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Research Article

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Posted Date: May 4th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-9379301/v1>

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Additional Declarations: No competing interests reported.

Building AI Capability in Medical Imaging: A Co-Designed Continuing Professional Development Framework and Evaluation

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Abstract

Background: Artificial intelligence (AI) is increasingly embedded in medical imaging workflows, yet many imaging professionals report limited preparation to evaluate, implement, and govern AI tools safely. This educational gap risks inappropriate reliance on AI systems and undermines effective clinical oversight and patient safety.

Methods: We undertook a Three-phase mixed-methods study to co-design and evaluate a tiered AI education framework for healthcare professionals, with an emphasis on medical imaging. A hybrid co-design workshop involving 52 healthcare stakeholders identified AI knowledge gaps, role-specific needs, and training preferences, informing a Three-pathway framework spanning foundational AI literacy, imaging-focused proficiency, and policy and governance. Two continuing professional development courses - *AI Literacy in Healthcare* and *AI in Medical Imaging*- were subsequently designed and delivered to over 300 healthcare professionals. Pre- and post-course surveys (132/59 responses for AI literacy; 26/30 for AI in medical imaging) captured self-reported changes in knowledge, confidence, and understanding of ethical and regulatory issues; quantitative data were analysed descriptively and qualitative free-text responses thematically.

Results: Workshop participants reported widespread gaps in foundational AI literacy, critical appraisal skills, and awareness of governance and regulatory requirements, and strongly endorsed the need for structured, role-specific training. For the AI literacy course, participants reported substantial short-term gains in core AI concepts, clinical use cases, and responsible AI principles, alongside increased confidence in discussing AI with colleagues and patients. Among imaging professionals, the AI in medical imaging course was associated with marked perceived improvements in understanding AI model training and validation, performance metrics, AI explainability, bias, and workflow integration with PACS/RIS, and in readiness to engage with AI-enabled imaging tools under appropriate human oversight.

Conclusion: A co-designed, tiered AI education framework can address heterogeneous AI literacy and capability needs across the healthcare and medical imaging workforce, strengthening confidence and perceived preparedness for safe AI adoption. The proposed pathways offer a clinically grounded, governance-aware, and scalable structure that healthcare organisations and educators can adapt to support progressive, role-aligned AI capability building in medical imaging and related domains.

Keywords: Artificial intelligence education, AI literacy, Continuing professional development, Co-designed curriculum

1 Introduction

The growing use of artificial intelligence (AI) in medical imaging is reshaping image interpretation, professional roles, and accountability structures in healthcare [1–9]. For example, the Topol Review set out how digital technologies, including AI, will transform clinical roles and workforce requirements across the NHS [1]. AI tools are now routinely deployed for tasks such as triage, detection, segmentation, and workflow management, yet training for imaging professionals lags behind these clinical realities [2, 3, 10–12]. Consequently, many radiographers and radiologists engage with AI systems lacking preparation to critically appraise outputs, recognise limitations, or contribute confidently to governance and oversight [2, 3, 10]. This misalignment between rapidly increasing AI adoption and comparatively slow educational reform raises concerns for patient safety, workforce readiness, and the quality of imaging services [1–3].

In the United Kingdom, professional organisations and educational authorities advocate that AI education must extend beyond technical skills to include role-specific competencies, clinical scenarios, ethical considerations, and governance awareness [3, 12–14]. For instance, the NHS AI Lab and Health Education England propose a role-based educational approach spanning foundational literacy through to specialist and leadership roles [13]. While co-design methods are recommended to align training with end-users’ real-world needs and constraints, empirical studies on developing, delivering, and evaluating such programmes remain scarce. Recent work in medical

imaging and broader health professions education highlights fragmented efforts, variable depth of AI content, and limited evaluation beyond short-term knowledge or attitudinal change. For example, surveys of radiographers and educators consistently report low formal exposure to AI content and uncertainty about how best to embed AI topics in already crowded curricula [10–12].

Against this backdrop, there is a growing consensus that AI capability-building must be structured, role-stratified, and explicitly grounded in ethics, governance, and appropriate human oversight, rather than delivered as generic or purely technical training [1, 13, 14]. The NHS AI Lab’s work on healthcare workers’ confidence in AI, for example, emphasises foundational AI literacy for all staff, with more advanced, role-specific education for those leading, procuring, or implementing AI [13]. However, few studies demonstrate how such frameworks can be practically co-designed with stakeholders and operationalised through continuing professional development (CPD) for imaging professionals [10–12].

This paper makes Four interrelated contributions to the emerging field of AI education in medical imaging.

1. conducts a user-centred elicitation approach to identify AI knowledge gaps, role-specific AI training needs, and implementation barriers in AI adoption in healthcare with specific focus on medical imaging.
2. presents a co-designed, role-stratified AI professional training framework that distinguishes between foundational literacy, imaging-focused proficiency, and strategic policy and governance, explicitly aligning educational content with heterogeneous professional responsibilities (e.g., [13]).
3. Demonstrates large-scale delivery and evaluation of the AI literacy and proficiency training pathways through two CPD courses delivered to multidisciplinary healthcare cohorts, demonstrating how the framework can be embedded in practice.
4. proposes empirical evaluation evidence on self-reported AI literacy, perception, confidence, and governance awareness among imaging and non-imaging healthcare professionals, generating design principles for future AI curricula and CPD programmes.

To our knowledge, this study is among the first empirical evaluations of a co-designed, tiered AI curriculum for imaging professionals that explicitly integrates governance and appropriate confidence, offering a reusable framework with defined survey domains for knowledge and confidence gains that others can adapt and test. By linking stakeholder-identified needs directly to measurable educational outcomes, the study proposes a promising model to support governance-aware AI adoption in medical imaging and related domains.

2 Literature Review

2.1 The AI literacy challenge in healthcare and medical imaging

Recent studies highlight substantial gaps in how well healthcare professionals are prepared for digital technologies, particularly AI in medical imaging [1, 10, 12, 13]. Survey

work with UK radiographers shows that many use AI-enabled tools in practice yet have received little or no formal training, and report uncertainty about governance frameworks, evaluation methods, and safe use [2, 10, 13]. This mismatch between growing clinical exposure and limited education is concerning because AI-enabled decision-support tools are now routinely embedded in workflows and influence both diagnostic and operational decisions; imaging professionals must interpret algorithmic outputs that affect case prioritisation, image interpretation, and downstream actions, making insufficient AI literacy a serious risk for practice [1, 2, 14]. Similar concerns have been raised in broader medical education, where learners frequently report basic awareness of AI but limited confidence in applying or critically appraising AI tools in clinical contexts [3, 10].

Educational research also shows a gap between perceived familiarity with AI and actual competence [10–12]. Crotty et al. report that although students and practitioners often describe themselves as broadly aware of AI, many lack a solid understanding of core principles and terminology and have few opportunities to develop practical evaluation skills within formal programmes, leaving them uncertain about engaging analytically with AI outputs and raising concerns for patient safety and professional accountability [3, 10, 13]. Curriculum-focused studies reinforce these challenges: across UK medical imaging programmes, AI content is variably implemented, constrained by tight curricula, uneven staff expertise, and rapid technological change, which often results in introductory or largely theoretical content and inconsistent graduate readiness [11, 12]. Consequently, many imaging practitioners encounter AI systems in clinical settings without adequate preparation to critically assess outputs, identify limitations, or participate in governance processes [1–3, 10]. Taken together, this work underscores that AI literacy must encompass not only terminology and basic concepts but also evaluation, governance, and integration into imaging workflows.

2.2 Existing training approaches and their limitations

Current AI training in medical imaging lacks coherence, progression, and role alignment [3, 10–12]. In higher education, efforts to integrate AI content vary widely, often limited to standalone introductory lectures rather than integrated skill development, with substantial variation in both depth and scope across UK medical imaging programmes [11]. Many curricula recognise the importance of AI but rely on isolated lectures or broad overviews rather than longitudinal designs that support progressive capability-building [11, 12]. As a result, learners may gain familiarity with AI terminology but lack the evaluative or practical competencies needed for safe clinical engagement [10–12]. Crotty et al. also noted that undergraduate AI education in medical imaging often focuses on theory rather than applied competence, with limited emphasis on interpreting model outputs, understanding validation, or recognising clinical limitations [10]. They caution that this imbalance may result in graduates who are aware of AI but lack the confidence and skills to critically appraise AI tools in practice [3, 10].

Beyond formal education, Continuing Professional Development (CPD) opportunities for qualified professionals are also highly variable. Doherty et al. identified

several AI-focused initiatives for medical imaging staff, but these programmes differed markedly in structure, duration, learning objectives, and evaluation methods [12]. Many focused on short-term knowledge gains or attitudinal change, with limited assessment of behavioural outcomes, transfer to practice, or sustainability [12, 13].

National workforce reports indicate that, without systematic training pathways, many clinicians depend on self-directed learning, vendor demonstrations, or informal peer support to develop AI-related skills [1, 13]. While these methods may encourage local innovation, they often lead to uneven capability, varying confidence, and limited understanding of governance or regulation [2, 13, 14]. This is especially concerning in medical imaging, where many AI tools are regulated as medical devices and require informed oversight from end users [15].

Taken together, the literature shows that current AI training in healthcare and medical imaging is mostly opportunistic rather than strategic [1, 12]. Programmes often lack clear progression from foundational literacy to applied skills and governance, and are rarely tailored to specific professional roles [10–12]. These limitations point to the need for structured, role-based educational frameworks that provide a staged pathway from basic literacy to applied proficiency and governance capabilities, and that are explicitly aligned with clinical, organisational, and regulatory responsibilities [13, 14].

2.3 From Trust to Appropriate Confidence: The Case for Role-Specific, Co-Designed Frameworks

As AI becomes more embedded in clinical practice, the focus has shifted from simply encouraging acceptance of AI to fostering appropriate confidence among healthcare professionals [1, 13]. Rather than uncritical trust or blanket scepticism, appropriate confidence involves understanding when and how to rely on AI systems and when human judgement should take priority [3, 14]. UK policy guidance consistently positions education as central to achieving this balance, emphasising that confidence should stem from understanding evidence standards, governance frameworks, and clinical context, not merely familiarity with the technology [1, 13].

NHS-led initiatives to strengthen healthcare workers’ confidence in AI emphasise that training should be role-based and integrated within organisational and governance structures, rather than delivered through generic, standardised programmes [13]. The guidance recognises that clinicians require different forms of AI knowledge depending on their roles, whether they function as end users, decision-makers, technical developers, or organisational leaders [13].

International guidance shows similar priorities. The World Health Organisation’s (WHO) framework on AI ethics and governance advocates for workforce education that extends beyond technical content to address accountability, transparency, human oversight, and patient autonomy [14]. The WHO positions healthcare professionals as essential participants throughout the AI lifecycle, requiring sufficient understanding to engage meaningfully in deployment, monitoring, and oversight activities [14]. UK regulatory guidance for software and AI as medical devices similarly emphasises that users must be capable of interpreting AI outputs, recognising system limitations, and responding appropriately to failures or unexpected behaviour [15]. The Medicines and

Healthcare products Regulatory Agency (MHRA) connects safe deployment directly to users who understand validation processes, post-market surveillance, and the necessity of human oversight throughout the AI lifecycle [15].

Empirical research in medical imaging reinforces these policies and regulatory perspectives. Stogiannos et al. (2024) found that radiographers prioritise clear governance, leadership involvement, and multidisciplinary collaboration when implementing AI tools [2]. These findings indicate that confidence in AI depends as much on organisational context and governance structures as it does on technical knowledge alone.

Collectively, this literature demonstrates the need for educational approaches that are both role-specific and co-designed. Rather than treating AI literacy as a single, uniform competency, effective frameworks must distinguish between basic comprehension, applied domain-specific skills, and strategic governance capabilities [1, 12–14]. Co-design provides a practical method for aligning educational content with the actual needs, constraints, and responsibilities of healthcare professionals, fostering confidence that is informed, critical, and contextually appropriate [12, 13].

Despite widespread agreement on their importance, empirical studies demonstrating how role-specific, co-designed instructional frameworks can be practically developed, implemented, and evaluated remain limited [10–12]. While co-design is broadly endorsed in the literature, most evaluations remain confined to theoretical discussion or early-stage exploration [10–12].

2.4 Educational Implications for Medical Imaging Practice

Literature converges on essential competencies extending beyond awareness to applied practice [2, 3, 10, 15]. These include:

- **Critical evaluation:** Studies indicate that imaging professionals seek education that enables them to evaluate AI systems, interpret outputs within clinical contexts, and understand how algorithmic tools integrate into existing workflows [2, 3, 10].
- **Interpretability:** Understanding outputs within imaging workflows (PACS/RIS integration) and recognising limitations [3, 10]. Rainey et al. emphasised that AI education should be anchored in clinical reasoning and interpretation, rather than remaining at the level of abstract theory [10].
- **Governance:** Navigating regulatory requirements (MHRA [16] SaMD), incident reporting, and human oversight [15]. Stogiannos et al. (2024) similarly reported that radiographers value practical guidance on governance and accountability alongside technical competencies [2]. Many AI-enabled imaging tools are regulated as software or medical devices, placing responsibility on imaging professionals for validation, monitoring, incident reporting, and maintaining human oversight [15]. Without sufficient education in these areas, practitioners may struggle to fulfil their professional and regulatory duties [14, 15].
- **Ethical awareness:** Addressing bias, data privacy, and accountability across AI lifecycle stages [14].
- **Workflow integration:** Designing hybrid human–AI processes with appropriate oversight [1, 2].

