ORIGINAL INVESTIGATION

Australian perspectives on artificial intelligence in veterinary practice

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Abstract

While artificial intelligence (AI) and recent developments in deep learning (DL) have sparked interest in medical imaging, there has been little commentary on the impact of AI on the veterinarian and veterinary imaging technologists. This survey study aimed to understand the attitudes, applications, and concerns among veterinarians and radiography professionals in Australia regarding the rapidly emerging applications of AI. An anonymous online survey was circulated to the members of three Australian veterinary professional organizations. The survey invitations were shared via email and social media with the survey open for 5 months. Among the 84 respondents, there was a high level of acceptance of lower order tasks (e.g., patient registration, triage, and dispensing) and less acceptance of high order task automation (e.g., surgery and interpretation). There was a low priority perception for the role of AI in higher order tasks (e.g., diagnosis, interpretation, and decision making) and high priority for those applications that automate complex tasks (e.g., quantitation, segmentation, reconstruction) or improve image quality (e.g., dose/noise reduction and pseudo CT for attenuation correction). Medico-legal, ethical, diversity, and privacy issues posed moderate or high concern while there appeared to be no concern regarding AI being clinically useful and improving efficiency. Mild concerns included redundancy, training bias, transparency, and validity. Australian veterinarians and veterinary professionals recognize important applications of AI for assisting with repetitive tasks, performing less complex tasks, and enhancing the quality of outputs in medical imaging. There are concerns relating to ethical aspects of algorithm development and implementation.

KEYWORDS
artificial intelligence, convolutional neural network, deep learning, machine learning, radiography, veterinary

Abbreviations: AI, artificial intelligence; ANZCVS, Australian and New Zealand College of Veterinary Scientists; AVA, Australian Veterinary Association; DL, deep learning; VNCA, Veterinary Nurses Council of Australia.

1 | INTRODUCTION

While artificial intelligence (AI) is generally applied for problem solving, advances in deep learning (DL) have also driven clinical and research applications of AI in image segmentation and interpretation.[1,2] Although there has been a growing body of research and commentary on the impact of AI in medical image analysis, less information is available in the veterinary diagnostic imaging literature. AI in human medicine has not transformed medical image analysis yet and not every imaging department will have data suitable for AI. There are ethical, legal, and social barriers to the application of AI in medical image analysis which have been previously detailed[3,4] and this will likely also will need consideration in the veterinary field. With the AI landscape evolving in veterinary diagnostic imaging, there is a need for all stakeholders to understand the general principles, applications, and opportunities of AI. Yet there remains uncertainty amongst these key stakeholder groups about the role and implementation of AI.

The current interest around AI stems from the improving performance of machine learning (ML) and DL algorithms against experienced radiologists[1,5,6] and one can expect transferrable advantages in veterinary radiology. If ML and DL algorithms outperform experienced veterinary clinicians, then those algorithms are approaching the problem differently and this insight can help to improve the training of the human observer. In many cases, it is not transparent to users or to the developers how the algorithm made its prediction, a situation that has been referred to as the "black box," as a metaphor for algorithms allowing very powerful predictions that cannot be directly explained.[7] This black box situation may create larger errors outside the training set (external validity).[3–6] Digging into the black box sometimes reveals discouraging secrets about the AI algorithms' weightings. Moreover, the ground truth continues in most cases to be associated with an expert human or group of humans. If the data classifications are established by human interpretation, then AI is not outperforming humans, it is outperforming less experienced humans.

At the time of writing, a quick search of the Pubmed search engine utilizing the following Boolean string: (machine learning or artificial intelligence or deep learning) and veterinary and (radiology or radiography or diagnostic imaging or ultrasonography or scintigraphy or computed tomography or magnetic resonance imaging) revealed some interesting trends around AI in veterinary diagnostic imaging. Ninety-three articles were identified from 1997 to 2021 with a steep increase in the publication number from 2017 onwards with 70% of the articles published in the past 5 years. While some articles remain mostly limited to the research side of veterinary medicine,[8,9] there is already published veterinary literature evaluating the clinical veterinary applications of AI.[10–14] Despite the lack of regulation and often lack of independent product evaluation, there are already some commercially available solutions that are designed to potentially help the veterinarian with radiographic interpretation. The rise reflects research response to the advances in AI in a market-driven economy; albeit with the lag phase associated with the research cycle. There have been numerous predictions about the magnitude of the deleterious effects of AI on the workforce. Certainly, the doomsday predictors warning of "the singularity" is one extreme of a spectrum. At the other extreme of the spectrum is perhaps those that deny any role for AI. Only time will reveal the role of AI in veterinary image analysis, but the emerging landscape suggests an important integration of AI and the human-driven ecosystem (AI augmentation).

