Using Evidence-Based Veterinary Medicine and Artificial Intelligence to Support Clinical Decision Making in Veterinary Practice

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KEYWORDS

• Clinical decision-making • Bias • Evidence-based veterinary medicine • Diagnosis
• Artificial intelligence

KEY POINTS

- Clinical decision making can be reflexive or reflective. It can be limited by incomplete information and working memory capacity and be subject to bias.
- Evidence-based veterinary medicine can provide a structure to make clinical decision-making explicit and reduce bias.
- Diagnosis is a complex process and is the first step in understanding the animal's prognosis and treatment options. The appropriate use of diagnostic tests requires veterinarians to understand both the diagnostic test and how to apply the results to the individual patient.
- Artificial intelligence (AI) can provide veterinarians with tools with the potential to improve the speed and accuracy of diagnosis and access to tests; as well as improving access to, and presentation of, information that supports clinical decision making.
- Veterinary professionals need to develop a sufficient understanding of tools that use AI to integrate them safely into their practice.

INTRODUCTION

Clinical decision-making is a major part of veterinary work. These decisions involve options for how to assess the patient's problem (diagnosis) and how to prevent or manage disease (treatment). The presence of options implies choice. Consequently,

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0195-5616/26/© 2026 Elsevier Inc. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

Abbreviations	
AI	artificial intelligence
EBM	evidence-based medicine
EBVM	evidence-based veterinary medicine
LLM	large language model
LR	likelihood ratio
NPV	Negative Predictive Value
PICO	Population/Patient, Intervention, Comparison/Control, Outcome
PPV	Positive Predictive Value
RCT	Randomized Controlled Trial

the study of decision-making becomes the study of how and why certain choices are made, and perhaps how they could be made better.

Much of the initial study of decision making took place in economics and proposed that when making decisions humans behave as "rational actors," who makes choices based on assessment of all the available information to achieve the best outcome, based on their personal goals. However, fully rational choices are often not possible because of incomplete information, time constraints and limitations in cognitive ability to formulate and solve complex problems. This led to the theory of "Bounded Rationality" that recognizes that information gathering itself has a cost; therefore, people often use heuristics or shortcuts in making decisions and will often settle for decisions that are "good enough" rather than optimal.[1]

It is now believed that the human brain has access to 2 different pathways for thinking and making decisions.[2–4] The first type of decision making, variously called system 1, intuitive, fast and reflexive thinking, is largely unconscious and feels effortless, leading to quick judgments and gut feelings. In veterinary practice this is the system veterinarians use when they rely on pattern recognition, for example, when presented with an 8 year old entire bitch with anorexia and polydipsia 3 weeks after her season, veterinarians will quickly have pyometra has a potential diagnosis. This has the advantage of being quick but can be subject to cognitive biases.

The second type of decision making, referred to as system 2, rational, analytical, slow or reflective thinking, requires conscious effort, such as consideration of the evidence and explicit reasoning. In practice this is when veterinarians stop to consider the differential diagnoses for anorexia and polydipsia and consider how they will test their hypotheses. This approach is less prone to bias but takes time and effort and errors can be introduced where there is either too little or too much information, leading to cognitive overload, particularly of working memory capacity.

HEURISTICS AND BIASES

In practice veterinarians use a combination of system 1 (intuitive/pattern recognition) and system 2 (analytical/evidence-based) approaches to decision making, but to do this effectively veterinarians need to understand their own decision-making processes (metacognition). Many approaches to decision making are developed from experience, enabling veterinarians to use mental shortcuts (heuristics) to make efficient decisions in common situations and reserving the more deliberative decision-making processes for those cases where there is complexity or uncertainty. While these heuristics are well recognized, and even essential, it is important that veterinarians recognize the benefits and risks of employing this approach.

