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Measuring AI preparedness in health professions education: Evidence from a national survey of medical radiation science students and new graduates

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A B S T R A C T

Introduction: Artificial intelligence (AI) in medical radiation science (MRS) is increasingly embedded in everyday clinical workflows. As AI systems assume more operational roles, questions arise not only about technical competence, but about professional judgement, ethical responsibility, and what it now means to be “ready for practice”. This study benchmarks perceived AI preparedness among Australian MRS students and new graduates.

Methods: A national cross-sectional online survey was conducted with final-year students and recent graduates from accredited Australian MRS programs. The Medical Artificial Intelligence Readiness Scale for Medical Students (MAIRS-MS) assessed preparedness across Cognition, Ability, Vision, and Ethics. Internal consistency and factor structure were evaluated, and group differences examined by exposure to formal AI education and AI tools during placement. One open-ended question explored participants' reflections on preparedness and education, analysed using reflexive thematic analysis.

Results: Seventy-eight participants responded (72 with complete MAIRS-MS data). The MAIRS-MS demonstrated acceptable-to-excellent internal consistency and a well-fitting four-domain structure. Ethics scored highest and Cognition lowest, with Ability and Vision intermediate. Participants who reported receiving formal AI education had higher preparedness scores than those who did not (79.1 ± 12.0 vs 70.5 ± 13.0, $p = 0.01$), as did those with clinical exposure to AI tools during placement (80.1 ± 11.2 vs 69.5 ± 13.0, $p < 0.01$). Qualitative analysis identified four interrelated themes: variable confidence and readiness; ethical responsibility and professional identity; navigating different “styles” of AI in education and practice (clinical AI vs generative AI); and structural misalignment between university teaching and clinical realities.

Conclusion: Graduates expressed strong ethical orientation toward AI use but weaker confidence in foundational AI knowledge and applied understanding. This imbalance may limit critical appraisal of AI outputs in clinical practice.

Implications for practice: The MAIRS-MS offers a pragmatic framework for benchmarking and evaluating AI education. Findings support curricula that strengthen foundational AI knowledge, integrate authentic clinical AI experiences, and make professional accountability explicit in AI-enabled practice.

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Introduction

Artificial intelligence (AI) has moved beyond a theoretical technology in healthcare and is now increasingly embedded within clinical workflows.[1] For medical radiation science (MRS) professionals, these technologies are evolving toward greater task-level autonomy, including the augmentation of patient positioning and protocol selection, image interpretation, and the embedding of visualisation tools that enable automated classification, segmentation, and decision support.[2–4] These technologies are widely expected to alleviate excessive workloads and reduce service bottlenecks while maintaining diagnostic accuracy and treatment efficacy.[5]

In the Australian context, MRS comprises the regulated professions of diagnostic radiography, radiation therapy, and nuclear medicine technology. These professionals are highly skilled in applying imaging and treatment technologies to maximise diagnostic and therapeutic benefit, while also serving as the primary interface between these technologies and the patient experience. Some authors envision the next generation of practitioners working closely with AI in collaborative, assistive models,[6,7] others argue that this integration might not consistently deliver the promised performance gains, prompting calls for AI and humans to occupy distinct roles.[8,9] Evidence shows that automation bias and automation neglect can undermine effective AI–human collaboration.[8,10] Moreover, hidden sources of workload may emerge, such as the potential for "double work" as practitioners cross-check outputs and reconcile discrepancies between AI and humans.[11] For the practitioner, this could translate into increased workload and an overall shift in the role towards monitoring, verifying, and responding to AI-supported outputs within clinical workflow.