In veterinary diagnostic imaging, a shift toward improved patient care (and outcomes) could be driven by AI and DL. It is less probable that the paradigm shift will have any major influence on the scope of practice of our people. It is more probable that AI and DL will influence those who take stewardship of data curation and management; typically the veterinary technologists and the referring veterinarian. But rather than the threat of redundancy, there is potential for re-defining the roles and responsibilities in data management integrated with data science and existing PACs administration/management. It is conceivable, indeed probable, that the workforce in veterinary imaging may increase rather than decrease with immersion in AI research and development. In any given large veterinary imaging institution, there may be the creation of data scientist positions with potential for growth in overall numbers of staff. For imaging technologists and veterinary nurses, shunting of roles to PACS and data managers with increasing roles for data curation may occur. There may also be an increase in veterinary diagnostic imaging research personnel.

The applications of AI in the general veterinary community, and more specifically in veterinary diagnostic imaging are currently an unknown and controversial quantity in the general veterinary world. AI is slowly becoming incorporated into veterinary diagnostic imaging and will have an increasing part tomorrow. Individuals should consider educating themselves on the principles of AI and DLe, not because DL research or development demand it, but because one needs to understand AI and its limitations in order to engage in discussion, shape developments, and inform strategy related to AI. It is probable that AI will drive the emergence of new roles and redefine some aspects of scope of practice while role redundancy is possible but less likely. Legal and ethical challenges are being understood in parallel to algorithm development and implementation. It is, therefore, important to understand the attitudes and perceptions of general practitioner veterinarians, veterinary radiologists, veterinary nurses, and imaging technologists. This will help inform a framework for maintaining client care, ensuring safety, and meeting professional training needs as AI emerges in the clinical setting. Such insight is also valuable in informing strategy development for professional bodies in the veterinary sector. This study was performed to provide an Australian perspective on artificial intelligence in veterinary practice.

2 | MATERIAL AND METHODS

2.1 | Selection and description of subjects

The study was a survey design, approved by and conducted in accordance with requirements of an institutional ethics committee (protocol number HH202202). The anonymous survey (fully available in the Supporting Information) was conducted using the online Survey-

Monkey (momentiuve.ai, San Mateo, California, USA) instrument open for a 20-week window in mid-2022. Invitations to participate in the survey were sent to members of three professional bodies: the Australian and New Zealand College of Veterinary Scientists (ANZCVS), the Australian Veterinary Association (AVA), and the Veterinary Nurses Council of Australia (VNCA). The online survey allowed more flexible and inclusive participation and allowed survey completion at the convenience of participants and in private. While there were no specific control measures or groups included in the survey, there were a number of control questions included in the survey for reference and context. For example, a number of rating style questions included AI applications in general life activities to contrast AI applications in veterinary practice. A comparative analysis was also conducted between the various professional groups (e.g., veterinarians, veterinary radiologists, nurses, and technologists).

There were no exclusion criteria applied because the full membership of organizations represent the key "perspective" being sought. A willingness to complete the survey was the only inclusion criteria. Participants were recruited from the full membership of AVA, ANZCVS, and VNCA making power and sample size calculations redundant. Despite the inclusive nature of the survey, full membership participation was not expected.

2.2 | Data recording and analysis

The invitations to participate in the survey were sent to members of the three organizations via email, and the AVA and VNCA's websites and encouraged twice to participate and note the deadline of submission using the AVA and VNCA's Facebook sites. Among the 19 questions that comprised the survey were questions targeted at demographic information and others using scaled responses about participant perception and attitudes to AI applications. All survey responses and information were anonymized at collection and, therefore, constituted non-identifiable data. Institution ethics approval was sought from and provided by the Charles Sturt University Human Research Ethics Committee (H22002).

The survey was developed based on previously published instruments[14] and adapted following multi-disciplinary feedback, including internal and external stakeholders. The survey was structured to maximize insights gleaned while minimizing the time required for completion in order to minimize disruption for participants. The purpose of the survey was to understand the attitudes, applications, and concerns among general practice veterinarians, veterinary specialists, specialist veterinary radiologists, veterinary nurses, veterinary students, and veterinary radiography professionals with respect to the emerging applications of AI.