There are now growing lists of heuristics and biases that are recognized to impact decision making, both in everyday life and in professional work (**Table 1**).[5,6] Once it is

Table 1
Examples of Heuristics and Biases in Small Animal Practice

Bias	Description	Example	Benefit	Risk
Availability bias	Judging the likelihood of a condition based on how easily cases come to mind	Having recently seen several cases of parvovirus assuming that a vomiting puppy is likely to have parvovirus	Rapid recall of potentially relevant information	May overestimate prevalence and overlook other diagnoses, for example, foreign body.
Anchoring bias	Giving too much weight to an early piece of information and failing to adjust for new data	Seeing a Cavalier King Charles Spaniel with a cough and a heart murmur—and assuming it is in heart failure	Provides a starting point for diagnosis	May lead to premature diagnosis without considering all the information
Attribution bias	Making assumptions about patients or clients based on personal characteristics or behavior	Assuming how much a client will spend based on the way they are dressed or the car that they drive	Making assumptions saves time and reduces cognitive load	External appearances can be misleading
Automation bias	A tendency to uncritically accept information from automated systems	Believing spurious blood test results without question.	Where machines are properly calibrated and tests validated, they provide useful information	Overvaluing the test result even if it doesn't fit with other clinical data.
Commission bias	A tendency to favor intervention (diagnostics or treatments) over watchful waiting	Performing diagnostics in a young dog with uncomplicated, afebrile diarrhea	May identify early disease that can be treated (Addison's, etc.)	Increases the risk of false-positive results and overdiagnosis, leading to further diagnostics or treatment.
Confirmation bias	The tendency to seek and remember information that supports pre-existing beliefs.	Seeking a published paper that provides evidence for your preferred treatment option.	Where beliefs are well-founded, seeking to confirm your beliefs can be efficient.	Failure to seek information that supports alternative diagnostic or treatment options

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Table 1
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Bias	Description	Example	Benefit	Risk
Framing effect	The tendency for decisions to be influenced by the way information is presented rather than the facts themselves.	Describing the survival rate as 80% rather than the mortality rate as 20% can affect how the client views the procedure	Can be used to encourage preventive health care interventions	Can lead to misleading interpretation and a lack of fully informed consent
Omission bias	A tendency to avoid action due to fear of causing harm, even when inaction carries a higher risk	Watching response to oxygen therapy and avoiding thoracocentesis in a markedly dyspnoeic dog with a large pleural effusion	Oxygen therapy may improve the dog's cardiovascular stability initially	Hypoxia from untreated pleural space disease is likely to worsen with time
Representativeness bias	Assuming that an individual fits the typical presentation of their group	A 2 year old Labrador with skin disease is assumed to have atopy.	Rapid pattern recognition can be fast and accurate	Atypical presentations, comorbidities, or individual variations may be missed
Satisficing	Stopping data collection once a plausible explanation has been reached	In a cat with confirmed hyperthyroidism, discussing treatment options without considering comorbidities.	Can be time-effective and cost-effective if correct	Can miss comorbidities, such as chronic renal disease in hyperthyroid cats
Sunk cost fallacy	The tendency to continue to stick with a decision even if it is not working because of past investment.	Continuing a course of treatment because of prior input (time, money, emotion), even if it is not in the best interests of the animal	Protects previous investment and belief that you were doing the right thing	Can be detrimental to animal welfare

understood that decision making is subject to bias, a decision-maker can put in place mitigation strategies. The most important of these is to be aware when one is using system 1 (intuitive) thinking and to check one's thinking using more explicit system 2 approaches.

HOW CAN EVIDENCE-BASED VETERINARY MEDICINE SUPPORT CLINICAL DECISION-MAKING?

The principles of evidence-based medicine (EBM) have a long history; however, the term is now more usually applied to an approach to medicine which involves the "conscientious, explicit and judicious use of current best evidence in making decisions about the care of individual patients."[7] A paper outlining this approach stated 4 assumptions that show the importance of integrating system 1 and system 2 decision making.[8]

1. Clinical experience and the development of clinical instincts are a crucial and necessary part of becoming a competent clinician.
2. The study and understanding of basic mechanisms of disease are necessary but insufficient guides for clinical practice.
3. Understanding certain rules of evidence is necessary to correctly interpret literature on causation, prognosis, diagnostic tests, and treatment strategy.
4. A final assumption of the new paradigm is that physicians whose practice is based on an understanding of the underlying evidence will provide superior patient care.