As noticed, the literature supports the development of staged, role-sensitive educational pathways that begin with foundational AI literacy and progress toward applied proficiency and governance understanding. However, few studies demonstrate how such pathways can be developed through stakeholder engagement or evaluated in real-world settings. Addressing this gap is critical for enabling safe, sustainable AI adoption in medical imaging, and motivates the co-designed, tiered framework and CPD evaluation presented in this study.

3 Methodology

3.1 Overall study design

We adopted a three-phase, mixed-methods co-design approach [17, 18] to develop and evaluate an educational framework for AI in medical imaging (Figure 1). In Phase 1, a hybrid co-design workshop with multidisciplinary stakeholders identified AI knowledge gaps, role-specific training needs, and implementation barriers. Phase 2 translated these insights into a structured, role-stratified framework comprising AI Literacy, AI Proficiency, and AI Policy and Governance pathways. Phase 3 operationalised the literacy and proficiency pathways through two continuing professional development (CPD) courses and used pre- and post-course surveys to assess short-term changes in self-reported knowledge, confidence, ethical awareness, and workflow-related competencies.

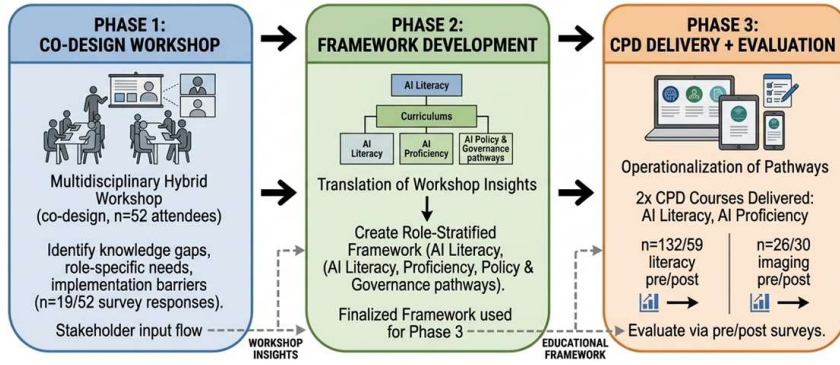


Fig. 1: Three-phase mixed-methods design. Phase 1 (co-design workshop) → Phase 2 (framework development) → Phase 3 (CPD delivery + evaluation). Arrows show stakeholder input flow; n=52 workshop, n=132/59 literacy pre/post, n=26/30 imaging pre/post.

3.2 Phase 1: Knowledge elicitation and Co-design workshop

3.2.1 Setting and participants

Phase 1 consisted of a one-day co-design workshop held in February 2025 in a hybrid format, combining in-person and online participation. The workshop was convened at a UK university site, with remote access provided via videoconferencing to maximise accessibility for geographically dispersed stakeholders. Participants were recruited through National Health Service (NHS) Trust networks, specialist societies, and academic partnerships. Eligible individuals included healthcare workers (e.g., admin, radiographers, and nurses), professionals (e.g., radiologists and clinicians), clinical researchers, and industry stakeholders involved in healthcare technology and service delivery. Summary characteristics of workshop respondents, including professional role, years of experience, familiarity with AI and frequency of AI use, are reported in Section 4.1. Before holding the evaluation and co-design workshop, ethical approval was obtained from Aston University (Ethics Approval Number: EPS21072) and we also submitted IRAS application (353193) which was also approved.

3.2.2 Workshop procedures

The co-design workshop followed a structured sequence of activities designed to elicit stakeholder needs, surface barriers and enablers, and iteratively refine the educational framework. The workshop started by providing a shared baseline of knowledge and framed the subsequent discussions around safe, governance-aware AI adoption. Participants moved into small, mixed-profession groups to work through real-world scenarios involving bias, transparency, workflow integration, and accountability. These scenario-based discussions were used to elicit role-specific experiences with AI, perceived risks, and areas of uncertainty, and to identify priority topics for education. Following this, the draft tiered AI education framework was presented, outlining the proposed AI Literacy, AI Proficiency, and AI Policy and Governance pathways. Facilitators invited structured feedback through plenary discussion and live polling, focusing on the perceived practicality, relevance, and sufficiency of the framework for different roles. The workshop concluded with a plenary session in which participants collaboratively identified priorities for implementation, potential delivery formats, and organisational enablers and barriers to participation. Insights from these discussions directly informed subsequent refinement of the framework and the design of the Phase 2 CPD courses.

3.2.3 Data collection

Two electronic surveys were administered during the knowledge elicitation workshop. Survey 1 was administered at the start of the workshop to document participants' baseline experience with AI, perceived training needs, and attitudes towards AI education. The nine-item instrument was informed by initial focus groups and prior literature on AI literacy and workforce readiness in healthcare and medical imaging [2, 10, 13]. It covered four domains: (1) professional background and experience; (2) familiarity with and use of AI; (3) confidence and perceived preparedness to engage with AI in practice; and (4) perceived benefits, concerns, and preferred training pathways.

Survey 2 was administered immediately after the presentation of a draft tiered educational framework that we proposed based on initial focus groups with healthcare professionals. The survey assessed perceptions of the framework’s clarity, practicality, and alignment with participants’ roles, as well as preferences for training delivery. The 12-item instrument spanned five domains: (1) overall framework evaluation (including balance between theory and practice); (2) perceived AI skills gaps; (3) self-assessed AI knowledge for non-computing respondents; (4) interest in enrolling in each of the proposed pathways; and (5) preferred delivery formats, barriers, and enablers. A single open-text item invited participants to describe specific AI-related challenges they wished training to address. Descriptive results for Surveys 1 and 2, including participant characteristics and training preferences, are presented in Sections 4.1, 4.2, and 4.3.

Quantitative data from Surveys 1 and 2 were exported and two researchers independently read all responses, generated a shared themes focusing on perceived AI knowledge and skills gaps, priority clinical and organisational challenges, and desired features of AI education (e.g. delivery modes, activities, and supports). These themes were subsequently used to refine the content and structure of the educational framework and to inform the design of the Phase 2 CPD courses.

3.3 Phase 2: Role-Stratified AI Education Framework for Medical Imaging Professionals

Drawing on the Phase 1 workshop findings and current policy guidance from the NHS AI Lab, WHO, and MHRA, a Role-Stratified AI Education Framework for Medical Imaging Professionals was developed to address identified AI knowledge and capability gaps among healthcare professionals in a role-stratified, tiered, and governance-aware manner [13–15]. The proposed framework underpins the CPD courses evaluated in Phase 3, and it was organised around three core principles:

- Recognising key stakeholders, including healthcare workers, clinicians, leaders, developers, and patients, and understanding their diverse needs.
- Developing tiered learning pathways that enable participants to pursue training relevant to their roles, with content progressing from foundational literacy to advanced topics in AI implementation and governance.
- Supporting continuous learning to ensure education remains aligned with new developments, ethical considerations, and regulatory updates.

The proposed framework was iteratively refined using feedback from the co-design workshop as well as a series of focus groups with healthcare professionals to ensure alignment with real-world clinical, organisational, and regulatory responsibilities.

The framework recognises five key stakeholder roles in AI adoption, consistent with NHS AI Lab classifications [13]:

- **Beneficiaries (patients and carers):** individuals affected by AI-enabled care who require accessible information about AI applications, transparency, and ethical safeguards.

- **Healthcare workers using AI for administrative or operational tasks:** end users who need to understand AI applications, transparency, and ethical aspects in everyday workflows.
- **Healthcare professionals using AI for clinical practice:** radiologists, medical physicists, radiographers, and clinicians requiring practical competence in interpreting and responding to AI-assisted imaging results.
- **Strategic leaders:** policymakers, clinical and digital leaders who oversee AI ethics, governance, procurement, and impact assessment at organisational level.
- **Developers and integrators:** data scientists, AI developers, and IT professionals responsible for AI model development, integration into imaging systems, and clinical validation.

The proposed framework is organised as a tiered architecture comprising four pathways mapped to the above stakeholder groups: AI Literacy (foundational awareness and trust), AI Proficiency (imaging-specific applied competence), AI Policy and Governance (strategic AI fluency for decision-makers), and Advanced Data Science in Medical Imaging and Healthcare. Figure 2 provides a visual summary of this AI capability development framework and its core components. This approach ensures that content and depth are proportionate to role-related responsibilities and decision-making authority.

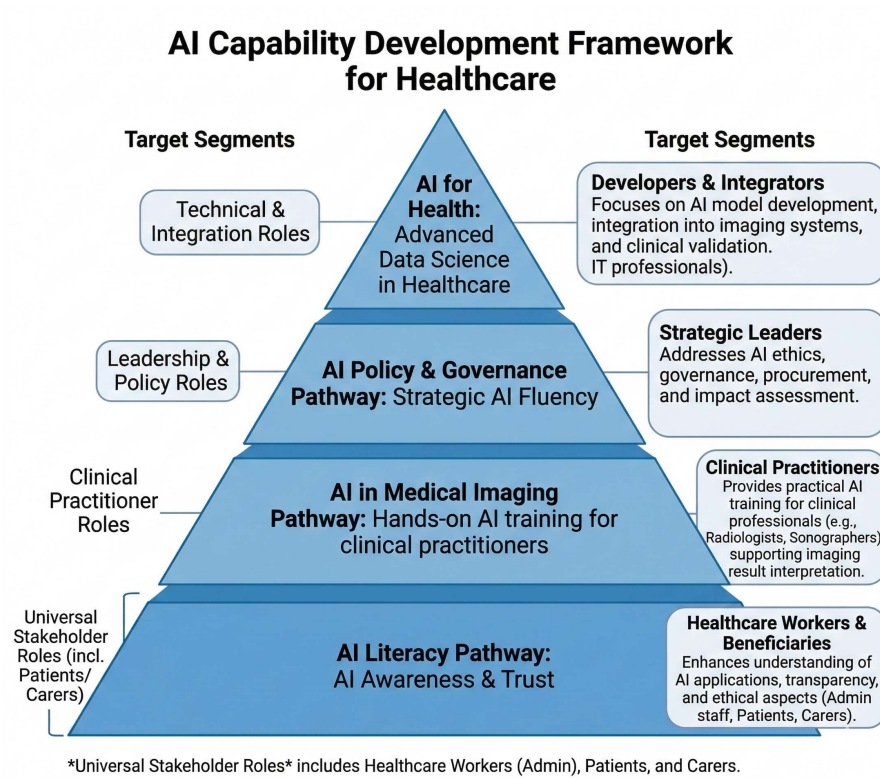


Fig. 2: Role-Specific AI Capability Development Framework for Healthcare

3.3.1 Tier 1: AI Literacy Pathway (Awareness and Trust)

The AI Literacy Pathway is an entry-level course designed for healthcare workers and beneficiaries (patients and carers) who interact with AI-enabled systems but do not develop or configure them. The primary aims are to build foundational AI knowledge, reduce anxiety and misconceptions, and encourage appropriate trust in healthcare AI systems. This approach aligns with recommendations that all healthcare professionals should achieve basic AI literacy, including an understanding of terminology, data use, and ethical considerations, before progressing to more advanced training [1, 13]. The pathway therefore serves as a common foundation upon which more specialised clinical and governance competencies can be built. Graduates of this pathway are positioned to progress to role-specific training, such as the AI Proficiency and AI Policy and Governance pathways, with a shared conceptual and ethical baseline.

The learning outcomes of this pathway is defined as follows:

1. Define key AI concepts [19] and core technologies, and distinguish AI from traditional software (LO1).

2. Explain the role of AI in automation and decision-making across multiple sectors, including healthcare (LO2).
3. Recognise common ethical and legal challenges associated with AI, including bias, data privacy, and regulatory compliance (LO3).
4. Describe emerging AI trends, including large language models (LLMs) and predictive analytics, and their potential impact on patients and healthcare staff (LO4).
5. Discuss real-world healthcare AI use cases, articulating both opportunities and risks, to support informed participation in local AI-related decisions (LO5).

3.3.2 Tier 2: AI Proficiency Pathway (Hands-on AI Training for Clinicians and Medical Imaging Specialists)

This pathway is designed for radiologists, medical physicists, radiographers, sonographers, and clinicians who need to understand, evaluate, and deploy AI tools within medical imaging workflows. It builds on foundational literacy (tier 1) by developing the technical and critical competencies required for the safe evaluation and implementation of AI within medical imaging practice. The pathway focuses on applied competence, critical appraisal, and workflow integration, with a strong emphasis on maintaining appropriate human oversight. By combining applied understanding of AI methodologies with clinical, regulatory, and governance considerations, the pathway supports responsible integration of AI tools into existing workflows.

The learning outcomes of this pathway is defined as follows:

1. Explain how machine learning (ML), deep learning (DL) [20], and convolutional neural network (CNN)-based models operate in the context of medical imaging tasks and modalities (LO1).
2. Apply and interpret AI tools for image classification, detection, segmentation, and quantitative analysis, while recognising their limitations in clinical contexts (LO2).
3. Critically evaluate AI model performance, generalisability, explainability, and potential sources of bias (LO3).
4. Design and critique AI-enabled imaging workflows that incorporate appropriate human oversight and align with existing PACS/RIS infrastructure (LO4).
5. Navigate regulatory, ethical, and organisational requirements for the safe deployment of AI in medical imaging, including risk management and governance considerations (LO5).