2.3 | Statistics

In conjunction with descriptive statistics, radar analysis (Microsoft Excel version 2207) was undertaken for grouped rating data

TABLE 1 Demographic data of respondents

Variable	Number (%)
Gender (n = 86)	
Female	53 (61.6)
Male	29 (33.7)
Did not identify	4 (4.7)
Age (years) (n = 86)	
25-34	14 (16.3)
35-44	29 (33.7)
45-54	17 (19.8)
55-64	16 (18.6)
65+	10 (11.6)
Employment (n = 84)	
Veterinary hospital	31 (36.9)
Veterinary clinic	18 (21.4)
Academic institutions	18 (21.4)
Consultant	4 (4.8)
Retired	4 (4.8)
Other	9 (10.7)
Location (n = 86)	
New South Wales	20 (23.3)
Victoria	18 (20.9)
Queensland	18 (20.9)
Western Australia	10 (11.6)
South Australia	6 (7.0)
Australian Capital Territory	4 (4.7)
Tasmania	2 (2.3)
International	8 (9.3)
Role (n = 86)	
Veterinarian	41 (48.2)
Veterinary radiologist	9 (10.6)
Other veterinary specialist	15 (17.6)
Veterinary nurse	13 (15.3)
Academic	2 (2.3)
Other	6 (7.0)
Work function (n = 86)	
Clinical / care	58 (68.2)
Management	12 (14.1)
Education	10 (11.8)
Research	4 (4.7)
Other	2 (2.3)
Years of experience (n = 85)	
0-5	1 (1.2)
6-10	11 (12.9)
11-20	24 (28.2)
21-35	31 (36.5)
36+	18 (21.2)