The principles of EBM have been adapted to many areas of health care, including veterinary medicine, with evidence-based veterinary medicine (EBVM) being described as using the current best evidence in making clinical decisions.[9]

EBVM has come to be associated most strongly with the explicit use of research literature in making decisions about the care of individual patients. However, it has come under criticism, both because of limitations in the literature and because the importance of clinical expertise and taking account of the individual circumstances and the context in which the veterinary care is being delivered have sometimes been devalued.[10,11] This has led to the definition of EBVM being updated to stress the importance of clinical expertise and taking into account each patient and owners' individual circumstances to make the best possible decision about a veterinary patient.[12,13]

Within human medicine there is a well-recognized hierarchy of evidence in which Randomized Controlled Trials (RCTs) and, more particularly, systematic reviews and meta-analysis of numbers of these trials form the "best evidence."[14] However, in veterinary medicine the evidence-base may be more limited, and research suggests that problems with design, such as low sample size, the reporting of multiple outcomes, along with consistently poor reporting of primary outcomes and failure to identify funding sources may limit the reliability of even RCTs.[15,16]

Despite these limitations, EBVM does provide veterinarians with a structure to integrate evidence into clinical decisions and, by making the process more explicit, can help veterinarians to identify and overcome bias in their decision making.

The 5 As model provides a useful framework for integrating evidence into clinical practice:

- *ASK:* The first step is to formulate a question to help you identify the most relevant evidence. One way of defining your question is to use the PICO method (Population/Patient, Intervention, Comparison/Control, Outcome), which helps you explicitly identify the question that you are trying to answer. An example of how to formulate a PICO question is given in **Table 2**.

Table 2
Example PICO Question: In Female Dogs, Does Neutering versus Non-neutering Reduce the Risk of Mammary Tumors?

Component	Description	Example
Patient or **P**opulation	Who is the relevant patient or population? Be as specific as possible, for example, puppies, geriatric patients, pregnant bitches, spaniels?	Female dog (dog, dogs, bitch, bitches, canine)
Intervention	What intervention are you interested in? What is the management strategy, diagnostic test, or type of food, drug, or surgical procedure that you are testing?	Neutering (spaying, neutering, ovariohysterectomy, ovariectomy, gonadectomy)
Comparison/**C**ontrol	What is the main alternative? Is there a control or alternative management strategy or intervention that you are particularly interested in comparing? Sometimes, when you want to know if the intervention above is better than doing nothing, the comparator will be "no intervention."	Not neutering
Outcome	What are you trying to achieve, measure, improve, effect? What are the patient-relevant consequences of the intervention?	Mammary tumors (mammary, breast, tumor, cancer, (neoplasia, neoplasm, mass, lump, carcinoma)

- *ACQUIRE:* The next step is to use this question to build a search strategy to find the most relevant evidence.[17]
- *APPRAISE:* It is then important to appraise the evidence, as even published evidence can be subject to bias.[18]
- *APPLY:* This step involves applying the evidence to your practice.
- *ASSESS:* Finally, there is a need to evaluate the impact of the evidence on your practice.

There are a wide range of resources available to guide veterinarians through this process including those from RCVS Knowledge,[19] the University of Nottingham,[20] and the EBVM Association.[21]

HOW CAN ARTIFICIAL INTELLIGENCE SUPPORT CLINICAL DECISION-MAKING?

Artificial intelligence (AI) has been described as the capacity of computational systems to perform tasks typically associated with human intelligence, such as perception, learning, reasoning, problem solving and decision-making.

Tools using AI are already becoming part of everyday lives and are increasingly becoming part of professional lives, as AI-based scribing tools and decision aids make their way into consulting rooms.

The ability of AI to organize data, identify patterns, and make predictions lends itself to an expanded role within veterinary health care, with the potential to improve diagnostics, the analysis of population health data, and in biomedical research.[22,23]

In terms of clinical decision-making, AI tools have a role to play in supporting both diagnostic and treatment decisions. Many areas of diagnostics already rely on machines to generate images or analyze samples; the integration of AI tools can expand this role to the analysis of the results. The benefits of AI tools in diagnosis can include improved accuracy in detecting and classifying various abnormalities.[24] In terms of treatment decisions, the role of AI tools is most likely to be in making information accessible to the clinician at the point of care and improving the efficiency of the decision-making process.[25]

To integrate the tools into clinical decision-making, it is important that veterinarians have a basic understanding of how they work and develop the ability to critically evaluate their outputs.[26,27]

- *Machine learning* is a type of AI using algorithms and statistical models to enable computers to "learn" and make predictions without being explicitly programmed. The algorithms are "trained" on large data sets to identify patterns and associations and then use this information to make predictions about new data sets. Machine learning can be subdivided based on whether the data have already been labeled (supervised learning) or whether the machine is left to identify patterns in the data (unsupervised learning).
- *Artificial neural networks* are computer systems composed of layers of connected nodes that mimic the neurons and synapses of the nervous system. Deep learning uses these layered neural networks to find patterns and analyze complex relationships in data, including images or text. However, as the processing of the data is hidden, it can be difficult evaluate the outputs.
- *Generative AI* is a type of AI that can create new content, including text and images. Although it is "trained" on a large data set, it uses generative algorithms to generate new content which is based on, but not identical to, the training data.