As AI technologies reshape clinical workflows and professional responsibilities, international professional bodies and regulators have highlighted the evolving expectations placed on practitioners in the workplace and the need for appropriate training. In the Australian context, the regulator, the Medical Radiation Practice Board of Australia (MRPBA), emphasises the importance of practitioners maintaining oversight of technology to ensure the safe integration of AI, requiring the development of the necessary knowledge, skills, and attributes for safe and effective clinical use.[12] The Australian Society of Medical Imaging and Radiation Therapy (ASMIRT) position paper[13] similarly emphasises the central role of education and the need to update the curriculum to understand AI applications. Clinical guidance reports, such as those from the Royal College of Radiologists, similarly call for education and training frameworks to ensure awareness of clinical implementation and the limitations of AI tools.[14] Initiatives by the Health and Care Professions Council (HCPC), National Health Service (NHS), and the Society and College of Radiographers in the UK have embedded AI awareness into professional standards and training, with offerings such as a webinar series and e-learning modules underscoring a national priority to prepare practitioners for AI integration.[15–17]

Together, these professional and regulatory initiatives point to higher education as a central professional responsibility, preparing graduates not only for employment but also for professional judgement and action in an evolving technological clinical environment.[18] Many countries worldwide adopt a standards-based approach where students complete coursework and are assessed against explicit professional standards. These define the minimum capabilities or competencies (thresholds) a graduate must demonstrate to be considered for professional registration. These standards evolve in response to changes in clinical practice and technology, including the growing role of AI. In Australia, the MRPBA has recently updated its Professional Capabilities,[19] positioning MRS practitioners as responsible agents in the use of AI-supported technologies, with explicit requirements for oversight, critical analysis, and informed decision-making to ensure safe, high-quality care. While the MRPBA does not expect graduates to be AI developers, it does expect them to be informed, to understand regulatory and national frameworks for safe use, and to be ethically responsible users of AI, with practising professionals retaining accountability for clinical decisions. In this context, preparedness refers to perceived readiness to engage with and apply AI, encompassing awareness, confidence, and foundational knowledge, and is distinct from competence and performance.

Scholarship on how educational approaches should respond to AI in the field has begun to emerge. The existing literature promotes curriculum redesign to equip students to engage ethically and safely with AI, alongside the development of educators' knowledge base to strengthen faculty expertise.[20–25] Although there have been multiple student-focused studies examining attitudes and perceptions of AI[26,27] there remains limited empirical evidence examining validated indicators of AI-related competence for entry-level practitioners.[28] Specifically, there is a lack of validated measurement of AI preparedness within medical radiation science professions at the critical transition to practice. This study addresses this gap by applying the Medical Artificial Intelligence Readiness Scale for Medical Students (MAIRS-MS) framework[29] and examining how preparedness relates to factors such as educational experiences and clinical exposure.

This paper establishes a baseline profile of AI preparedness among final-year students and recent MRS graduates, drawing on a national survey of MRS students and new graduates to inform evidence-based curriculum and assessment design.

Methods

Study design

A cross-sectional online survey was conducted in accordance with the Checklist for Reporting Results of Internet E-Surveys (CHERRIES) guidelines.[30] All participants received an online participant information sheet outlining the study purpose, the voluntary nature of participation, and measures to ensure data confidentiality. Informed consent was obtained electronically at the commencement of the survey.

The instrument

The survey incorporated the Medical Artificial Intelligence Readiness Scale for Medical Students (MAIRS-MS).[29] The MAIRS-MS was initially developed to assess perceived preparedness to engage with AI among medical students and has demonstrated acceptable reliability and construct validity across multiple preparedness domains.[29] Although the instrument has not previously been applied to MRS professionals, its underlying constructs are not discipline-specific and align with contemporary expectations of AI-enabled healthcare practice. These constructs are: Cognition (knowledge and understanding of AI concepts); Ability (perceived skills and confidence in using AI tools); Vision (awareness of future opportunities, limitations, and implications of AI); and Ethics (understanding of ethical, legal, and professional responsibilities associated with AI use in healthcare). The MAIRS-MS has also been used and validated in learner and professional groups beyond medicine, including allied health populations,[31–33] supporting its conceptual relevance and reliability across healthcare disciplines. The survey also included two binary items capturing participant-reported exposure to AI: whether they had received formal AI education/coursework (e.g., lectures, workshops, or tutorials) and whether they had engaged with or used AI tools during clinical placement. An open-ended question invited participants to reflect on their preparedness to work with AI in their profession and on the perceived contribution of their education to this preparedness.