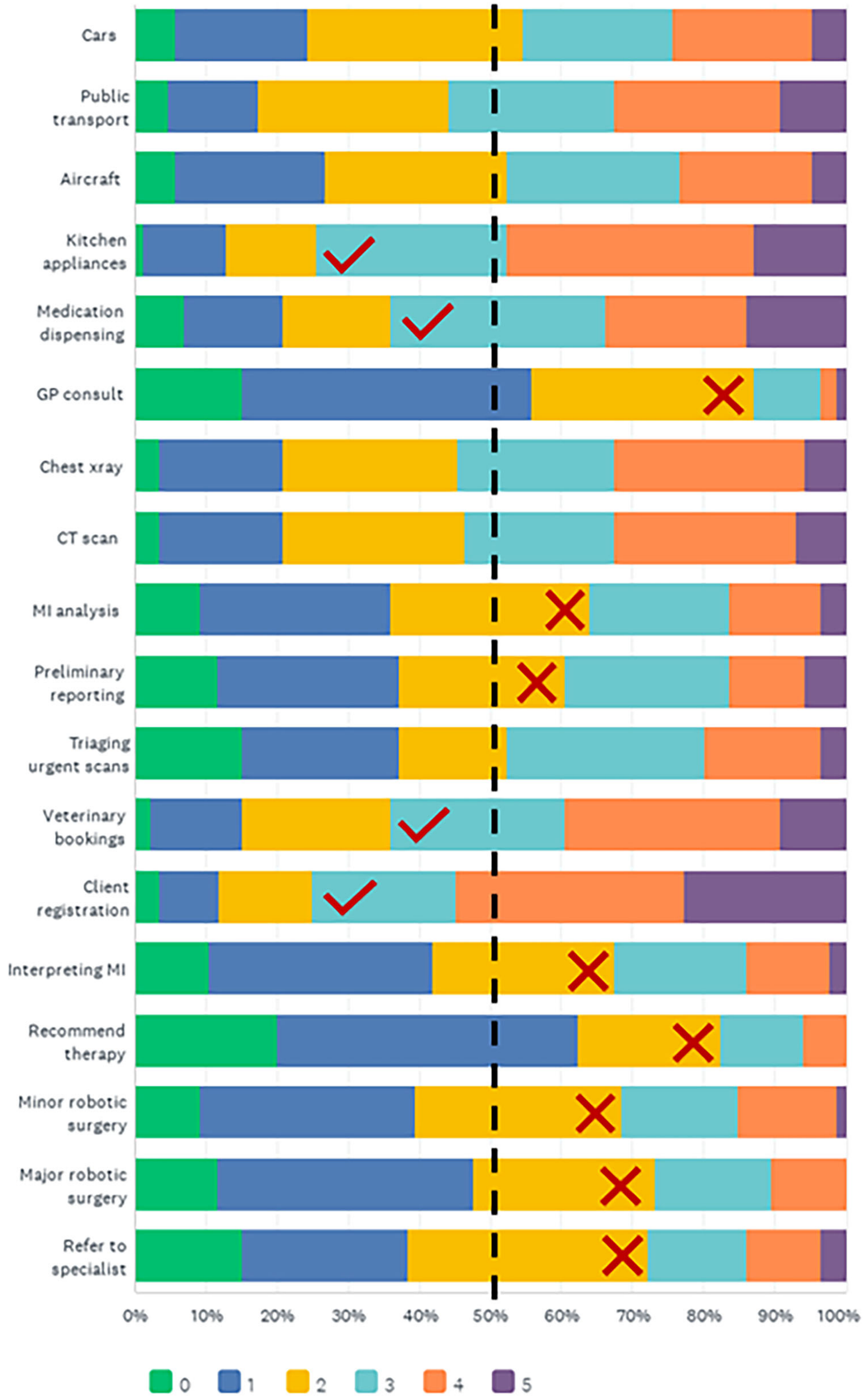

FIGURE 1 The degree of automation respondents were prepared to accept in their own lives. 0 = no automation; 1 = assistance for human in control; 2 = partial automation with human engaged; 3 = conditional automation with human ready but not required; 4 = high automation with optional human input; 5 = full automation. The red tick indicates those variables where respondents indicated greater acceptance of AI in their lives (cumulative total of category 0, 1, and 2 less than 40%) and red crosses where there was lower acceptance (cumulative total of category 0, 1, and 2 greater than 60%). Absence of markers suggested less definitive attitudes. Abbreviations: GP, general practitioner; CT, computed tomography; MI, medical image. [Color figure can be viewed at wileyonlinelibrary.com]

FIGURE 2 The perception of the role AI will play in clinical questions over the next 10 years. 0 = no role; 1 = AI assistance for human in control; 2 = AI augmentation or support for human activities; 3 = AI automation with human ready but not required; 4 = human augmentation with human supervision of AI; 5 = AI autonomy. The red tick indicates those variables where respondents indicated had a greater role for AI over the next 10 years (cumulative total of category 0, 1, and 2 less than 40%) and red crosses where there was lower anticipated role (cumulative total of category 0, 1, and 2 greater than 60%). Absence of markers suggested less definitive attitudes. [Color figure can be viewed at wileyonlinelibrary.com]

comparison. Statistical analyses were performed by a researcher with graduate training in epidemiology and biostatistics (GC). Inferential analysis with Chi-square analysis (for the categorical data), Student's *t*-test, and grouped ANOVA F test (for the continuous data) were used to evaluate the statistical significance among the data (JMP 15.2.1, SAS Institute). A p-value < 0.05 was considered to be significant. The inclusive nature of the survey and the validity of diverse perspectives across memberships meant that the expected influence of participation bias on the results did not impact the significance of the perspectives gained.

3 | RESULTS

On average, the survey took 12 min and 57 s to complete among the 86 respondents. Peak response rates were associated with the week that the reminders on the AVA and VNCA's Facebook pages were sent followed by the first week of data collection. The most common respondent defined by a collection of median responses was a female veterinarian aged 35–44 years working in a veterinary hospital in NSW with client care or clinical activities (Table 1). The mean years of experience among respondents was 23.6 years with a median of 20 years and a range of 2.5–53 years.

With respect to the degree of AI automation respondents were prepared to accept in their own lives (Figure 1), there was greater acceptance of AI automation in client management (e.g., bookings and registration) than for medical images analysis. There was a greater acceptance of AI-augmented CT or thoracic radiographs than for AI-augmented medical image analysis. There was also greater acceptance of AI for manual and repetitive tasks and lower acceptance for decision-making and logic (Figure 2). While AI education was considered important for those in veterinary radiology, AI education was not important for clients or the public (Figure 3, top). There was a significant difference between the current level of AI expertise among respondents (Figure 3, bottom left) and their desired level of AI expertise (Figure 3, bottom right). Despite support for AI in veterinary practice, respondents expressed a high degree of concern regarding accuracy, medico-legal issues, and validity but were confident with the usefulness of AI and the absence of threat of human redundancy (Figure 4). In terms of the development of AI guidelines in veterinary practice, 70.6% of respondents indicated it should be the responsibility of veterinary regulatory authorities, 67.1% professional associations, 52.9% specialist veterinary associations, and 37.7% government regulators. Responsibility for errors occurring with AI implementation was perceived to be a shared issue between the developers and commercial vendors (48.8% and 61.6%, respectively) while 41.9% indicating errors were the responsibility of the user at the data interface (nurses, technologists, and veterinarians) and 30.2% apportioning responsibility at the information interface (reporting). Integrating AI algorithms with existing software applications was reported as the most appropriate way (47.7%) to implement AI in clinical practice ahead of integration with image display and stand-alone software applications (each 18.6%). Less than 20% of respondents indicated that their workplace was prepared for the implementation of AI