3.3.3 Tier 3: AI Policy and Governance Pathway (Strategic AI Fluency for Decision Makers)

This pathway is designed for healthcare policymakers, hospital executives, clinical directors, chief clinical nurses, information officers, and AI governance leads who are responsible for organisational strategy, procurement, and oversight of AI systems. Its primary aim is to develop strategic AI fluency, defined as the ability to interpret technical and ethical information, make proportionate risk-based decisions, and establish

governance structures that enable innovation while safeguarding patients, staff, and organisations.

The learning outcomes of this pathway is defined as follows:

1. Interpret and apply AI policy frameworks and regulatory requirements relevant to healthcare contexts and jurisdictions (LO1).
2. Design and oversee governance structures that support the safe, ethical, and accountable deployment of AI systems (LO2).
3. Evaluate the ethical, social, and organisational implications of AI systems and integrate these considerations into strategic management (LO3).
4. Lead or scrutinise AI procurement and implementation processes, ensuring that safety, interoperability, governance, and lifecycle management are prioritised alongside system performance (LO4).

3.3.4 Tier 4: Advanced Data Science in Medical Imaging and Healthcare

The Advanced Data Science in Medical Imaging and Healthcare Pathway is intended for data scientists, AI developers, clinical informaticians, and technical researchers who design, build, and maintain AI systems for diagnostic imaging and wider healthcare applications. It extends beyond Tier 2's applied clinical competence and Tier 3's strategic governance focus by targeting end-to-end model development, validation, deployment, and lifecycle management in line with emerging good machine learning practices and regulatory expectations for AI as a medical device. In doing so, the pathway aims to ensure that those leading technical work on AI systems can align robust data science practice with clinical, ethical, and governance requirements.

Participants are expected to have prior experience in programming, data analysis, and basic machine learning. The emphasis is on advanced methods, trustworthy AI practices, and translation into real clinical environments, including integration with picture archiving and communication systems (PACS), radiology information systems (RIS), and electronic health records. Graduates of this pathway are positioned to collaborate effectively with clinical leaders and regulators, contribute to the design of safe and explainable AI tools, and support continuous monitoring and improvement of deployed systems.

The learning outcomes of this pathway is defined as follows:

1. Design and implement end-to-end data pipelines for medical imaging and multi-modal clinical data, including data curation, annotation workflows, preprocessing, augmentation, and partitioning for training, validation, and testing (LO1).
2. Develop, train, and fine-tune advanced machine learning and deep learning models for imaging tasks (e.g. detection, segmentation, reconstruction, and report generation), selecting appropriate architectures and optimisation strategies for specific clinical problems (LO2).
3. Apply techniques for model evaluation, uncertainty estimation, explainability, and robustness testing, including assessment of generalisability across sites, modalities, and populations, and mitigation of dataset shift and bias (LO3).

4. Implement deployment-ready solutions that integrate AI models into clinical environments (e.g. PACS/RIS or workflow orchestration tools), incorporating human–AI interaction design, fail-safes, logging, and performance monitoring to support safe human oversight (LO4).
5. Align model development and deployment with relevant regulatory and governance frameworks for AI and software as a medical device, including documentation, risk management, post-market surveillance, and collaboration with clinical and organisational stakeholders (LO5).

While the AI Policy and Governance (tier 3) and Advanced Data Science in Medical Imaging and Healthcare (tier 4) pathways were co-designed as part of the overall AI educational framework, they were not delivered/implemented during the current study (phase 3). Accordingly, the empirical evaluation presented in the Results section focuses on the AI Literacy and AI Proficiency pathways only, which were prioritised based on immediate workforce needs identified during the co-design process. Tier 3 and 4 pathways are therefore presented as a theoretically informed extension of the framework. Insights generated from the design, delivery, and evaluation of the first two pathways, particularly regarding confidence, role-specific learning needs, and appropriate trust in AI, are expected to inform the future refinement, contextualisation, and evaluation strategy for this strategic-level training.

3.4 Phase 3: Course Delivery and Evaluation

Following the co-design workshop, the educational framework was operationalised through two continuing professional development (CPD) courses explicitly mapped to the AI Literacy (Tier 1) and AI Proficiency (Tier 2: AI in Medical Imaging). Each course was designed to align learning activities and outcomes described in Phase 2.

3.4.1 CPD Course delivery

The AI Literacy in Healthcare CPD course (tier 1) was delivered over 4 weeks (through an ethically approved NHS recruitment process) to over **250 multidisciplinary cohorts** of healthcare professionals and workers in June 2025. The AI in Medical Imaging CPD course (tier 2) was delivered over 5 weeks (through an ethically approved NHS recruitment process) to over **60 medical imaging workers**, including radiologists, radiographers, imaging scientists, and clinicians with direct involvement in imaging workflows, during July 2025.

Both courses combined structured teaching with interactive components, such as case-based discussions, worked examples, and guided group reflection. These pedagogical choices reflected Phase 1 participants’ preferences for practical, scenario-based learning and were intended to support transfer from conceptual understanding to workplace practice. Participation in the courses and associated evaluation surveys was voluntary.

3.4.2 Evaluation design and participants

The impact of both courses was evaluated using a pre–post survey design without a control group. For each course, participants were invited to complete an online

pre-course survey immediately before the first session and a post-course survey immediately after the final session. Pre- and post-course responses were not individually linked; analyses therefore compared group-level responses at each time point.

3.4.3 Pre- and post-course survey instruments

The study utilised purpose-designed survey instruments, including pre- and post-course surveys for both the AI Literacy in Healthcare and AI in Medical Imaging courses. These were developed by the research team to assess baseline knowledge and post-course changes in understanding, confidence, and perceptions of AI. A version of all survey instruments is provided as supplementary material (Additional File 1).

For Tier 1 (AI Literacy in Healthcare), pre-course items assessed role, prior AI exposure, familiarity with core AI concepts and healthcare use cases, and confidence in discussing AI, recognising ethical and legal issues (e.g. bias, data privacy), and engaging critically with AI tools at a general level. Post-course items repeated key familiarity and confidence measures and added perceived usefulness, intended practice change, and readiness to contribute to AI-related discussions and decisions without requiring technical implementation skills [21].

For the AI in Medical Imaging course (tier 2), surveys focused on more specialised outcomes, including familiarity with imaging AI models (classification, detection, segmentation), confidence in interpreting AI outputs within workflows, and ability to evaluate performance, generalisability, and bias, together with understanding PACS/RIS integration and imaging-specific regulatory and governance issues. Post-course items emphasised perceived readiness to evaluate, use, and support deployment of imaging AI tools with appropriate human oversight and relevance to clinical roles [22].

Across both courses, five-point Likert scales were used for familiarity, confidence, and attitudinal items, complemented by open-ended questions on learning experience, perceived value, and further training needs, ensuring alignment between survey content, learning outcomes, and the staged co-designed framework [21]. Pre-/post-response rates were 132 and 59 for AI Literacy and 26 and 30 for AI in Medical Imaging, respectively, providing baseline and follow-up measures of knowledge, confidence, attitudes, and intended application of AI in practice.

Two researchers independently reviewed responses from open-ended survey items to identify recurring themes related to perceived relevance, practical application, remaining uncertainties, and future learning needs.

3.4.4 Ethical considerations

Participation in both courses and associated evaluation surveys was voluntary. Survey responses were collected anonymously, and no identifiable personal or clinical data were recorded. Participants were informed that anonymised data would be used for evaluation and research purposes, and completion of the surveys was treated as informed consent in accordance with the approved protocol.

The study received approval from the UK Health Research Authority (HRA) (Integrated Research Application System (IRAS) Project ID: 353193). All procedures were conducted in line with institutional governance processes and applicable data protection requirements.

4 Results

4.1 Results of Survey 1 (Baseline AI Perceptions and Training Needs)

Baseline survey responses captured a multidisciplinary group spanning radiologists, clinicians, and other healthcare-related roles, with experience ranging from early-career to highly experienced practitioners (Figure 3). Participants reported a broad spread of prior AI exposure: most described themselves as moderately or very familiar with AI, while a smaller group reported only slight or no familiarity. AI use in practice was heterogeneous, with occasional use most common and responses spanning never to very often.

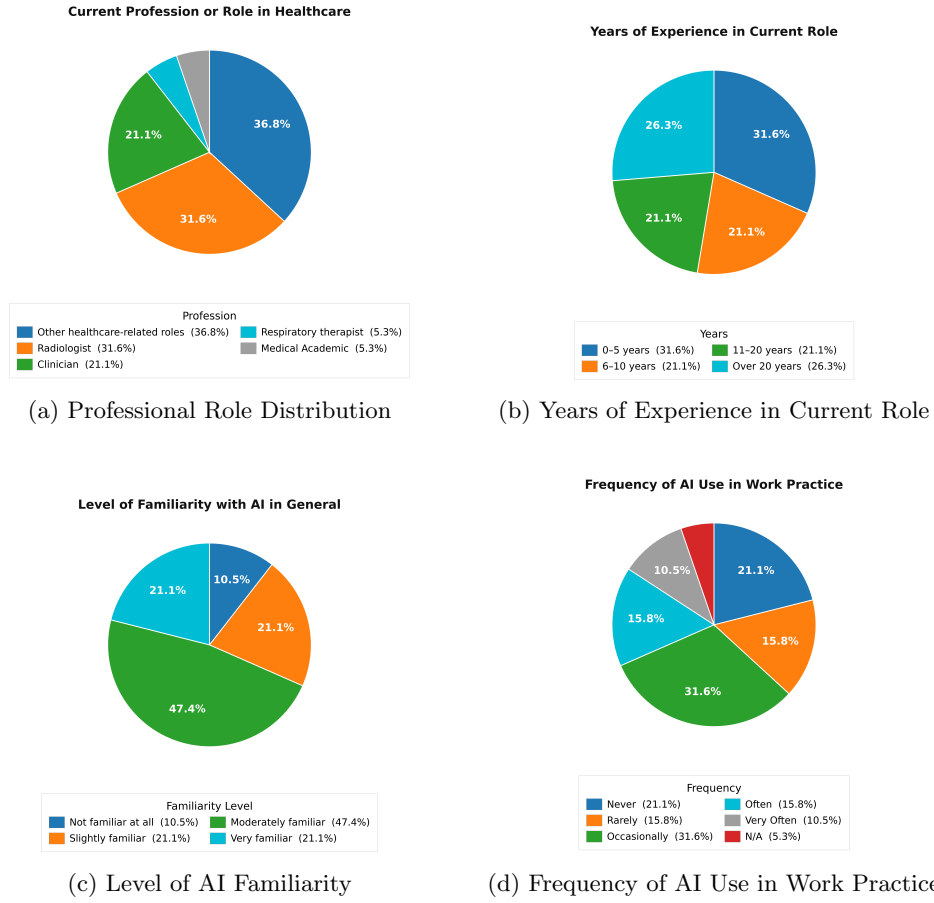


Fig. 3: Survey 1 participant background characteristics: (a) current profession or role in healthcare; (b) years of experience in current role; (c) self-reported level of AI familiarity; (d) frequency of AI use in work practice.

4.1.1 Perceived AI capabilities, training adequacy and skills gaps

Figure 4a summarises self-reported confidence across nine AI competency areas. Confidence was highest for conceptual and risk-related knowledge (for example, understanding AI risks and ethical implications) and lower for hands-on and governance-oriented skills such as interacting with AI-assisted tools, assessing diagnostic reliability, and understanding bias, data privacy, and transparency. Figure 4b shows predominantly neutral or negative views about formal preparation: most respondents did not feel that healthcare organisations provide sufficient AI training, and many were unsure or unconvinced that they could develop adequate skills independently.

4.1.2 Perceived benefits and concerns around AI in medical imaging

As illustrated in Figure 5a, respondents most frequently highlighted faster processing and reporting times (30.4%) and improved diagnostic accuracy (25%) as key benefits of AI in medical imaging, followed by reduced workload for healthcare professionals (23.2%) and enhanced patient outcomes (19.6%). Figure 5b shows that similar proportions expressed concern about potential bias in AI outputs (26.5%), loss of human oversight and lack of transparency in AI algorithms (each 20.6%), with additional worries about ethical or legal implications (17.6%) and impacts on job roles and responsibilities (11.8%).

4.1.3 Routes to AI skill development

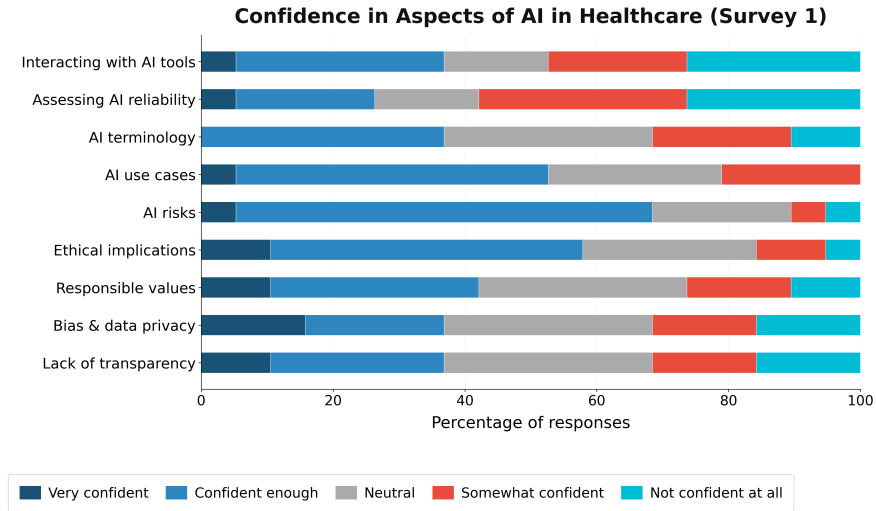
Figure 5c indicates that respondents primarily relied on informal and self-directed learning routes. The most frequently reported approach was self-directed learning through keeping up with research, accounting for the largest proportion of responses. A substantial proportion of respondents also reported having no AI-related skills. Formal training pathways were less commonly reported, with smaller proportions indicating participation in vendor training or continuing professional development (CPD) in higher education. Only a minority of respondents cited postgraduate teaching, conferences, collaborations with experts, or involvement in research as routes to developing AI skills.