THE ROLE OF ARTIFICIAL INTELLIGENCE IN DIAGNOSIS

The skills of effective diagnostic reasoning are essential to the practice of veterinary medicine. Determining the cause of an animal's clinical signs is often the first step in understanding the animal's prognosis and treatment options. Achieving an accurate diagnosis in the face of uncertainty is a multifaceted, variable process that draws on aspects of both system 1 and system 2 thinking (**Table 3**). The diagnostic process can be split into three-stages: formulation of a diagnostic hypothesis, refinement and defining the final diagnosis.[28] It is interesting to note that research shows definitive diagnoses are rarely made during first-opinion consultations in veterinary medicine, with most of the veterinarian's time spent managing ongoing problems and making decisions about new ones before a diagnosis is made.[29]

AI is already being used to support the diagnostic process in several areas, including diagnostic imaging, histopathology and cytology.[30–32] These innovations have the potential to improve veterinary care in a number of ways.

- *Speed of diagnosis:* AI tools have the potential to yield faster results, especially in areas involving imaging interpretation.[33–35]
- *Reduced cost/barriers:* AI tools may enable in-house diagnostics that cost less and are less invasive than currently available diagnostic tools.[36]

Table 3
Diagnostic Strategies

Stage	Strategy	Example
Initiation	Pattern recognition	When elements of the history or clinical examination trigger a hypothesis—for example, marked hunger, weight loss, and polyuria/polydipsia trigger the possibility of Diabetes Mellitus.
	Spot diagnosis	Similar to Pattern Recognition, but from an unconscious recognition of a non-verbal pattern. This is usually visual (eg, Nictitans Gland Prolapse) or auditory (eg, the hacking cough associated with canine infectious tracheobronchitis).
	Owner/Caregiver labeling	When owners tell you what they think the diagnosis is. This can be very accurate, especially if the owner has experience with this diagnosis (eg, feline urethral obstruction). It should be considered and used to direct subsequent refinement questions.
	Presenting complaint	Where the veterinarian acknowledges the reason for the visit, for example, inappetence. This is the most commonly used initiation strategy in human primary care, and this is likely similar in veterinary health care.
Refinement	Restriction—Rule outs	This depends on knowledge of the most common differential diagnoses for the presenting problem, and the ability to create a shortlist of serious diagnoses that must be ruled out. For example, for acute vomiting in a young Labrador, the most common cause is dietary indiscretion; however, it would be sensible to consider ruling out a gastrointestinal foreign body.
	Stepwise refinement	This can either be anatomical (localization of right hindlimb lameness to stifle pain) or pathological process (recognizing stifle instability).
	Probabilistic reasoning	The use of clinical signs or diagnostic tests to rule in or rule out a diagnosis. This strategy requires knowing the degree to which a positive or negative result of a test adjusts the probability of a given disease, for example, canine pancreatic lipase immunoreactivity in the diagnosis of canine pancreatitis.
	Pattern recognition fit	Where veterinarians compare clinical signs to previous cases and recognize a disease when the pattern fits. It relies on the memory of known patterns rather than on specific rules, for example, dogs with variable degrees of gastrointestinal symptoms that do not respond as expected to treatment may lead to testing for hypoadrenocorticism.
	Clinical prediction rule	This is a formal version of pattern recognition based on a well-defined and widely validated series of similar cases. An example of this in canine medicine would be the Clinical Prediction tool for hyperadrenocorticism[50]