FIGURE 3 Top, how important AI education is for those students currently being taught AI. 0 = not important; 1 = minimal importance; 2 = some importance; 3 = important; 4 = very important; 5 = essential. Bottom left, how respondents ranked their own current understanding of AI showed more than 85% was low understanding (0-2 responses) for all categories. Bottom right, how respondents rated their desired understanding of AI showed about 25% wanted understanding (3-5 responses) for all categories. 0 = no understanding; 1 = minimal understanding; 2 = some insight; 3 = competent; 4 = proficient; 5 = expert. The red tick indicates those who respondents indicated high priority (greater than 70% for 3–5 responses) for AI training and red crosses where there was lower priority (70% for 0–2 responses). Abbreviations: ANN, artificial neural network; ML, machine learning; CNN, convolutional neural network. [Color figure can be viewed at wileyonlinelibrary.com]

while 57% indicated that their department was not prepared for AI implementation.

There were no other statistically significant associations for responses noted among the variables related to age, the type of facility in which the respondent practiced, or the state the respondent was from. There was also no statistically significant relationship demonstrated for responses across variables based on the respondents years of experience. There was a statistically significant lower degree of support within veterinary radiologists for AI-based medical image interpretation than for other veterinarians (including specialists; $P = 0.039$). There were no other statistically significant differences among the variables based on professional qualification. Similarly, there was a statistically significant higher degree of support within those with a management function for AI-based medical image interpretation than for those with other veterinary work functions ($P = 0.017$). There were no other statistically significant differences among the variables based on work function. Men demonstrated a statistically higher degree of acceptance of AI than females in medical image analysis ($P = 0.038$), minor robotic surgery ($P = 0.029$), major robotic surgery ($P = 0.010$) (Figure 5 top), and a role in triage reporting ($P = 0.033$), and incidental findings ($P = 0.025$; Figure 5 bottom). Conversely, females indicated a higher degree of importance for AI training of nurses ($P = 0.029$), para-veterinary personnel ($P = 0.004$), and technologists ($P = 0.041$) compared to males. Females also reported a higher degree of concern than males for AI accuracy ($P = 0.005$) and ethical issues ($P = 0.038$). There were no statistically significant differences among the variables between this veterinary-based survey and the same survey distributed among human medical imaging professionals.[14] Indeed, there are few deviations in the mode response between the two survey populations (Figure 6). Perhaps the most interesting deviation is the greater acceptance of AI augmentation of thoracic radiography and CT, for both acquisition and interpretation, among veterinary professionals compared to human medical imaging professionals.