4.2 Results of Survey 2 (Framework Evaluation and Training Preferences)

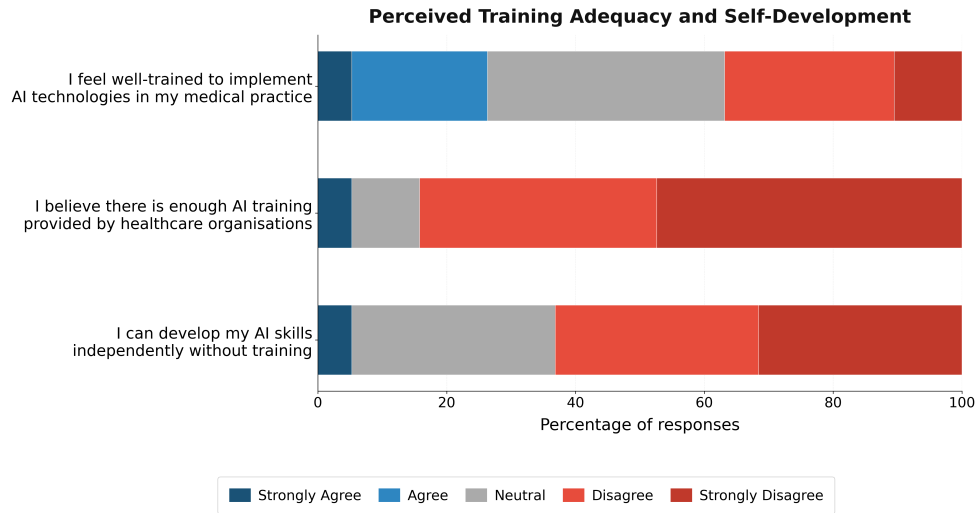
Survey 2, completed after presentation and discussion of the three-pathway framework, captured participants' views on its practicality, perceived skills gaps, preferred pathways, and training preferences.

4.2.1 Perceived practicality and skills gap

As shown in Figure 6a, most respondents agreed that the framework was practical and implementable and that it struck an appropriate balance between theory and practice, while a small minority expressed reservations. Consistent with Survey 1, almost all respondents perceived a system-wide AI literacy gap, and self-rated AI knowledge



(a) Self-reported confidence across nine AI competency areas



(b) Perceived training adequacy and self-development

Fig. 4: Survey 1 perceived AI capability and training adequacy: (a) self-reported confidence across nine AI competency areas, showing higher confidence for conceptual and risk-related knowledge than for hands-on and governance-orientated skills; (b) perceived training adequacy and self-directed skill development, showing predominantly neutral or negative responses across all three statements.

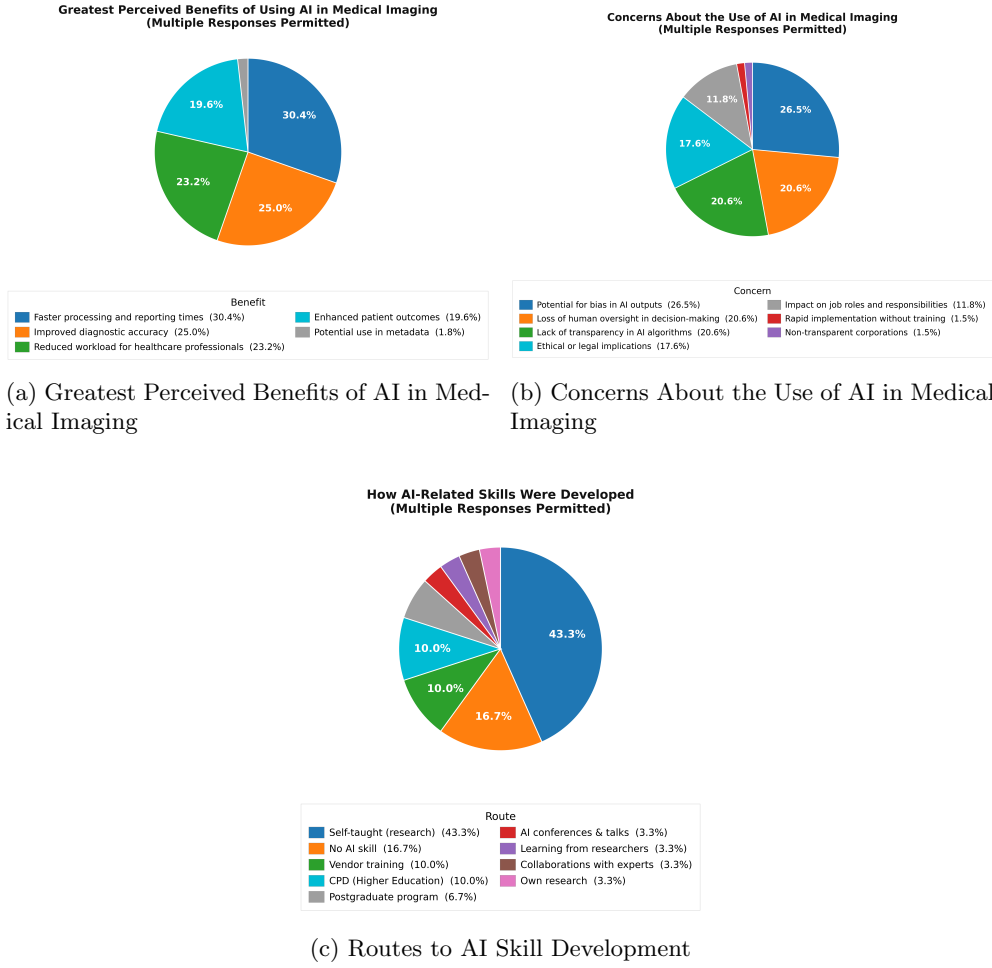
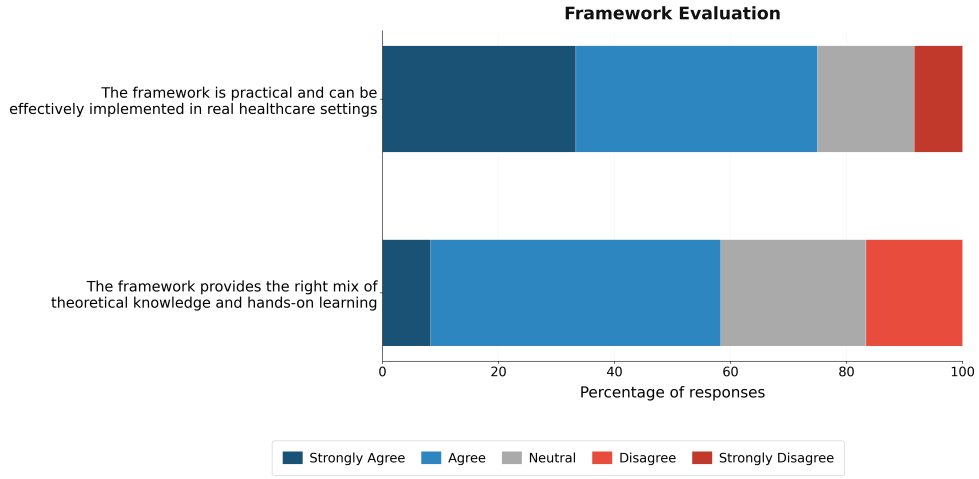


Fig. 5: Survey 1 perceived benefits, concerns, and skill development routes: (a) greatest perceived benefits of using AI in medical imaging (multiple responses permitted); (b) concerns about the use of AI in medical imaging (multiple responses permitted); (c) routes through which respondents developed AI-related skills for use in medical practice (multiple responses permitted).

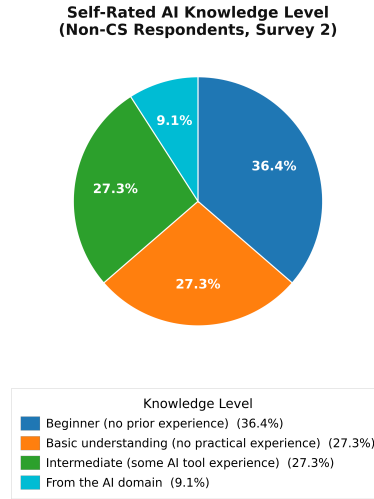
levels (Figure 6b) ranged from beginner to intermediate, with beginners and those with only basic understanding forming the largest groups.

4.2.2 Pathway interest and reasons for attendance

Figure 7a shows high levels of interest in both the AI Literacy and AI in Medical Imaging courses, with a majority reporting that they were very interested. As illustrated in Figure 7b, the AI Proficiency Pathway attracted the strongest preference, followed by



(a) Framework evaluation: perceived practicality and theory–practice balance



(b) Self-rated AI knowledge level among non-CS respondents

Fig. 6: Survey 2 framework reception and baseline AI knowledge: (a) perceived practicality and theory–practice balance of the proposed framework; (b) self-rated AI knowledge level among non-computing respondents.

AI Literacy, AI Policy and Governance, and the advanced data science pathway. The leading motivations for attendance (Figure 7c) were to understand how AI is applied in healthcare, to improve the ability to evaluate AI tools, and to address ethical and regulatory concerns, each endorsed by around three quarters of respondents.

4.2.3 Preferred formats, activities, and settings

As shown in Figure 8a, hybrid delivery was the most preferred format, followed by in-person workshops and self-paced online modules. Figure 8b indicates that weekly sessions and self-paced learning with optional live sessions were viewed as the most practical course settings. Learning activity preferences (Figure 8c) favoured lectures and expert talks and hands-on AI tool demonstrations, with case studies and group discussions also frequently selected.

4.2.4 Barriers and enabling factors

Figure 8d highlights lack of time as the dominant barrier to enrolment, with lack of prerequisite knowledge and unclear relevance to specific roles also commonly cited. As shown in Figure 8e, CPD accreditation and flexible scheduling were the most powerful enrolment motivators, followed by practical case studies and opportunities for networking and discussion.

4.2.5 Open-ended priorities and AI challenges

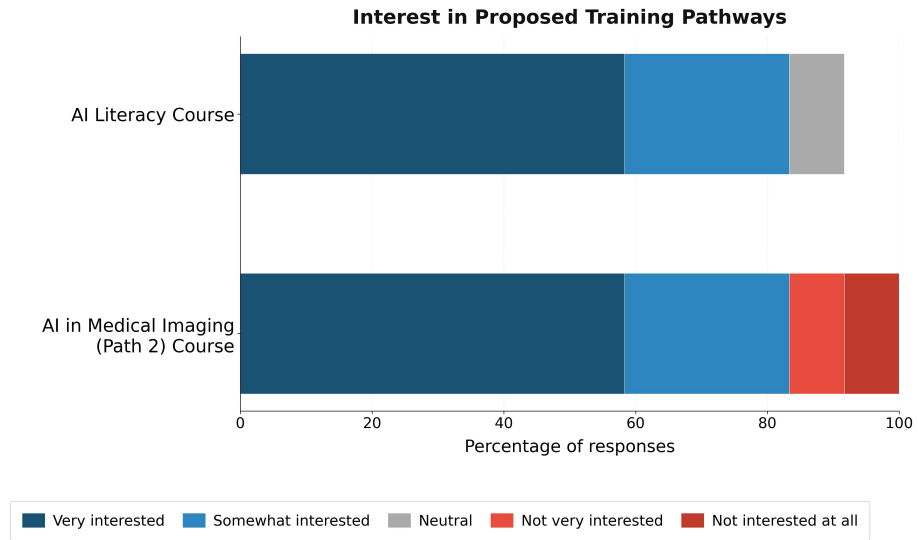
Open-text responses highlighted priorities such as integrating disparate AI tools into existing clinical and IT infrastructures, ensuring ethical and responsible use, optimising AI workflows, and addressing subspecialty needs. Participants also emphasised system-level constraints, including variable readiness and resourcing across hospitals, underscoring the importance of education that addresses both individual competence and organisational conditions for AI implementation.