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Table 3
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Stage	Strategy	Example
Definition	Known diagnosis	This is where there is a sufficient level of certainty to start appropriate treatment or to rule out serious disease without further testing, for example, cat bite abscess, where one could do more testing (cytology or culture and sensitivity); however, this would be unlikely to change the treatment.
	Further tests ordered	Sometimes a standard test can be used to rule in or rule out the disease (eg, total T4 for feline hyperthyroidism).
	Test of treatment	When the diagnosis is uncertain, one can assess the response to treatment. For example, a frusemide trial in a dog with suspected congestive heart failure where further diagnostics are not possible.
	Test of time	One can use the anticipated course of the suspected disease to predict when a patient should improve or become more unwell. This can allow the diagnosis to become more obvious. For example, waiting 1–2 wk before diagnostics in mild canine diarrhea.
	Ongoing uncertainty	Where there is ongoing uncertainty, there are various strategies veterinarians can use: • Repeat consultations • Organization of second opinions or referral • Sharing uncertainty with the owner • Exploratory investigation

- *Improved accuracy:* AI tools have the potential to identify changes that are not detectable by humans and reduce diagnostic errors. However, as with humans, their accuracy depends on training and experience[37,38]

Although the creation of AI prediction models and diagnostics has the scope to support clinical decision-making in veterinary patients, veterinarians must be mindful of the potential harms of implementation if they have not rigorously assessed these tools before use. When evaluating these tests, veterinarians must look at both the population of animals on which the data were trained, as well as the population of animals on which the test has been validated, to assess any possible bias.

As with all diagnostic tests, the diagnostic accuracy of AI-based or AI-assisted tests should be assessed within a diagnostic test accuracy trial. In this trial, a population of animals that would receive this test in clinical practice would receive both the new test and a reference standard (the most accurate method for diagnosing the condition). The results of the new test would then be compared with those of the reference standard to calculate sensitivity and specificity. There are already recognized tools for the critical appraisal of diagnostic accuracy trials, and these can be adapted for diagnostic tests incorporating AI.[39–41]

It is essential that any differences in sensitivity and specificity between AI-based diagnostics and previous pathways are quantified. This knowledge allows veterinarians to balance the benefits of speed and accessibility against any alteration in the test's accuracy.

INTERPRETING DIAGNOSTIC TESTS

The appropriate use of diagnostic tests is often an important step in both making a diagnosis and informing clinical decisions regarding treatment or patient management. When selecting a diagnostic test, veterinarians need evidence both about the accuracy of the diagnostic test and how to interpret the results of the test.

There are three measures that can help in the interpretation of the diagnostic tests:

SENSITIVITY AND SPECIFICITY

- The sensitivity of the test is the proportion of animals with the disease who correctly test positive.
- The specificity of the test is the proportion of animals without the disease who correctly test negative.

Although the sensitivity and specificity of a test may be known, this information alone is insufficient to determine the likelihood that the patient has the disease being tested for. This requires probabilistic reasoning using either Positive and Negative Predictive Values or Positive and Negative Likelihood Ratios.

POSITIVE AND NEGATIVE PREDICTIVE VALUES

- The Positive Predictive Value (PPV) is the proportion of animals with a positive test that have the disease.
- The Negative Predictive Value (NPV) is the proportion of animals with a negative test that don't have the disease.

PPV and NPV are directly and inversely proportional respectively to the prevalence of the disease in the population. Veterinarians can rely on a positive test result reflecting a true positive much more in animals where the disease is more likely. If a test is used in a population where the disease is uncommon, the PPV will decrease (a smaller proportion of animals with a positive test actually have the disease), and the NPV will increase (a greater proportion of animals with a negative test are clear of the disease), even if the sensitivity and specificity remain the same.

POSITIVE AND NEGATIVE LIKELIHOOD RATIOS

- A positive likelihood ratio (LR) is the likelihood of a positive test result in a diseased animal compared with a healthy animal. The higher the value, the more likely a positive test indicates true disease.
- A negative LR is the likelihood of a negative test result in a diseased animal compared with a healthy animal. The smaller the value, the more likely a negative test result truly indicates the absence of disease.

Predictive values and LRs can be used to interpret test results using Bayes' Theorem, which combines pre-test information with the test result to update the post-test probability. Bayes' Theorem is something that veterinarians use every day without much consideration. For example, imagine reporting blood results for 2 dogs you examined yesterday. Both had a blood panel, including a total T4, and both T4 results were below the reference range. One was a 9 year old Labrador with lethargy, weight gain, skin changes, hypercholesterolaemia and mild anemia. The other was a clinically normal 9 year old Labrador whose bloodwork was done as part of a wellness check.