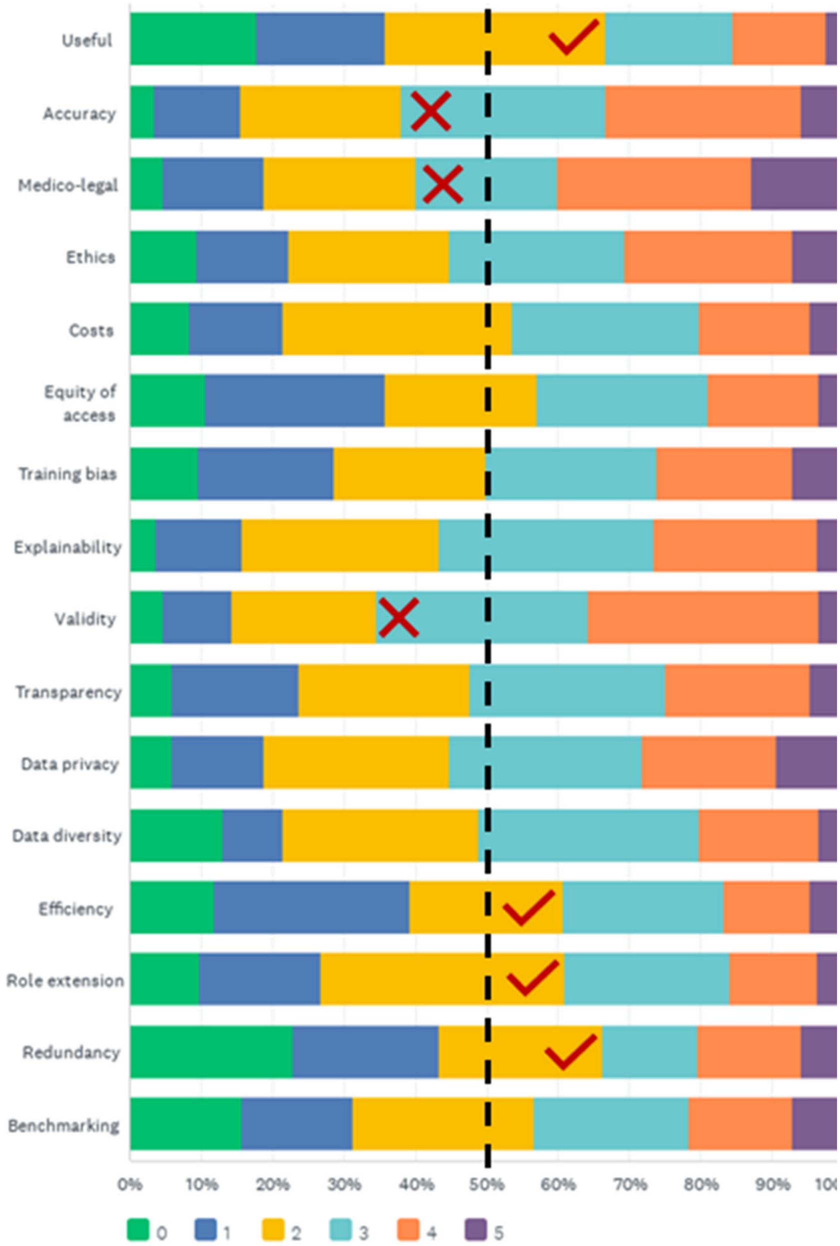

FIGURE 4 How respondents rated the extent of their concerns of AI. 0 = no concern; 1 = slight concern; 2 = mild concern; 3 = moderate concern; 4 = significant concern; 5 = extreme concern. The red tick indicates those variables where respondents indicated low levels of concern (cumulative total of category 0, 1, and 2 greater than 60%) and red crosses where there was high concern (cumulative total of category 0, 1, and 2 less than 40%). Absence of markers suggested less definitive attitudes. [Color figure can be viewed at wileyonlinelibrary.com]

4 | DISCUSSION

It was interesting to evaluate the degree of AI automation respondents would consider in their own lives (Figure 1). The control style questions revealed general support for AI automation in everyday tasks that were mundane (e.g., kitchen appliances) and those more complex tasks (e.g., public transport and medication dispensing). The general opposition to AI automation of general veterinary practitioner visits despite acceptance of AI automation for complex imaging procedures like thoracic radiography and CT was counter-intuitive and difficult to explain. Perhaps it reflects the importance of human interaction and judgment for the general practitioner visit and that less of a human interface for imaging procedures was required. This might reflect concerns about safety and a preference among respondents for autonomy and/or control. This observation might also be reflected in the veterinary practice targeted questions where respondents revealed a high degree of support for AI augmentation of less complex tasks (e.g., patient triage and patient registration) and lower levels of support for AI augmentation in more complex tasks (e.g., image analysis (extracting information from the data) and image interpretation (reporting of the study)).

Not surprisingly then, there was a trend among respondents indicating lower priority for the development of AI tools for complex tasks (e.g., diagnosis, prognosis, and decision making) in contrast to a high priority for AI applications that automate complex but menial tasks (e.g., registration, quantitation, segmentation, image reconstruction, and data mining) or those AI applications that could enhance image quality (e.g., dose reduction and noise reduction).