4.3 Results of Course Delivery and Impact Evaluation

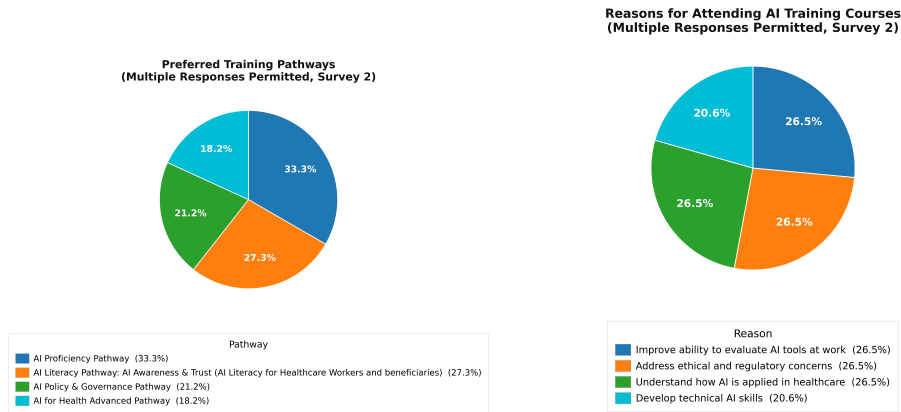
4.3.1 AI Literacy in Healthcare: Changes in Knowledge, Ethics, and Practice Readiness

Participant Characteristics

The AI Literacy in Healthcare course attracted a broad multidisciplinary cohort. As illustrated in Figure 9a, the 132 pre-course respondents were predominantly professionals in other healthcare-related roles (65.2%), followed by clinicians (23.5%), individuals not in healthcare (6.8%), and radiologists (4.5%). Figure 9b shows that the large majority had received no formal AI training prior to the course (87.1%), and Figure 9c indicates that AI tool exposure was mixed: 47.7% had used or been involved with AI tools in their professional role, 37.9% had not, and 14.4% were unsure.



(a) Interest levels in the proposed AI training pathways

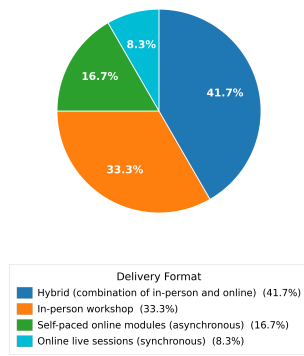


(b) Preferred training pathways to join

(c) Reasons for attending AI training courses

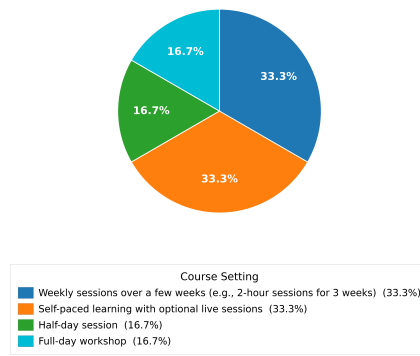
Fig. 7: Survey 2 pathway interest and attendance motivations: (a) interest in the AI Literacy and AI in Medical Imaging courses; (b) preferred training pathways to join (multiple responses permitted); (c) main reasons for attending AI training courses (multiple responses permitted).

Preferred Mode of AI Training Delivery Format (Survey 2)



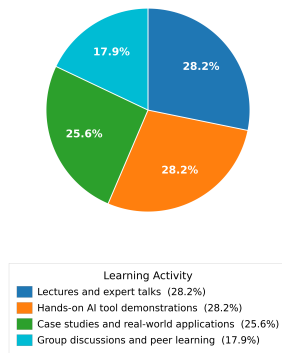
(a) Preferred training delivery format

Preferred Course Settings (Survey 2)



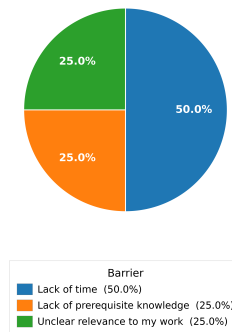
(b) Preferred course settings

Preferred Learning Activities (Multiple Responses Permitted, Survey 2)



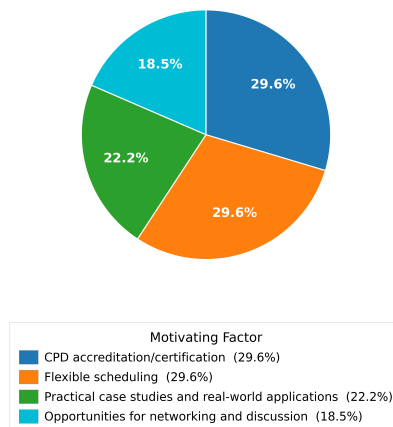
(c) Preferred learning activities

Barriers to Enrolment in AI Training (Multiple Responses Permitted, Survey 2)



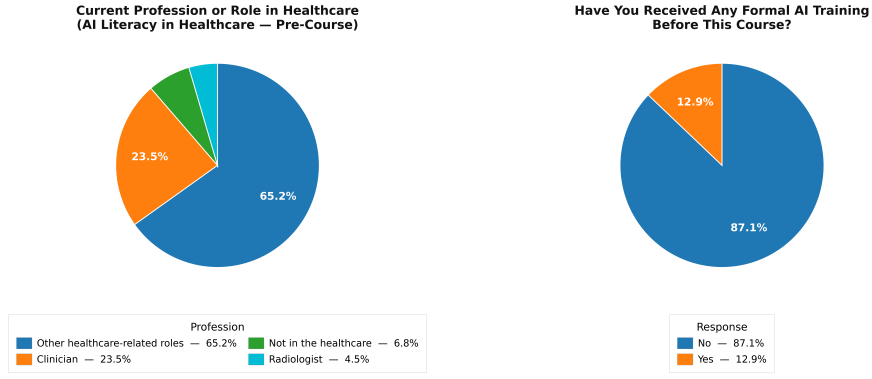
(d) Barriers to enrolment

Factors Encouraging Enrolment in AI Training (Multiple Responses Permitted, Survey 2)



(e) Factors encouraging enrolment

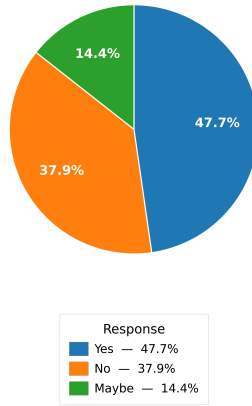
Fig. 8: Survey 2 training preferences and enrolment factors: (a) preferred mode of AI training delivery; (b) preferred course settings; (c) preferred learning activities (multiple responses permitted); (d) barriers to enrolment (multiple responses permitted); (e) factors encouraging enrolment (multiple responses permitted).



(a) Professional role distribution

(b) Prior formal AI training

Have You Ever Used or Been Involved with AI Tools or Systems in Your Professional Role?



(c) Prior involvement with AI tools or systems

Fig. 9: AI Literacy in Healthcare course, pre-course participant characteristics: (a) current profession or role in healthcare; (b) whether participants had received any formal AI training prior to the course; (c) prior use of or Involvement with AI tools or systems in a professional role.

Preparedness for AI in Professional Practice

Pre-post survey data from 132 pre-course and 59 post-course respondents showed consistent upward shifts across all items in the *AI in Professional Practice* domain. Participants reported feeling better prepared to deal with AI-driven changes in their field, more interested in applying AI knowledge to their practice, and more aware of the risks of using AI tools without appropriate understanding. Gains were largest for feeling “well prepared to deal with AI-driven changes” and for intentions to apply

course learning in practice, with smaller but still positive shifts in beliefs that healthcare professionals need foundational AI literacy and that AI can improve healthcare delivery.

Because pre- and post-course samples were not individually matched and ratings are self-reported, these results should be interpreted as indicative of short-term perceived change rather than definitive evidence of competence gains. Taken together, however, Figure 10 suggests that the course strengthened participants’ sense of readiness and attitudes towards AI in professional practice.

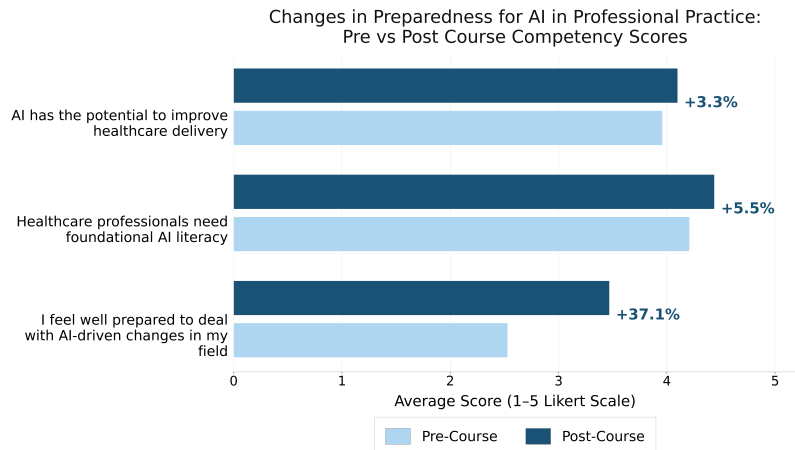


Fig. 10: Pre- to post-course score changes in the domain *AI in Professional Practice*.

Foundational AI Literacy Concepts

Substantial pre–post improvements were observed across all items capturing foundational AI literacy. Participants reported greater confidence in explaining core AI concepts (for example, the meaning of “black box” AI [23]), distinguishing rule-based from machine learning systems, and describing in broad terms how healthcare AI models are trained, validated, and tested. They also reported being better able to differentiate between AI applications that are already in routine use and those that remain experimental, and to articulate how bias can emerge in AI systems through data, model design, and deployment choices [24].

Figure 11 illustrates that these shifts were consistent across individual items rather than driven by a single question, supporting the interpretation that the course helped establish a shared conceptual vocabulary and baseline understanding needed for meaningful participation in AI-related discussions.

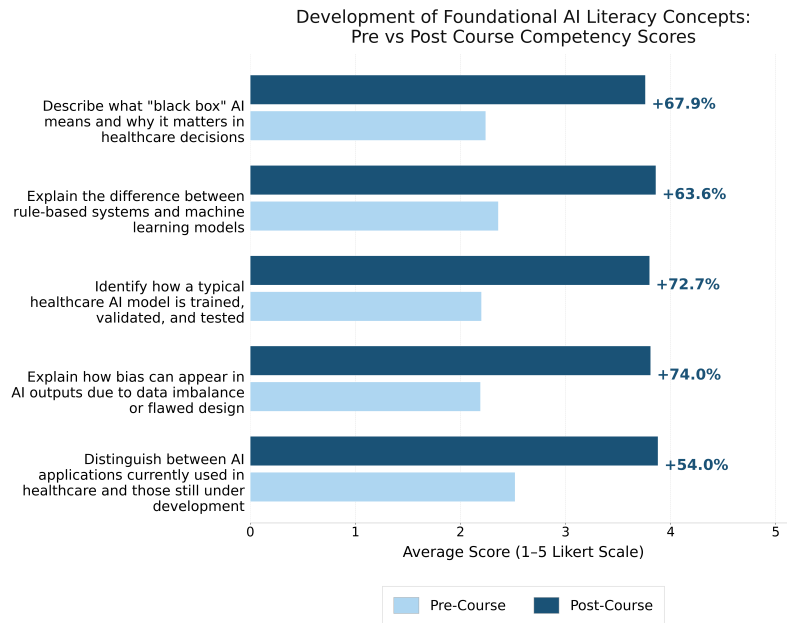


Fig. 11: Pre- to post-course score changes in the domain *Foundational AI Literacy Concepts*.

Ethics, Risk, and Responsible AI Awareness

Participants also reported notable gains in ethics, risk, and responsible AI awareness. Post-course ratings indicated improved confidence in describing risks and limitations of AI in clinical and operational tasks, explaining why human oversight is essential, and reflecting on potential impacts of AI on patients, colleagues, and wider society. Self-reported ability to recognise ethical issues such as fairness, bias, and discrimination, and to appreciate the importance of data privacy and security, also increased.

Across items in this domain, relative improvements between pre- and post-course mean scores ranged from 33.91% to 51.64%, indicating a substantial perceived strengthening of ethical and risk-related understanding (Figure 12). These findings suggest that the course did not only convey technical concepts but also foregrounded responsible AI principles, aligning with calls for governance-aware AI education in healthcare.

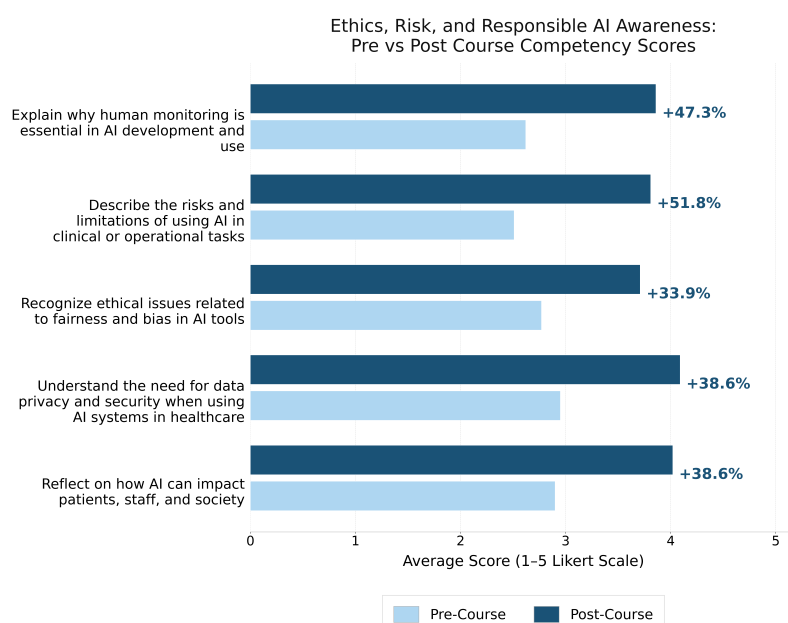


Fig. 12: Pre- to post-course score changes in the domain of Ethics, Risk, and Responsible AI Awareness.