Although the test results are identical, the history and clinical findings give the first dog a much higher pre-test probability of hypothyroidism. Therefore, the low T4

meaningfully increases the suspicion of hypothyroidism in that dog. Conversely, in the second dog, one would remain appropriately cautious. The subsequent diagnostic and treatment decisions reflect this difference in post-test certainty.

This is one of the reasons why a complete clinical history and physical examination is important in veterinary patients to ensure veterinarians get the most information from every diagnostic test ordered. It also highlights how diagnostic tests can cause harm in lower-prevalence populations. You may have picked up early hypothyroidism in the second dog; however, the risk of a false positive is increased. Even if subsequent testing rules out hypothyroidism, that dog will have had to undergo further testing, and the owner will have had to contend with the concern of illness and additional testing costs.

Pre-test probability is just as important when interpreting AI-assisted diagnostic technologies. Consider an AI radiology tool that is used alongside manual interpretation of radiographs. This tool flags radiographic changes consistent with a gastrointestinal foreign body in 2 dogs. One of these dogs was presented for recurrent dysuria and hematuria with no gastrointestinal symptoms, and the other has been vomiting for 2 days. Although a foreign body is possible in the dog with urinary tract disease, the risk that this is a false positive is high. Many vets improve the accuracy of radiographs by engaging the opinion of a colleague or imaging expert. Those second reviewers tend to have been given information about the patient to allow them to contextualize their findings. This AI tool may improve efficiency by working as a proxy for this second human review. It is important to appreciate that the AI result is based solely on the image and lacks the Bayesian reasoning of a second human, even if the flag is delivered in natural language, similar to a colleague's opinion. This has the potential to reduce certain forms of bias, such as anchoring bias. However, other biases, such as automation bias, can enter the decision-making process. As with low T4 levels, it falls to the clinician to consider the pre-test probability for both dogs and to decide how the findings of this AI-powered test might alter the certainty of our radiographic diagnoses.

THE ROLE OF ARTIFICIAL INTELLIGENCE IN MAKING TREATMENT DECISIONS

Making decisions about treatment involves integrating information from a range of sources, considering the advantages and disadvantage of different options and in many cases managing uncertainty.[42]

The current focus on spectrum of care and contextualized care has highlighted the need to consider a range of treatment options and discuss these with the owner, to enable them to make an informed decision about the most appropriate treatment for their animal and their personal circumstances. While it is possible to collect and present this information in traditional ways, for example, using a Value Matrix,[43] technological tools, including those using AI can support these tasks.

Information on treatment options is usually obtained from education, textbooks, and the published literature, but this information needs to be integrated with information about the individual animal, for example, any comorbidities and how well it would tolerate particular treatments. It is also important to consider information about the circumstances and preferences of the owner. This is the process of EBVM and relies heavily on explicit system 2 decision making, especially when there is a need to discuss the options with the owner and gain informed consent, However, under time pressure it is difficult to explicitly consider all the options, leading to a tendency to use shortcuts and introducing bias into the decision making process.

AI tools, especially those based on large language models (LLMs), can support treatment decisions through the ability to search and synthesize large amounts of information and can be used to search for evidence, identify relationships or patterns, and suggest treatments. Their ability to rapidly find and summarize large volumes of information can support the decision-making process by reducing cognitive load.

LLMs are AI systems designed to process and generate human language. They are trained on large data sets and use a type of neural network architecture that excels at capturing patterns in text. They then use statistical prediction to generate the next word in a sequence, creating responses to prompts that mimic natural language.

In health care, LLMs have shown potential in processing extensive medical literature, in generating differential diagnoses and answering exam-style questions, achieving performance comparable to human experts.[44] To date, the use of LLMs in veterinary practice has focused on generating and extracting data from patient notes, although its potential use in supporting clinical decision making has also been acknowledged.[45]

However, alongside discussion of the potential uses of LLMs in veterinary practice, a number of concerns have been raised. These include concerns about intellectual property, privacy, and data security, as well as the accuracy of the text that has been generated.[45,46]

When considering the use of AI tools in making treatment decisions, it is important to understand if the AI tools that you are using are just retrieving data or whether they have generative AI capacities that create new content that can include "hallucinations," including generating references that sound plausible but do not in fact exist. The plausibility and confidence of the outputs from LLMs can lead to the belief that the results must be accurate (automation bias).

