. argued that if clinical decisions are affected for AI systems used in clinical trials, disclosure should be made to patients even if written consent is not required. Such a strategy engenders trust with caregivers while empowering patients. Similar arguments could be made for owners and animals. The importance of these considerations depends on the technology itself and how it can alter or change the course of patient care: due diligence
to ethical and legal considerations should scale according to this extent.

Stay relevant
The pace of healthcare technologies can be unrelenting, which seems more so for AI technologies. Staying relevant often requires decommissioning technologies after they are no longer clinically useful. Like any other sophisticated system, AI technologies may no longer be helpful in the clinic and require decommissioning and adopting a different AI technology. Given the energy needed to adopt and use AI technologies in the clinic safely, the technology must contribute meaningfully to patient care. A periodic review of the existing technology and regular surveys of existing best practices and newer AI technologies would ensure that clinical procedures are relevant, practical, and efficient.

Conclusions
Based on a literature review, this 9-point implementation framework can support veterinary practices in leveraging AI. In summary, the framework consists of 9 steps, which should be approached by all parties but may need to be adapted in their description to serve the needs of individual organizations.
1. Establish an AI implementation team consisting of stakeholders across the organization
2. Ensure appropriate training of team members to understand AI basics
3. Define the use case or purpose of the AI system
4. Determine data needs, availability, and quality
5. Develop or procure the appropriate model
6. Consider ethical and legal obligations
7. Create an implementation plan
   (a) Training and engagement
   (b) Ongoing monitoring
8. Manage change
9. Stay relevant
While this work is loosely based on the “5 pillars” of success defined by Harris et al,10 it expands to encapsulate considerations for veterinary medicine. Notable differences relevant to veterinary medicine are the ethical and legal implications when using AI technologies and the owner’s right to know whether AI technologies are used in their pets’ care. Safe stewardship of AI technologies in the veterinary clinic will rely on establishing a multidisciplinary team, promoting education and training among end users, and engendering trust. The adoption of AI developed with GMLP will aid in trust and transparency.

Acknowledgments
None reported.

Disclosures
The authors have nothing to disclose.

Artificial intelligence tools (Grammarly) were used for spell check and grammar.

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