Participants and recruitment

Eligible participants were Australian final-year students enrolled in an MRS program and recent MRS graduates (≤18 months post-qualification). No respondents identified as nuclear medicine practitioners; therefore, findings reflect radiography and radiation therapy participants only. Final-year students and recent graduates were included because both groups had recent experience of pre-registration education and current or very recent exposure to clinical practice, making them well placed to comment on AI preparedness at the transition to practice. Recruitment took place between 1 August 2025 and 1 December 2025 through university mailing lists across all Australian university programs offering eligible MRS disciplines, professional association newsletters, targeted social media posts (e.g., LinkedIn), and snowball sampling. No incentives were offered, and participation was voluntary.

The survey was administered using QualtricsXM (Qualtrics, Provo, UT, USA). The platform was configured to record anonymised IP addresses to prevent duplicate entries. No personally identifiable data were collected.

Survey administration and response rates

The survey was distributed via open online channels (professional email lists, social media, and peer networks). As individual invitations and page views were not tracked, it was not possible to determine the number of recipients or calculate view, participation, or response rates.

Incomplete data

Partially completed surveys were retained for analysis of demographic characteristics and open-ended responses. An initial threshold for partial domain completion was considered; however, to ensure consistency and comparability across domains, quantitative scoring of the MAIRS-MS was restricted to complete domain responses only. Accordingly, MAIRS-MS analyses were conducted using complete-case data, while incomplete responses were retained for descriptive and qualitative analysis.

Data analysis

Quantitative data were analysed using R (version 4.4.2; R Foundation for Statistical Computing, Vienna, Austria).[34] Internal consistency of the MAIRS-MS was assessed using Cronbach's alpha for each domain and for the overall scale, implemented with the *psych* package in R. Cronbach's alpha was used to assess the extent to which items within each domain consistently measured the same underlying construct. Confirmatory factor analysis (CFA) was conducted using the *lavaan* package in R to examine whether the predefined four-domain structure of the MAIRS-MS was supported in this cohort. Cronbach's alpha assesses consistency within domains; CFA, by contrast, evaluates whether items cluster together as intended to form distinct but related latent domains. Given the ordinal nature of the five-point Likert response scale, CFA was performed using an estimator designed for ordinal data rather than assuming responses were continuous, and model fit was assessed using the Comparative Fit Index (CFI) and the Root Mean Square Error of Approximation (RMSEA).

Differences in overall MAIRS-MS scores were examined according to exposure to formal AI education and engagement with AI tools during clinical placement. Group comparisons were conducted using the Wilcoxon rank-sum test, given the non-normal distribution of MAIRS-MS scores. All tests were two-sided, with statistical significance set at $p < 0.05$.

Qualitative analysis of the open-ended responses employed a hybrid reflexive thematic approach informed by Braun and Clarke's framework.[35] An initial set of sensitising codes was developed a priori to guide familiarisation, with additional codes generated inductively as analysis progressed. Coding and theme development were iterative and non-linear, with ongoing refinement to ensure themes remained grounded in participants' language and experiences. A second researcher reviewed the coding framework and thematic structure, with discrepancies resolved through discussion and iterative reference to the data.

Results

Demographics

A total of 78 participants provided informed consent. Of these, 72 participants provided complete MAIRS-MS responses and were included in scale-based analyses; partial responses were retained for descriptive and qualitative analyses where applicable. Participant demographic characteristics are included in Table 1.

Measurement properties of the MAIRS-MS

Internal consistency of the MAIRS-MS was acceptable to excellent across all domains in this cohort (Cronbach α range: 0.75–0.90) and excellent for the total scale ($\alpha = 0.93$). Confirmatory factor analysis was conducted to examine the four-factor structure of the instrument (Cognition, Ability, Vision, Ethics). Model fit indices indicated good fit to the data (CFI = 0.99; RMSEA = 0.05), consistent with the intended domain structure in this sample. Item loadings and factor correlations indicated that the domains were related yet empirically distinct.