Practical Application and Workplace Implementation

Pre-post comparisons in the *Practical Application and Workplace Implementation* domain showed smaller but still positive gains. Participants reported increased confidence in judging when clinical or operational problems might benefit from AI, in engaging colleagues in conversations about AI implementation, and in critically considering the impact of AI tools on their roles and services. They also indicated feeling more able to recognise AI-supported technologies in their workplace and to experiment with prompt engineering when using generative AI systems.

As shown in Figure 13, effect sizes in this domain were more modest than for foundational concepts and ethics, which is consistent with the course's emphasis on literacy and critical appraisal rather than hands-on system configuration or deployment. Nonetheless, the direction of change suggests early translation of conceptual gains into workplace-oriented confidence and intentions.

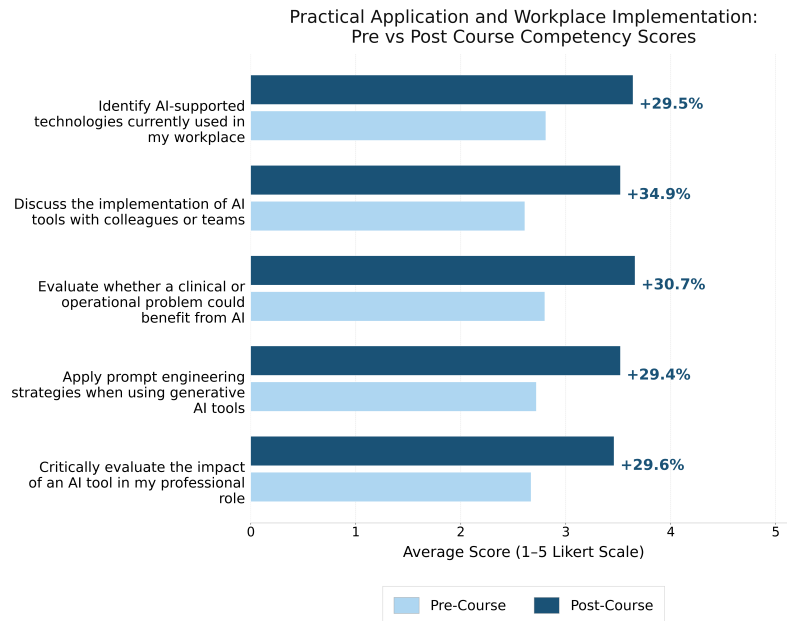


Fig. 13: Pre- to post-course score changes in the domain *Practical Application and Workplace Implementation*.

Intended Practice Changes: Post-Course Open-Ended Responses

To explore the anticipated impact of the AI literacy course on real-world practice, participants were invited to describe specific changes they planned to make in their work. All 59 post-course respondents provided a free-text response, of which 23 (39%) explicitly referenced AI, AI tools, or AI-enabled processes. Thematic analysis of these AI-related responses identified five main areas of intended change:

- **AI tools and applications** – plans to trial or make more systematic use of AI tools, deepen understanding of underlying models, and adopt more structured approaches to AI evaluation.
- **Data and training infrastructure** – intentions to improve data quality, explore data-sharing or synthetic data options, and engage more critically with how training data are sourced and curated.
- **Applications in day-to-day practice** – examples of using AI or large language models to support documentation, information retrieval, clinical decision support, or service improvement projects.
- **Clinical and specialty-specific needs** – interest in applying AI concepts to particular specialties (e.g. primary care, imaging-adjacent pathways) and to multidisciplinary planning of services.

- **Governance and regulation** – commitments to more responsible use of AI, including greater attention to safety, bias, accountability, and organisational policies when considering new tools.

These themes suggest that, for a substantial subset of participants, the course shifted AI literacy from abstract interest towards concrete, role-specific intentions for change in their clinical or organisational practice.

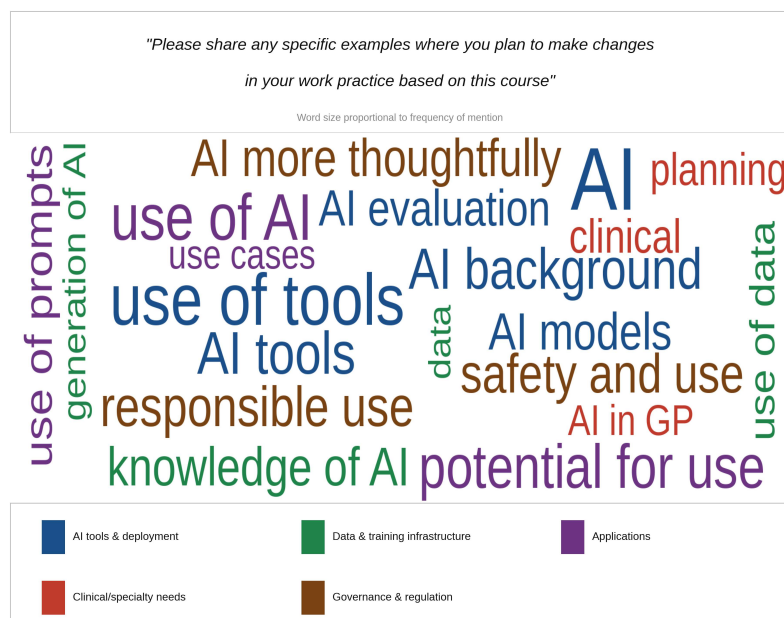
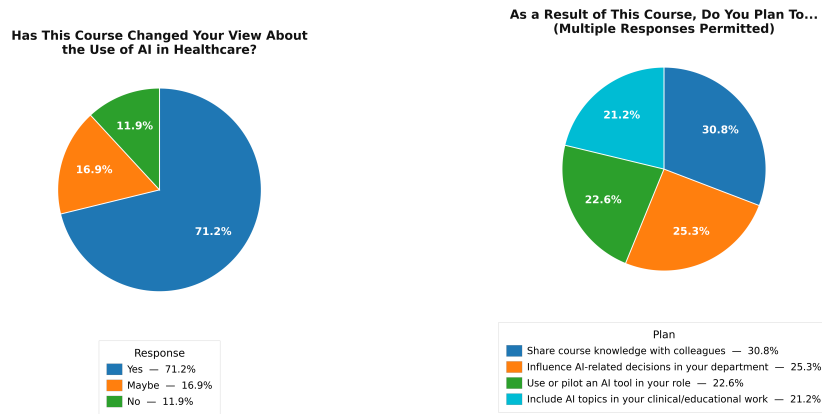


Fig. 14: Word cloud of open-ended post-course responses to the question: "Please share any specific examples where you plan to make changes in your work practice based on this course."

Perceived Impact and Intended Actions

Post-course responses further indicated a positive shift in participants' broader attitudes towards AI. As shown in Figure 15a, the majority of post-course respondents (71.2%) reported that the course had changed their view about the use of AI in healthcare, with a further 16.9% indicating a possible change. Only 11.9% reported no change. Figure 15b illustrates the range of concrete actions participants planned to take following the course: sharing knowledge with colleagues was the most frequently selected intention, followed by using or piloting an AI tool in their role, influencing AI-related decisions in their department, and including AI topics in clinical or educational work. Collectively, these responses indicate that the course not only strengthened conceptual understanding but also generated actionable intentions, suggesting early translation of course content into professional commitments.



(a) Has this course changed your view about the use of AI in healthcare? (b) Planned actions as a result of the course

Fig. 15: AI Literacy in Healthcare course, post-course impact: (a) whether the course changed participants' views about the use of AI in healthcare, with the majority reporting a positive shift; (b) concrete actions participants planned to take following the course (multiple responses permitted).

Summary of AI Literacy Course Impact

Across all four domains—professional preparedness, foundational concepts, ethics and risk, and workplace application—group-level pre–post comparisons indicate short-term improvements in self-reported knowledge, confidence, and intentions among course participants. The largest gains were observed in foundational AI literacy and ethical/risk understanding, with moderate but positive gains in practice-oriented items (Figure 16). Given the non-matched samples and reliance on self-report, these findings are best interpreted as evidence that the AI Literacy in Healthcare course successfully enhanced perceived capability and readiness to engage with AI, while highlighting the need for future work using objective assessments and longitudinal follow-up to examine sustained competence and behaviour change.

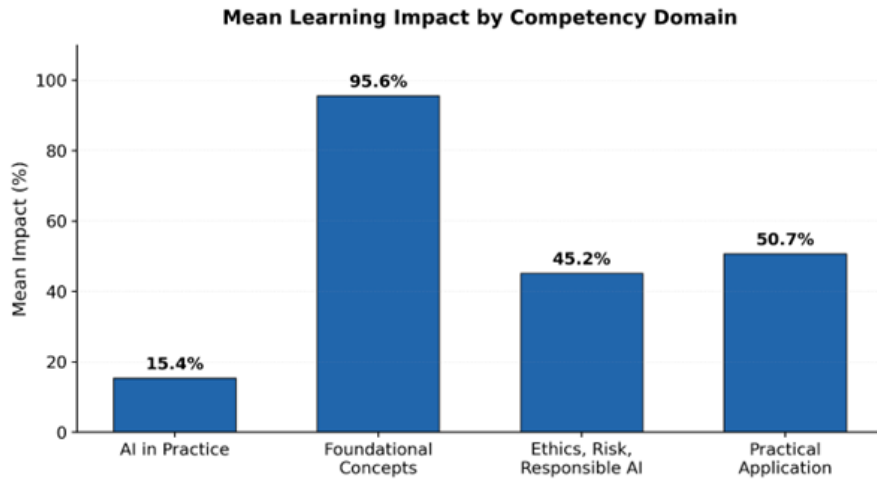


Fig. 16: Mean percentage learning impact by competency domain: AI Literacy in Healthcare course.

4.3.2 AI in Medical Imaging: Changes in Perception and Domain-Specific Understanding

Participant Characteristics

The AI in Medical Imaging course attracted a more specialist cohort of 26 pre-course respondents. As shown in Figure 17a, the largest group comprised professionals in other healthcare-related roles (53.8%), followed by clinicians (26.9%), radiologists (11.5%), and individuals not in healthcare (7.7%). Figure 17b shows that almost all participants had received no formal AI in Medical Imaging training prior to the course (92.3%), consistent with the limited availability of specialist imaging AI education identified in the literature. As illustrated in Figure 17c, prior engagement with AI tools was more evenly distributed than in the literacy cohort, with 42.3% having used or been involved with AI systems, 30.8% not having done so, and 26.9% unsure.

Changes in perception of AI in medical imaging practice

Pre-post survey data from 26 pre-course and 30 post-course respondents indicated more positive and nuanced views of AI in imaging practice following the AI in Medical Imaging course. Mean agreement that AI can significantly improve diagnostic accuracy in radiology and that healthcare professionals need foundational AI literacy was high at baseline and increased further after the course (both +0.40 on a 1–5 scale, approximately 9–10% relative gain). Perceived preparedness to deal with AI-driven changes in the field showed a larger shift, with the mean score increasing from 2.88 to 3.67 (+0.78; around 27% relative improvement), suggesting greater confidence in adapting to AI-enabled workflows.

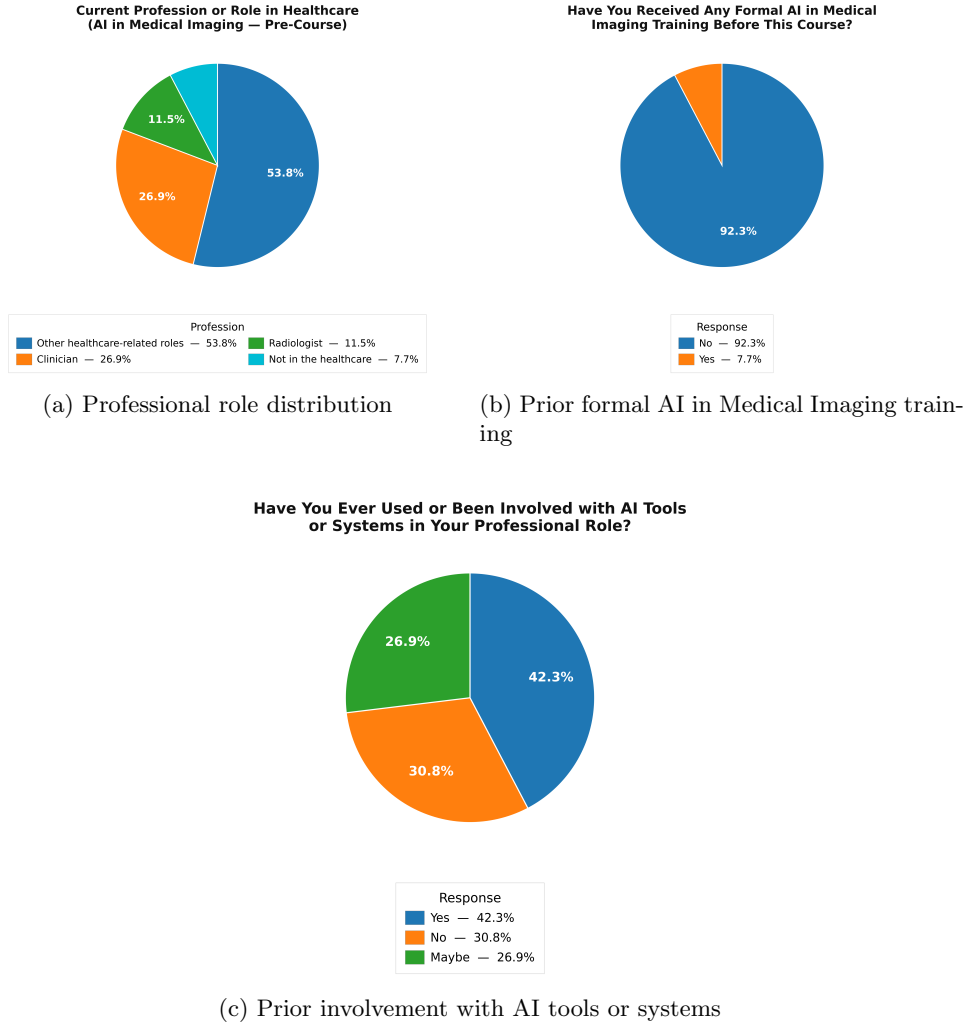


Fig. 17: AI in Medical Imaging course, pre-course participant characteristics: (a) current profession or role in healthcare; (b) whether participants had received any formal AI in Medical Imaging training prior to the course; (c) prior use of or involvement with AI tools or systems in a professional role.