An important challenge for AI in medical imaging and veterinary practice is disparity between current levels of understanding and the

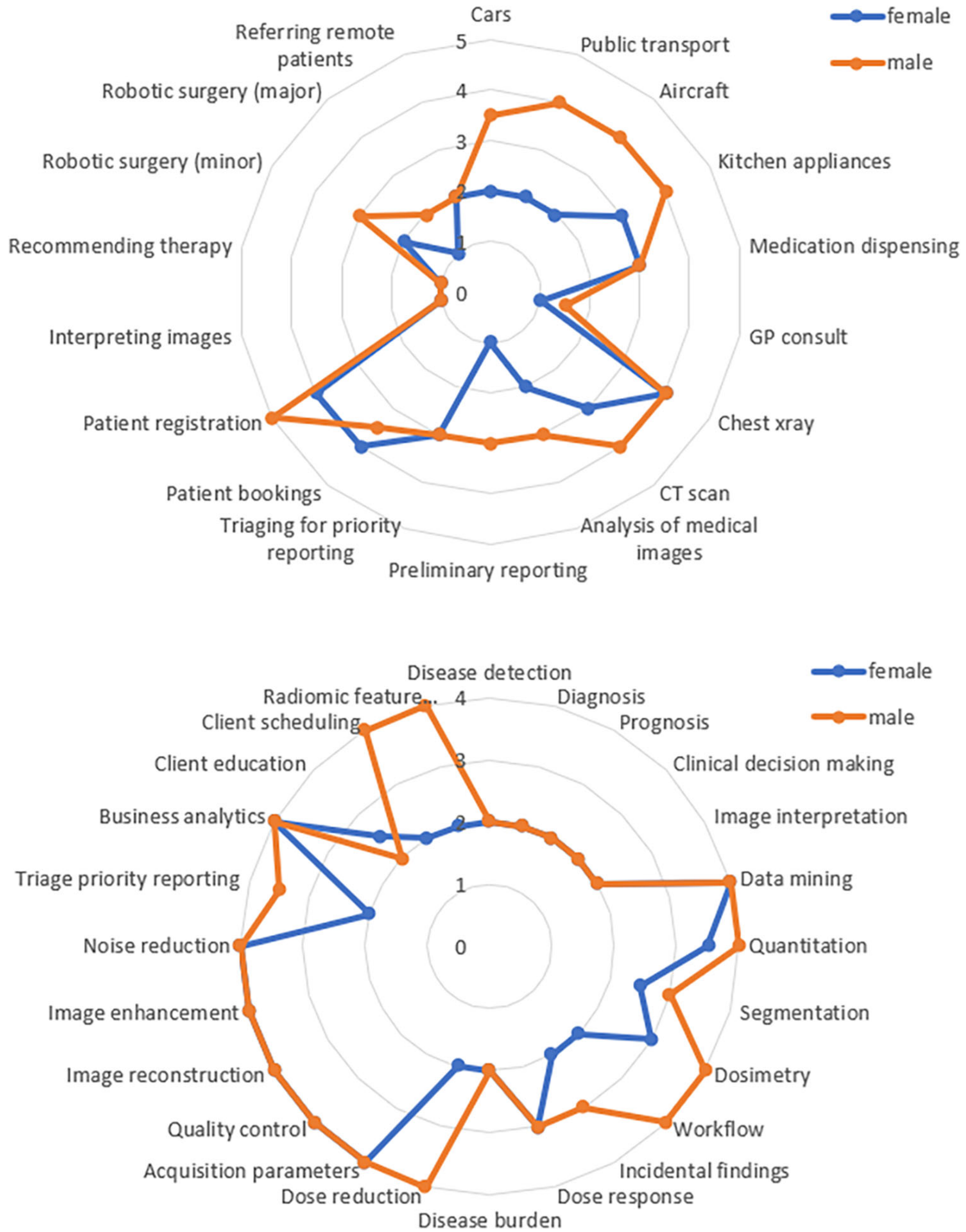

FIGURE 5 Top, radar plot of female versus male mode responses to willingness to have AI automate aspects of their lives. Bottom, radar plot of female versus male mode responses to the perception of the role AI will play in clinical questions over the next 10 years. Abbreviations: GP, general practitioner; CT, computed tomography. [Color figure can be viewed at wileyonlinelibrary.com]

desired level of understanding for AI-related topics. The language used in the AI space is misleading and complicates understanding of what AI is within the specific context of practice. More specific terms like intelligent imaging or engineered learning might provide more specific focus on what AI is in the imaging environment. This survey showed that more than 60% of respondents were broadly unfamiliar with the principles of AI while in the direct mirror to that, 60% of respondents would like a higher degree of understanding and capability in AI (Figure 3). These are not dissimilar results to a survey of human radiologists where more than 30% of respondents considered their AI knowledge below average in contrast to less than 5% who considered it excellent.[16] The impact of AI education among medical imaging practitioners on increasing AI use, optimization, and implementation has been previously reported.[17–19] Among respondents, AI education was considered important in the training of specialist veterinarians and veterinary radiologists while, in contrast, AI education or insight was not considered important for clients or the general public.