Table 1
Demographic characteristics of the sample

Characteristic	n = 78[a]
Discipline	
Medical imaging/Radiography	67 (86%)
Radiation therapy	11 (14%)
Gender	
Man	28 (36%)
Woman	50 (64%)
Age Range	
Under 25	52 (67%)
25-29	13 (17%)
30-24	8 (10%)
35-39	2 (2.6%)
40-44	1 (1.3%)
45-49	1 (1.3%)
50 or over	1 (1.3%)
Prefer not to say	0 (0%)
Received formal AI education/coursework	
Yes	39 (50%)
No	39 (50%)
Engaged with AI tools during clinical placement	
Yes	35 (45%)
No	43 (55%)

[a] n (%).

MAIRS-MS domain-level and total scores were examined for the 72 participants with complete domain-level data and are presented in Table 2. To facilitate comparison across domains with different numbers of items, mean item scores were calculated on the original 1–5 Likert scale and are reported alongside the corresponding raw domain scores. Across domains, mean item scores were highest for Ethics and lowest for Cognition, with intermediate scores observed for Ability and Vision.

Participants who reported receiving formal AI education demonstrated higher mean MAIRS-MS scores than those who did not (79.1 ± 12.0 vs 70.5 ± 13.0; Wilcoxon $W = 887.5$, $p = 0.01$, $r = 0.32$). Participants who reported engaging with AI tools during clinical placement also had higher mean MAIRS-MS scores than those who did not (80.1 ± 11.2 vs 69.5 ± 13.0; Wilcoxon $W = 946.5$, $p < 0.01$, $r = 0.40$). Gender was not associated with MAIRS-MS score (Wilcoxon, $W = 484$, $p = 0.18$).

Table 3 highlights the MAIRS-MS items that were rated highest and lowest by participants. The highest-scoring items reflected perceived value and ethical awareness, whereas the lowest-scoring items related to applied skills in selecting, analysing, and integrating AI into clinical workflows. Taken together, the relatively higher Ethics scores and lower Cognition and applied-skill items suggest a disconnect between participants' sense of professional responsibility for AI use and their foundational AI knowledge and applied confidence.

Analysis of the open-ended responses identified four interrelated themes. A thematic alluvial map Fig. 1 illustrates relationships between themes and areas of conceptual overlap.

The four themes are presented below without implying a hierarchy; they reflect overlapping and interconnected qualitative patterns. Participant quotations illustrate how these themes were articulated in participants' experiences.

Theme 1: Confidence and conditional readiness for AI-supported practice

Graduates expressed varying levels of confidence, ranging from feeling unprepared to being highly confident. Across this range, readiness was frequently described as contingent on training, oversight, or on first being able to work independently without AI. This was reinforced by limited hands-on exposure undermining confidence even among those who recognised AI's clinical value.

"I feel like I am moderately prepared… but exposure to more AI tools and experience with them will allow me to feel more confident in my use." (Respondent – 54, RT)

"… few surface level lectures on AI which have in no way actually taught me what AI is and how it works … At this point I would only be a 'button pusher', if I was to use an AI technology and don't feel prepared at all to use it in an informed manner" (Respondent – 43,MI)

Table 2
MAIRS-MS mean item scores (1–5) and raw domain scores. Mean item scores are standardised to the original Likert scale to allow comparison across domains with differing numbers of items.

Domain	Mean item score (1–5)	SD	Mean (raw score)	SD	Range (Min- Max)
MAIRS-MS total (22–110)	3.3	0.6	73.4	12.9	44–100
Cognition- 8 items (8–40)	3.1	0.7	24.4	5.4	11–35
Ability – 8 items (8–40)	3.4	0.7	27.4	5.5	11–39
Vision – 3 items (3–15)	3.4	0.8	10.2	2.3	5–14
Ethics- 3 items (3–15)	3.8	0.8	11.4	2.5	4–15

*Theme 2**:** Ethical responsibility and professional identity in an AI-enabled workforce*

Participants voiced concerns about professional accountability, particularly regarding reliance on AI outputs, troubleshooting errors, and maintaining clinical judgement. Readiness was framed not only as technical competence but also as an ethical responsibility to ensure patient safety, with several respondents emphasising the need to remain competent without AI support.