Ratings for the statement that “there are significant risks in using AI tools in medical imaging without proper understanding” also increased (from 4.23 to 4.63), indicating heightened awareness of the need for informed, cautious adoption. Interest in applying AI knowledge to medical imaging practice remained high overall, with only minor change pre–post, consistent with a ceiling effect rather than lack of impact.

Collectively, these patterns, summarised in Figure 18, suggest that the course supported a more informed and balanced stance towards AI—maintaining enthusiasm while sharpening awareness of associated risks and training needs.

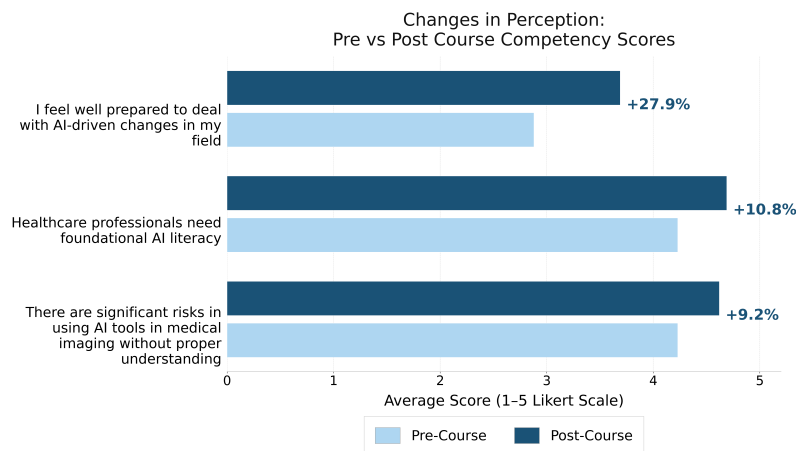


Fig. 18: Pre- to post-course changes in participants’ perceptions of the role of AI in medical imaging practice.

Changes in domain-specific understanding of AI in medical imaging

Larger gains were observed for items capturing imaging-specific AI understanding. The greatest improvement was in understanding how imaging AI models are trained and validated, where the mean score increased from 2.27 to 3.90 (+1.63; approximately 72% relative gain). Participants also reported markedly better ability to interpret AI model outputs in clinical imaging (from 2.04 to 3.30; +1.26, around 62%), to describe AI use cases in diagnostic imaging (from 2.31 to 3.60; +1.29, about 57%), and to explain the concept of explainable AI in medical imaging (from 2.38 to 3.83; +1.45, about 61%) [25]. Awareness of how bias can enter AI systems via datasets or model design similarly increased (from 2.65 to 4.07; +1.41, about 53%).

Taken together (Figure 19), these results show that the specialist course substantially strengthened domain-specific understanding, moving participants from predominantly “disagree/neutral” responses towards “agree” on key items related to training, validation, interpretation, explainability, and bias in imaging AI. As with the AI literacy course, these findings are based on non-matched, self-reported ratings and therefore provide evidence of perceived learning rather than objective competence gains, but the size and consistency of the shifts across items are encouraging.

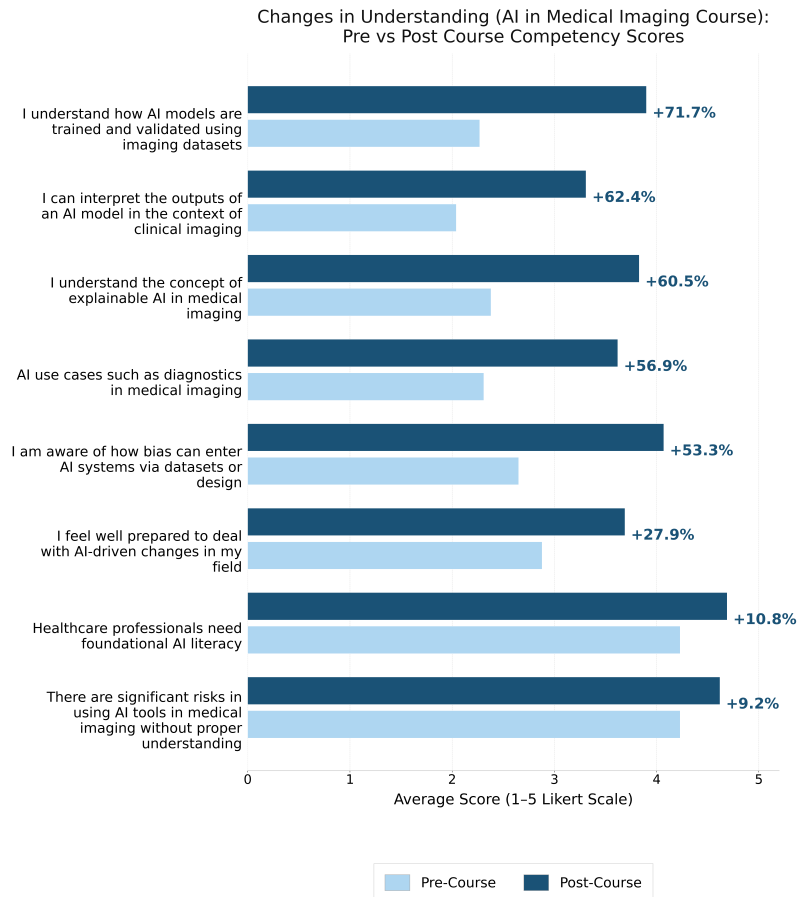


Fig. 19: Pre- to post-course changes in participants' domain-specific understanding of AI applications in medical imaging.

Intended application of learning: post-course open-ended responses

To understand how participants planned to translate their learning into practice, the post-course survey asked, "How do you intend to apply what you've learned from this course in your work?" All 30 respondents provided a free-text response, with 14 (47%) explicitly referencing AI tools, models, or imaging workflows. Thematic analysis of these AI-related responses identified four main areas of intended application:

- **AI tools and knowledge** – plans to explore, evaluate, or more systematically use AI tools in imaging, and to deepen understanding of underlying models and performance metrics.

- **Clinical and medical imaging applications** – intentions to apply course concepts to image interpretation, triage, workflow optimisation, and collaboration with radiology or imaging teams.
- **Enhanced understanding of AI and prompts** – using improved conceptual knowledge and prompt-engineering techniques to interact more effectively with AI systems, including generative models used for reporting support or education.
- **Clinical and specialty needs** – examples of embedding AI thinking into service development, quality improvement, and subspecialty planning (e.g. adapting content for particular imaging modalities or clinical pathways).

These themes, illustrated in the word cloud in Figure 20, indicate that the course helped participants move from passive awareness towards concrete, role-specific plans for AI integration within medical imaging contexts.

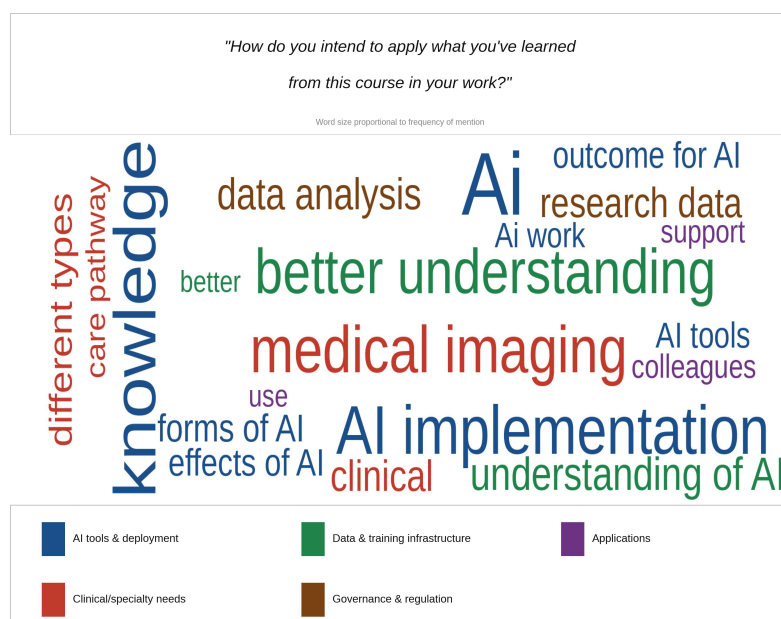


Fig. 20: Word cloud of open-ended post-course responses to the question: “How do you intend to apply what you’ve learned from this course in your work?”

Perceived Impact and Trust

Post-course responses from the AI in Medical Imaging course indicated strong positive shifts in participants’ views and professional confidence. As shown in Figure 21a, 73.3% of post-course respondents reported that the course had changed their view about the use of AI in medical imaging, with 6.7% indicating a possible change and 20.0% reporting no change. These proportions are consistent with the quantitative pre–post

gains reported above and suggest that domain-specific instruction was effective in reshaping attitudes alongside knowledge.

Figure 21b further shows that the course had a meaningful effect on participants' trust in AI solutions in medical imaging: 60.0% reported increased trust, 30.0% indicated a possible improvement, and only 10.0% reported no change. This pattern aligns with the framework's emphasis on fostering appropriate confidence, grounded in critical understanding rather than uncritical acceptance, and suggests that the specialist course successfully reinforced both capability and calibrated professional judgement regarding AI-enabled imaging tools.

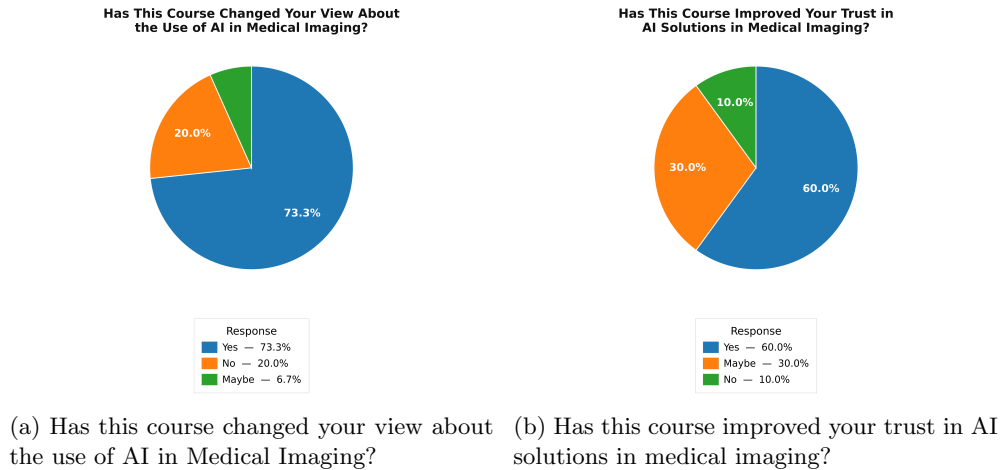


Fig. 21: AI in Medical Imaging course, post-course perceived impact: (a) whether the course changed participants' views about AI in medical imaging, with the large majority reporting a positive shift; (b) whether the course improved participants' trust in AI solutions in medical imaging, indicating that the course supported appropriate confidence rather than uncritical acceptance.

Summary of AI in Medical Imaging Course Impact

Overall, the AI in Medical Imaging course led to clear improvements in both perceptions of AI use in imaging and self-reported understanding of imaging-specific AI concepts (Figure 22). The largest relative gains were seen in items related to model training and validation, interpretation of outputs, explainable AI, and bias, aligning with the course's applied focus. Compared with the AI Literacy in Healthcare course, these findings suggest that the imaging course delivered more concentrated gains in domain-specific knowledge and confidence, complementing the broader foundational literacy developed in the general pathway. Future work using objective assessments and longitudinal follow-up will be important to determine how far these perceived

gains translate into sustained practice change and safer, more effective use of AI in medical imaging.