There is only a moderate level of concern associated with AI implementation in veterinary practice which contrasts the more heightened concern among human medical imaging communities. Medico-legal issues, accuracy, and validity posed the most concern for respondents (Figure 4) while no concern was reported with respect to whether AI was clinically useful or would cause redundancy. This is not dissimilar to the previously reported human imaging concerns[14] with the exception

FIGURE 6 Radar plot of this veterinary survey mode responses compared to the previously published human medical imaging professionals sample population.[14] Top, radar plot of mode responses to willingness to have AI automate aspects of their lives. Bottom, radar plot of mode responses to the perception of the role AI will play in clinical questions over the next 10 years. Abbreviations: GP, general practitioner; CT, computed tomography. [Color figure can be viewed at wileyonlinelibrary.com]

perhaps of the higher degree of concern for human ethics and privacy associated with data

While 50–60% suggested errors associated with AI implementations are the responsibility of developers and commercial vendors, over 40% also attribute error responsibility to AI users. This is particularly important given the lack of regulation and governance for AI in veterinary practice. Indeed, it would be appropriate for the professional bodies to develop guidelines, particularly with respect to the ethical use of AI. The previously developed guidelines for the ethical use of AI in nuclear medicine[3] are readily transferrable and could be considered for veterinary practice. The risk of liability may be a deterrent for AI adoption or drive a model where AI is selectively included on a case-by-case basis. Nearly 50% of respondents reported a preference for AI to be integrated into existing software packages with another 19% preferring that AI be integrated into existing image displays. This approach is likely to make it more difficult to identify when AI augmentation is part of the process and, as such, threatens transparency. Despite advances and enthusiasm for AI across the veterinary sector, only 20% of respondents indicated workplace readiness for AI implementation.

The investigation confronted a number of limitations. First, there was a poor response rate among the three professional bodies. This is likely to reflect a participation bias (or lack thereof) resulting from the early stage of integration of AI in the clinical environment. While this may result in increased responses from those with increased interest in AI, the results report self-assessed levels of AI understanding as low. Other possible reasons for the low participation could be members with no computers or internet access—the latter more likely in the more rural areas of Australia. Nonetheless, the results are considered to represent a valid snapshot of actual veterinary industry perspectives. Much of the data were collected as ordinal data and while mode values provide insight, they lack the integration power of continuous data and associated mean values. The radar analysis provides descriptive comparison without reflecting statistically significant trends. The data reflect an accurate representation of the attitudes and perspectives of a small sample of veterinary professionals in Australia to AI at the time of data collection. Since the vast majority of veterinary professionals chose not to participate—it could reflect a current attitude of disinterest or reluctance to change. Given the emerging nature of this technology, a repeat survey in 5 years should be considered and the current results should be collated against similar insights internationally for benchmarking.

5 | CONCLUSION

Australian veterinary practice recognizes the value and importance of AI applications in performing menial tasks, assisting with repetitive tasks, and enhancing the quality of outputs. Concurrently, there is a level of caution associated with medico-legal, validation, and accuracy issues in algorithm development and implementation. While Australian veterinary practices are generally not currently prepared for the assimilation of AI into practice, there is enthusiasm for education and development as a foundation for increased AI preparedness. The economics of AI is likely to be a barrier that requires further consideration.

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Category 1

(a) Conception and Design: Carstens, Currie, Hespel
(b) Acquisition of data: Currie
(c) Analysis and interpretation of data: Currie

Category 2

(a) Drafting the article: Currie
(b) Revising the article for intellectual content: Carstens, Currie, Hespel

Category 3

(a) Final approval of the Completed articles: Carstens, Currie, Hespel

Category 4

(a) Agreement to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved: Carstens, Currie, Hespel

CONFLICT OF INTEREST STATEMENT

The authors have declared no conflict of interest.

PREVIOUS PRESENTATION OR PUBLICATION DISCLOSURE

This study has not been presented nor published.

REPORTING CHECKLIST DISCLOSURE

None.

DATA AVAILABILITY STATEMENT

Data are available upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.