"I would like to make sure I am competent enough without the AI so that in case it malfunctions, I can still troubleshoot the problems." (Respondent – 62 - RT*)*

"I don't understand our responsibilities as a practitioner if AI makes a mistake." (Respondent – 37, MI)

Theme 3: Navigating AI styles in education and practice

Graduates distinguished between clinical AI tools embedded in imaging workflows and generative AI tools used primarily for learning or academic support. Several respondents critiqued what they perceived as an overemphasis on generative AI in education, advocating instead for a greater focus on clinically relevant AI systems they were likely to encounter in practice.

"I think there is an overemphasis on GenAI tools at university, whereas as Medical Imaging students, we need to be equipped to understand how AI might relate to improving imaging." (Respondent – 49, MI)

Theme 4: Structural misalignment AI education and clinical realities

Participants commonly described limited formal preparation for AI, with learning occurring inconsistently across university teaching and clinical environments. AI was often introduced conceptually or incidentally, while practical exposure was more likely to occur informally during placement or early employment.

"I believe I need a lot more training to feel comfortable in explaining and using AI independently for certain tasks. I believe you learn more in the workplace than university can teach." (Respondent – 28, RT)

"There was no uni preparation for AI, but on the job use and colleagues showing how they effectively use it." (Respondent – 7, MI)

Discussion

This study provides preliminary empirical support for the use of the MAIRS-MS with MRS professionals. Responses showed good internal consistency within each domain, and items clustered as intended within the scale's predefined structure, capturing distinct but related dimensions of cognition, ability, vision, and ethics. Taken together, these findings suggest that the MAIRS-MS functions as intended in the MRS professional context, extending

Table 3
Highest and lowest scoring MAIRS-MS items

Domain	Item	Mean (SD)
Highest		
Ability	*I find it valuable to use AI for education, service and research purposes*	4.00 (1.02)
Ethics	*I can conduct under ethical principles while using AI technologies*	3.87 (0.88)
Cognition	*I can define the basic concepts of statistics*	3.85 (0.68)
Ethics	*I can follow legal regulations regarding the use of AI technologies in healthcare*	3.79 (0.92)
Lowest		
Cognition	*I can differentiate the functions and features of AI related tools and applications.*	2.89 (1.09)
Ability	*I can choose the proper AI application for the problem encountered in healthcare*	2.87 (0.92)
Cognition	*I can properly analyse the data obtained by AI in healthcare*	2.63 (0.99)
Cognition	*I can organise workflows compatible with AI*	2.61 (1.05)

earlier validation work across a range of health professional groups.[29,31–33]

Beyond tool performance, domain-level results offer insight into how MRS professionals perceive their preparedness for AI-enabled practice. In an international context, the domain scores observed in this cohort broadly mirror findings across other health professions.[29] Cognition was consistently the lowest-scoring domain, indicating lower confidence in foundational AI knowledge across disciplines and geographic contexts. In contrast, the Ethics scores were relatively higher, suggesting a shared perception of professional responsibility, even in the absence of strong technical understanding. Overall preparedness in this study was higher than that reported in medical and health science cohorts in Saudi Arabia and Jordan,[36] and comparable to nursing cohorts in Türkiye.[33] Notably, Ability and Vision achieved similar scores. This pattern contrasts with much of the industry-focused literature, where future-focused questions typically receive higher ratings than perceived competence, reflecting optimism about AI's future role despite limited technical