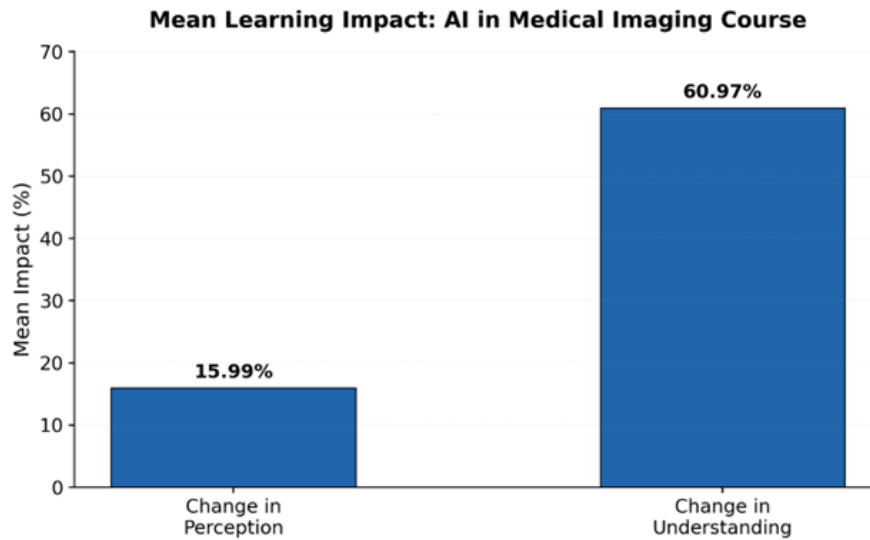


Fig. 22: Mean percentage learning impact: AI in Medical Imaging course.

5 Discussion

This study demonstrates that a co-designed, role-specific educational framework can address widely documented gaps in AI literacy across healthcare and medical imaging practice. By integrating stakeholder engagement, structured framework development, and evaluation through CPD delivery, the findings provide practical and empirical evidence on how AI education can be aligned with real-world professional needs and implementation challenges. Across all three phases, the results show a coherent progression from identifying need through co-design to measurable short-term educational impact. While the reliance on self-reported outcomes and non-matched pre-post samples limits claims regarding sustained competence or behavioural change, the findings offer important insight into how healthcare professionals perceive their readiness to engage with AI following targeted educational interventions.

5.1 Co-design and role-specific educational needs

The co-design phase reinforces existing evidence that healthcare professionals often feel underprepared to engage with AI-enabled systems [2, 10]. However, this study extends prior work by demonstrating that these gaps are not uniform across the workforce, but instead vary according to professional role, responsibilities, and proximity to AI implementation. Participants consistently emphasised the need for practical relevance,

ethical awareness, and clarity around governance and accountability, highlighting limitations in generic AI education approaches that fail to reflect the complexity of real-world clinical environments [2, 13].

The diversity of challenges identified—including AI tools and deployment, data infrastructure, governance and regulation, and specialty-specific applications—illustrates that AI capability in healthcare is inherently multidimensional. This reinforces the argument that effective AI education must integrate technical understanding with organisational, ethical, and clinical considerations, rather than treating these domains in isolation. The strong support for the co-designed framework further suggests that involving healthcare professionals directly in educational design enhances both perceived relevance and feasibility, supporting findings from participatory design literature [17, 18].

Importantly, preferences for hybrid delivery formats, shorter sessions, and interactive, hands-on approaches demonstrate that educational design must account for the operational realities of healthcare environments. These findings align with broader trends in health professions education, which emphasise flexibility, contextual relevance, and practice-oriented learning as essential for effective continuing professional development.

5.2 AI Literacy in Healthcare: Integrated outcomes and interpretation

The AI Literacy in Healthcare course produced consistent improvements across foundational knowledge, ethical awareness, and perceived preparedness for practice. The largest gains were observed in conceptual understanding, including key principles such as “black box” AI, model development and validation, and sources of bias. These improvements suggest that the course effectively addressed foundational knowledge gaps and established a shared conceptual baseline, which is widely recognised as necessary for meaningful engagement with AI in healthcare [1, 19].

Gains in ethical and responsible AI awareness were also substantial, indicating that participants not only developed technical understanding but also increased their awareness of issues such as data privacy, human oversight, and societal impact. This is particularly important given concerns in the literature that AI education may overemphasise technical capabilities at the expense of ethical and governance considerations. The findings suggest that embedding these elements within foundational training can support a more balanced and responsible approach to AI adoption.

Improvements in perceived preparedness and practical application were more moderate, reflecting the inherent challenge of translating conceptual knowledge into workplace competence within a short educational intervention. However, qualitative findings provide important insight into this transition. Participants described intentions to apply AI in practice through the use of AI tools, engagement with data and workflows, and increased attention to governance and regulatory considerations. These responses suggest that the course supported an early shift from passive awareness towards active, role-relevant engagement with AI.

The prominence of governance, safety, and responsible use within qualitative responses is particularly notable. It indicates that participants were beginning to

situate AI within broader professional responsibilities, including patient safety and organisational accountability. Taken together, these findings support the interpretation that the course functioned effectively as an entry-level pathway, establishing foundational knowledge and enabling participants to engage more critically and constructively with AI in their professional contexts. This aligns with recommendations that foundational AI literacy should serve as a basis for ongoing, progressive learning rather than a standalone educational endpoint [13].

5.3 AI in Medical Imaging: Integrated outcomes and role-specific impact

The AI in Medical Imaging course demonstrated a different but complementary pattern of outcomes, reflecting its specialist focus and audience. Substantial improvements were observed in domain-specific competencies, including understanding model training and validation, interpreting AI outputs in clinical contexts, explainable AI, and sources of bias. These findings indicate that the course successfully addressed more advanced, application-oriented knowledge required for integrating AI into imaging practice.

Changes in perception and preparedness were more moderate, which may reflect higher baseline familiarity and motivation among participants in this cohort. Unlike the broader healthcare group, imaging professionals are more likely to encounter AI systems directly in their workflows, which may explain both their initial interest and the nature of their learning gains.

Qualitative findings provide further evidence of this shift towards applied understanding. Participants described concrete intentions to integrate AI into imaging workflows, evaluate AI tools, and engage with implementation challenges such as data analysis and system integration. These responses suggest movement beyond conceptual understanding towards practical and operational thinking, which is essential for meaningful adoption of AI in clinical settings.

The contrast between the two courses highlights the importance of role-specific and staged educational pathways. While the foundational course supports broad awareness and critical engagement, the specialist course enables deeper, practice-oriented competence. Together, these findings provide empirical support for a tiered model of AI education, where different levels of training are aligned with professional roles and responsibilities.

5.4 From trust to appropriate confidence and professional accountability

Across both courses, participants demonstrated increased awareness of both the capabilities and limitations of AI. Improvements were observed not only in confidence but also in recognition of risks, bias, and the importance of human oversight. This supports a growing shift in the literature from promoting trust in AI towards fostering appropriate confidence [14, 24].

In this context, trust should not be understood as uncritical acceptance of AI-generated outputs, but as calibrated, knowledge-informed professional judgement. The

findings suggest that education which integrates technical, ethical, and governance dimensions can support this form of critical engagement. Participants appeared more willing to question AI outputs, consider limitations, and recognise their own role in oversight and decision-making.

Framing AI literacy as a safety-related competence may be particularly valuable. As AI becomes embedded within clinical workflows, the ability to interpret outputs, understand limitations, and apply professional judgement becomes integral to patient safety. This perspective positions AI literacy alongside other core competencies, such as safe prescribing or infection control, reinforcing its importance within clinical practice.

5.5 Educational and implementation implications

This study contributes to a growing body of literature by demonstrating how co-designed AI education frameworks can be operationalised and evaluated in practice. While many existing studies focus on attitudes or theoretical curricula, this work provides empirical evidence of implementation within a CPD context and highlights the value of aligning educational design with stakeholder needs.

Several key design principles emerge. First, role-specific pathways allow educational content to be tailored to different professional groups, ensuring relevance while avoiding unnecessary complexity. Second, embedding ethics, governance, and human oversight as core components ensures that AI education aligns with regulatory requirements and patient safety priorities. Third, flexible and modular delivery formats appear essential for participation within time-constrained healthcare environments.

These findings suggest that scalable AI education should move beyond one-size-fits-all approaches and instead adopt structured, progressive pathways that support development from foundational literacy to specialist competence and, ultimately, strategic and governance-level understanding.

5.6 Limitations

Several limitations should be acknowledged. The evaluation relied on self-reported measures, which may be subject to response bias and do not directly assess objective competence or behavioural change. Pre- and post-course responses were not fully matched at the individual level, limiting the ability to attribute changes to specific participants. The study also focused on short-term outcomes, and it is not possible to determine whether observed improvements were sustained or translated into practice over time.

The study was conducted within a UK healthcare context, which may limit generalisability to other healthcare systems with different organisational structures, regulatory environments, or levels of AI adoption. In addition, the governance-level pathway of the framework was not implemented or evaluated, and sample sizes for the specialist course were relatively modest, with potential selection bias towards participants already interested in AI.

5.7 Future work

Future research should focus on evaluating longer-term outcomes, including sustained knowledge retention, behavioural change, and impact on clinical practice. Incorporating objective measures of competence, such as performance-based assessments or workplace-based evaluations, would strengthen the evidence base.

Extending the framework to additional clinical domains, including nursing, pharmacy, and allied health professions, would support broader workforce readiness. The governance pathway warrants dedicated evaluation, particularly in relation to organisational decision-making and AI adoption. Further work should also explore how different levels of training interact to influence system-level outcomes, including patient safety, service efficiency, and quality of care. International studies would help assess generalisability and identify context-specific adaptations required for wider implementation.

6 Conclusion

This paper demonstrates that a co-designed, tiered educational framework can meaningfully address the heterogeneous AI literacy and capability needs of healthcare and medical imaging professionals. By integrating stakeholder engagement, structured framework development, and empirical evaluation through CPD delivery, the study provides practical evidence that role-specific AI education can strengthen conceptual understanding, ethical awareness, and perceived readiness for AI-enabled practice across diverse professional groups.

The AI Literacy in Healthcare course produced substantial short-term improvements in foundational AI literacy and responsible AI awareness, alongside increased confidence in engaging with AI-driven change in clinical and operational settings. The AI in Medical Imaging course complemented these gains by delivering focused, domain-specific improvements in understanding model training and validation, interpreting AI outputs, explainable AI, and sources of bias—competencies that are directly relevant to safe, workflow-integrated AI use in imaging practice. Across both courses, participants reported not only greater confidence but also heightened recognition of risks, limitations, and governance requirements, consistent with the notion of appropriate confidence rather than uncritical trust in AI systems.

The proposed three-pathway framework—spanning foundational AI literacy, imaging-specific proficiency, and policy and governance—offers a clinically grounded and scalable structure that healthcare organisations and educators can adapt to their own contexts. It illustrates how AI education can be aligned with distinct professional responsibilities, from frontline use through to strategic oversight, and embedded within existing CPD structures.

As AI tools become increasingly embedded in diagnostic and operational workflows, the capacity to critically appraise outputs, recognise limitations, and exercise informed human oversight represents not merely a desirable skill set but a core component of professional accountability and patient safety. Building on the evidence presented here, future work will focus on implementing and evaluating the governance-level pathway, incorporating longitudinal and performance-based measures of competence

and behaviour change, and extending the framework to other clinical domains and international healthcare settings to test its transferability and system-level impact.

Declarations

Human Ethics and Consent to Participate

Ethical approval for this study was obtained from Aston University Engineering and Physical Sciences Ethics Committee (Approval Number: EPS21072) and the UK Health Research Authority (HRA) through the Integrated Research Application System (IRAS Project ID: 353193). All procedures involving human participants were conducted in accordance with relevant ethical guidelines and regulations, including the Declaration of Helsinki.

All participants were provided with a detailed participant information sheet outlining the purpose of the study, data usage, and confidentiality measures. Informed consent was obtained from all participants prior to participation. Participation was voluntary, and all survey responses were collected anonymously.

Conflicts of interest / Competing interests

The authors declare that they have no competing interests.

Availability of data and materials

The datasets generated and analysed during the current study consist of anonymised survey responses and workshop data collected from healthcare professionals as part of the evaluation of the proposed CPD framework. Due to ethical concerns, the data for this publication cannot be made available.

Funding

This work was supported by the UK Engineering and Physical Sciences Research Council (EPSRC) through the Impact Acceleration Account (IAA) at Aston University (Grant Number: B00-56647-UKRI Impact Acceleration Account).

Consent to participate

Informed consent was obtained from all participants prior to participation in the study.

Consent for publication

Not Applicable

Authors' contributions

S.F. and A.A. designed the study and contributed equally as joint first authors to the manuscript. S.F. and A.A. led the co-development of the educational framework,

with contributions from A.E. S.F. led the delivery of the CPD courses, with contribution from A.E. to one session within the AI literacy course. A.R., J.M., and B.B. contributed clinical expertise, supported the refinement of the CPD course content to ensure clinical relevance, and provided contextual guidance within the NHS Trust setting.

S.F. and A.A. led the ethical approval process, participant recruitment, feedback collection, and data analysis. S.F. and A.A. prepared the first draft of the manuscript. All authors contributed to the interpretation of the findings, critically reviewed and revised the manuscript, and approved the final version.

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Acknowledgements

The authors would like to thank all participants who contributed to the co-design workshop and CPD courses for their time, engagement, and valuable insights. The authors also thank Izsara Blake (Senior Programme Manager, West Midlands Imaging Network) for her valuable support in promoting the CPD course and facilitating dissemination across NHS networks, and we would like to thank the funder for this project. This work was supported by the Engineering and Physical Sciences Research Council (EPSRC) through the Impact Acceleration Account (IAA) at Aston University.

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