LLMs that use a defined and subject-specific dataset, such as Vetlexicon[47] or BSAVA Rover[48] are more likely to provide more relevant and reliable, if more limited information, than models such as ChatGPT or Gemini that are trained on much larger, and less specific, data sets.

As with any evidence that is used to support clinical decision-making, evidence from AI tools should be subject to critical evaluation. If the information provided by an AI tool makes claims that do not fit with current knowledge and understanding, or if the information is critical, such as a dose for medication, it is recommended that the information is checked against other sources that are known to be reliable.

ETHICAL CONCERNS

The use of AI to support clinical decision-making in veterinary practice raises a number of ethical issues, particularly in respect of accuracy, accountability, and the potential for unintended harm.[49]

As stated above, the accuracy of diagnostic tools that use AI should be evaluated through diagnostic accuracy trials, which ideally should be published in peer-reviewed journals.

Veterinary professionals are responsible for their clinical decisions, including decisions about the tools they use to support clinical decision-making. They therefore have a responsibility to ensure that they have sufficient information about how AI tools work to be able to interpret the information that they give and explain this information to clients. However, there is a need for both education on how to design prompts to get the best and most accurate information from AI models and for frameworks that enable evaluation of the design, training, validation, and outputs of AI tools.[44,46]

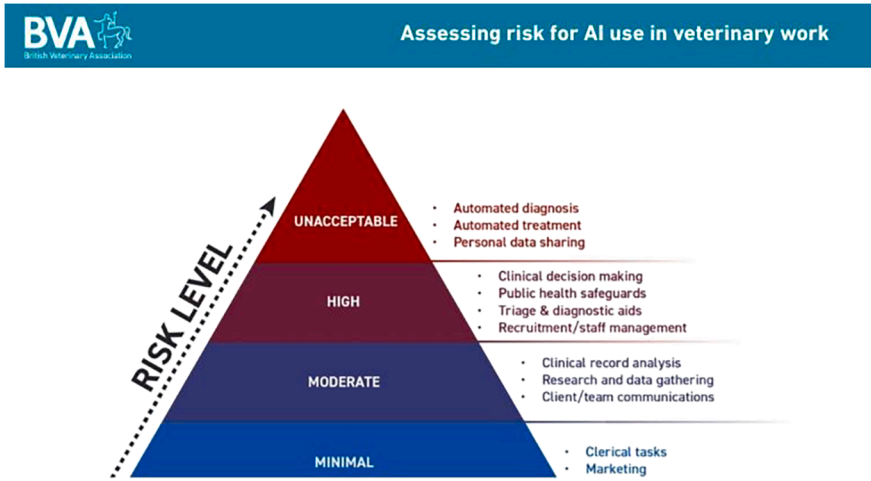


Fig. 1. Risk pyramid of AI use cases across the veterinary profession. AI, artificial intelligence. (*From* (c) British Veterinary Association.[42] May S. Toward a scholarship of primary health care. Veterinary Record. 2015;176(26):677–682. https://doi.org/10.1136/vr.h2521.[42])

The risk of unintended harms to animals through the use of AI tools increases with the degree of autonomy that the AI has in influencing clinical decisions (**Fig. 1**). It is therefore important that veterinary professionals have the knowledge and skills to use these tools wisely and the clinical expertise to evaluate their outputs and integrate them safely into clinical practice.

SUMMARY

Clinical decision-making around diagnosis and treatment is an important part of veterinary practice. To improve the effectiveness of the decision-making process, it is important to be aware of the limitations of human decision-making, which may be subject to bias and the limitations of working memory. EBVM can provide a framework for making the decision-making process more explicit and reducing bias, and AI tools can help manage large quantities of information, helping to reduce the cognitive load. However, veterinary professionals retain ultimate responsibility for their clinical decisions.

CLINICS CARE POINTS

- Develop awareness of your own clinical decision-making processes and whether you are being reflexive of reflective.
- Use the principles of EBVM to help reduce bias.
- Develop an understanding of when to use diagnostic tests and how to apply the results to the individual patient.
- Develop sufficient understanding of tools that use AI to integrate them safely into clinical decision-making in practice.

DISCLOSURES

The authors have nothing to disclose.

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