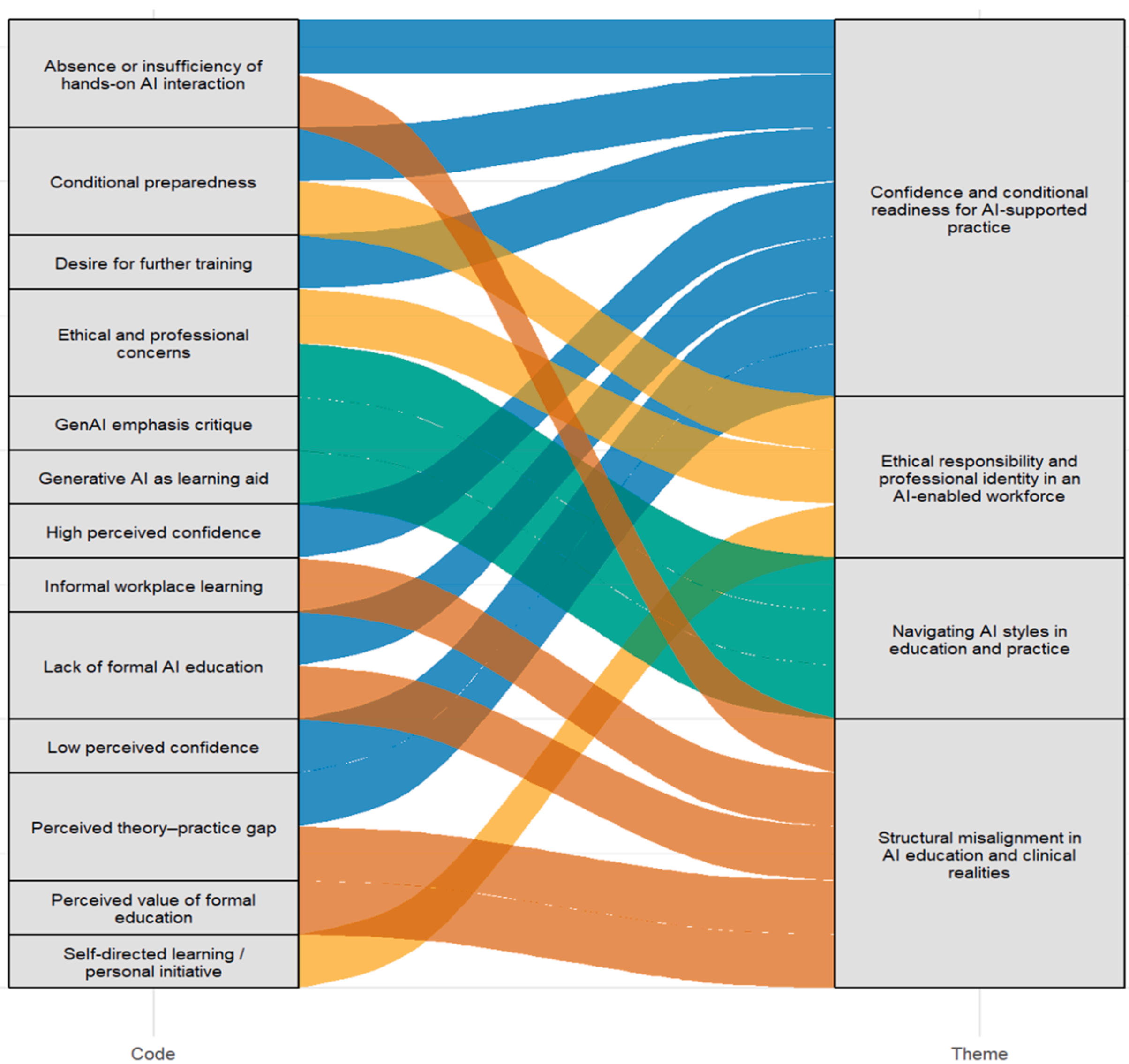

Figure 1. Alluvial map illustrating the relationships between qualitative codes and higher-order themes.

confidence or applied experience. Previous large-scale studies have similarly reported strong optimism about AI alongside concerns regarding job security, professional obligations, and medical error, with more positive attitudes observed among those with prior exposure to AI education.[37]

As highlighted in prior work, there is broad agreement that current levels of AI education remain insufficient. In the United Kingdom, for example, more than half of diagnostic and therapeutic radiographers report feeling inadequately trained, with few indicating confidence in AI-related skills.[38] Against this backdrop, the question facing educators is no longer whether AI education is required, but how it can be meaningfully integrated into professionally accredited curricula. The structure of the MAIRS-MS aligns conceptually with contemporary professional capability frameworks for MRS.[19] Cognition and Ability map closely to expectations of evidence-informed practice, safe use of clinical and digital systems, and effective workflow integration. Ethics aligns with established and emerging standards governing professional accountability and ethical decision-making. Further, the Vision domain reflects emerging expectations associated with professional leadership and stewardship[39], anticipating the opportunities, limitations, and risks of digital technologies, and applying health informatics in ways that support patient safety and system improvement.

In the context of specific educational interventions, these would need to be carefully considered across the four domains. Crotty et al. emphasised that authentic, practice-based AI education should focus on developing practitioners' capacity to critically interrogate AI tools, appraise their limitations, and reflect on the ethical and patient safety implications in real-world settings.[20] Similarly, Stewart and Clark described the importance of scaffolded educational approaches that strengthen foundational AI and informatics knowledge, alongside ethical and professional reasoning, cautioning that, without sufficient cognitive grounding, AI systems may be accepted uncritically, thereby undermining professional judgement.[24] Reinforcing this position, Alipio et al. argue that clinical departments increasingly expect graduates to understand both the capabilities and limitations of AI systems and to critically evaluate AI-generated outputs within established clinical governance frameworks.[28]

Ethical capability occupies a prominent place within contemporary professional capability frameworks, particularly in discussions of emerging digital and AI-enabled practice.[12] The higher relative Ethics scores may reflect the perceived transferability of existing ethical training, such as patient-centred care, professional codes of conduct, and research integrity, to AI-enabled practice. However, ethical challenges associated with AI are likely to be distinct. For example, the presence of AI within the workflow introduces complexity related to accountability[40] and bias,[41] impacting ethical decision-making. Furthermore, ethical education alone is unlikely to be sufficient. Although widely promoted, evidence suggests that its impact is more complex than simply completing discrete coursework. Education may enhance an individual's awareness and reasoning, however, ethical action in practice also depends on motivation, moral courage, organisational context, and leadership -not on knowledge of ethical principles alone.[42] Therefore, knowledge of AI is likely to improve the quality of judgement about AI outputs (e.g., ability to interrogate, contextualise, and verify), helping practitioners reason more soundly about ethical judgements. However, education may not remove vulnerabilities such as time pressure and workplace norms, hence the need for training that targets both cognition and behaviour-in-context.

An emerging risk is the misconception that routine use of tools such as large language models (LLMs) equates to AI readiness for clinical practice.[43] Simply using a tool does not necessarily mean the user has an in-depth understanding of how it works or how to troubleshoot it. Even a proficient understanding of AI without domain expertise is fraught with problems.[44] For example, routine use of generative AI for explanation or decision support may foster confidence in outputs that appear coherent and authoritative, even when those outputs are incorrect, incomplete, or inappropriate for the specific clinical context.

A further educational implication is that the increasing complexity of tools may erode learners' opportunities to understand the foundations of their respective professions within a complex, multidisciplinary healthcare team. Importantly, the assumption that contemporary learners are inherently digitally competent is unfounded; this narrative has been criticised for conflating familiarity with technology with critical information and digital literacy.[45] Defining "ready for practice" in an AI-enabled workplace should consider domain knowledge, the ability to interrogate AI outputs and recognise errors, and the capacity to integrate tools safely - rather than simply "being good with computers".

Consistent with the study's emphasis on ethical responsibility and professional identity in an AI-enabled workforce, education should make explicit that the use of AI does not dilute professional accountability. Educational strategies should therefore prioritise the development of foundational knowledge and professional judgement and make clear how these capabilities underpin safe and ethical patient care. This has implications for assessment and learning design, which should reward critical, problem-based reasoning, contextual decision-making, and the ability to interrogate and justify AI-supported outputs, rather than task completion or output-focused performance that may be optimised using AI tools. Accordingly, the core message for learners should remain unambiguous: practitioners, drawing on their domain expertise, remain responsible for the consequences of decisions that affect patient well-being.

Building on these perspectives, education may be most effective when designed to translate ethical orientation into practice through strategies such as AI-specific ethical case deliberation, simulation scenarios in which algorithmic outputs are intentionally fallible, and structured reflective "stop-points" (e.g., questioning data limitations, subgroup bias, patient communication, and contingency planning). These approaches explicitly target cognitive development while preserving ethical accountability in AI-supported clinical practice.

Implications for practice

Findings support the internal structure of the MAIRS-MS in an MRS cohort and align with broader workforce research showing high AI interest alongsideuneven foundational AI knowledge and limited formal training.[46] Exposure to education was associated with higher preparedness scores, consistent with prior literature linking education with more nuanced attitudes and clearer appreciation of professional responsibilities.

The four domains map naturally onto curriculum outcomes and professional capabilities, providing educators with a practical structure for targeting AI literacy, workflow integration, future-oriented judgement, and ethical governance. The MAIRS-MS can be used to establish baseline readiness and to re-administer following targeted interventions to evaluate change over time and to guide iterative curriculum refinement. MAIRS-MS data can also support universities, clinical departments, and professional bodies in aligning educational provision with professional accreditation requirements. Given the relatively lower scores in Cognition, Ability, and Vision, educators can design targeted learning that prioritises these areas while embedding ethical considerations within authentic clinical scenarios.

Strengths and limitations

Strengths of this study include the use of a structured instrument with a supported internal structure in an MRS cohort, and integration of quantitative and qualitative findings to contextualise AI preparedness. As a cross-sectional study, this work has several limitations. The sample was relatively small, which limits precision and the interpretation of subgroup comparisons. Recruitment relied on open online distribution, which prevented calculation of a response rate and may have introduced self-selection bias (e.g., participants with a stronger interest in AI may have been more likely to respond). Although recruitment was undertaken nationally through university and professional channels, the anonymous open-distribution design meant that institutional identifiers and participant location were not collected. Accordingly, the representativeness and geographic spread of the sample could not be fully characterised, and the findings should be interpreted as preliminary rather than nationally representative. Preparedness was assessed via self-report rather than objective measures of competence and therefore may not fully reflect demonstrated capability. However, the structured instrument used mitigates this concern by supporting consistency and interpretability of responses across participants. Qualitative insights were generated through a single open-ended question, intended to elicit focused contextual reflections on AI preparedness rather than to provide a comprehensive qualitative analysis. Future work should test how perceived readiness aligns with demonstrated competence using longitudinal designs and performance-based assessments.

Conclusion

The findings provide preliminary support for the use of the MAIRS-MS in the MRS professional context and establish a pragmatic baseline for informing the design, implementation, and evaluation of targeted educational interventions. Participants who reported prior AI education had higher MAIRS-MS scores, indicating an association between formal learning exposure and perceived preparedness. Although participants reported relatively strong ethical orientation, confidence in foundational AI knowledge was lower. This imbalance highlights a potential gap between professional values and the cognitive capacity required to critically appraise AI outputs in clinical practice. Although analytically distinct, these domains are likely interdependent, as the safe and ethical use of AI relies on understanding system limitations, bias, and uncertainty.

Ethics approval and consent to participate

Ethical approval for this study was obtained from Queensland University of Technology (QUT) University Human Research Ethics Committee (LR 2025-9642-24900).

There is no patient information published in this article.

Availability of data

Data required for this study may be made available by the author(s) upon reasonable request.

Author contributions

CE Conceptualisation, Methodology, Formal analysis, Data Curation, Visualisation, Writing – Original Draft, Project administration.

CC Conceptualisation, Methodology, Formal analysis, Data Curation, Visualisation, Writing – review & editing,

AM Conceptualisation, Methodology, Investigation, Writing - Original Draft.

TG Resources, Project administration, Formal Analysis, Validation, Writing – review & editing.

AS Project administration, Writing – review & editing.

EA Conceptualisation, Methodology, Project administration, Writing – review & editing.

CM Resources, Project administration, Formal Analysis, Validation, Writing – review & editing.

EG Resources, Project administration, Writing – review & editing.

Generative AI use

During the preparation of this work the authors used Microsoft CoPilot in order to assist with language editing only. After using this tool/service, the authors reviewed and edited the content as needed and takes full responsibility for the content of the published article.

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