CONTINUING MEDICAL EDUCATION AS A WORKFORCE LEARNING SYSTEM FOR ARTIFICIAL INTELLIGENCE IN CLINICAL PRACTICE

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ABSTRACT

Artificial intelligence (AI) is increasingly embedded in clinical decision support, documentation, imaging, predictive analytics, and workflow management. However, the educational systems responsible for preparing practicing physicians to use AI have not fully addressed the interpretive, ethical, and organizational demands of AI-supported care. This qualitative case study examined how continuing medical education (CME) shapes physicians' readiness to integrate AI into clinical practice. Guided by the Unified Theory of Acceptance and Use of Technology (UTAUT) and human resource development (HRD), the study analyzed semi-structured interviews with 14 physicians from diverse specialties within a large academic health system. Organizational artifacts, including CME announcements, internal communications, and evaluation materials, were also examined to support triangulation. Findings indicate that CME was most influential when it framed AI as support for clinical attention rather than as decision authority, developed interpretive judgment, reinforced physician accountability, connected formal instruction to informal workplace learning, aligned with clinical workflow, and supported trust calibration over time. The study argues that AI-focused CME should be designed as a longitudinal organizational learning system rather than a discrete instructional event. Implications are offered for technology integration, faculty development, and organizational learning in clinical education.

KEYWORDS

Artificial intelligence; continuing medical education; technology integration; clinical education; UTAUT; human resource development; professional learning

1. INTRODUCTION

Artificial intelligence (AI) has moved from speculative promise to routine presence in healthcare environments. AI-enabled tools now support image interpretation, diagnostic reasoning, risk prediction, documentation, patient triage, surveillance, and treatment planning. These tools are technical additions to clinical work. And they reshape how clinicians attend to information, distribute responsibility, interpret evidence, and justify decisions [1,2]. There has been a central question on how AI fit into doctoral education [3] and for medical educators, the central question has evolved to how professional learning systems should prepare clinicians to use AI safely, ethically, and intelligently [4]. One promising way may continuing medical education (CME) as a workforce learning system.

CME is essential to AI integration because many practicing physicians completed their formal training before AI became a routine feature of clinical care. Although CME is often used to update clinical knowledge, satisfy licensure requirements, or introduce new procedures, AI requires a broader form of professional learning. Physicians must be prepared to interpret

probabilistic outputs, recognize model limitations, identify bias, communicate AI use transparently to patients, clarify accountability, and incorporate AI recommendations into clinical reasoning without displacing professional judgment. These demands extend beyond technical adoption; they position AI integration as both a technology-in-education challenge and a workforce learning challenge. Recent scholarship supports this view by showing that clinicians face AI-related ethical challenges that traditional medical ethics education does not fully address and that physician training must evolve across the continuum of medical education, including the continuing education of practicing physicians [5,6].

The present study examines CME for AI integration through the combined lenses of the Unified Theory of Acceptance and Use of Technology (UTAUT) and human resource development (HRD) to account for the dual nature of AI adoption in clinical practice. UTAUT anchors the technology-in-education dimension of the study by focusing on how physicians perceive and respond to AI as an emerging educational and clinical technology. Its constructs help explain whether physicians view AI as useful, usable, socially supported, and adequately resourced within their practice environments [7,8]. HRD anchors the workforce learning dimension by positioning CME as an organizational mechanism for developing physician competence, supporting adaptation, and aligning professional learning with institutional change [9]. This distinction is important because AI integration cannot be explained only by whether physicians accept or resist a technology. It also depends on whether healthcare organizations create the learning conditions, developmental supports, and performance systems needed for physicians to use AI responsibly [10]. And so, in this study, UTAUT frames the technology-in-education challenge, while HRD frames the workforce learning challenge. Together, they support an examination of CME as a bridge between AI adoption and physician workforce development.

The study was guided by two research questions: (a) How do physicians make sense of CME activities that address AI and the factors they perceive as influencing AI integration in clinical practice? and (b) How do CME structures, processes, and organizational conditions shape physicians' performance expectations, effort expectations, perceived social influences, and facilitating conditions regarding AI use in practice? By addressing these questions, the study reframes CME as an organizational learning system that mediates the relationship between educational technology and clinical practice.

2. REVIEW OF LITERATURE

AI has been widely studied as a clinical decision-support technology with potential to improve diagnostic accuracy, efficiency, and personalization of care. In medical education, however, AI raises a distinct set of challenges. For example, argued that AI can transform medical education but also requires attention to implementation, curriculum design, and the changing role of educators [11]. Other studies have similarly found that AI education for health professionals remains uneven, with many programs emphasizing conceptual awareness rather than applied competence [12]. This is problematic because safe AI use depends not merely on understanding what AI is, but on knowing how to interpret and contest AI outputs in clinical contexts [13].

Research on AI adoption in healthcare has identified persistent barriers, including mistrust, workflow disruption, lack of explainability, ethical uncertainty, and perceived threats to professional autonomy [14-16]. Ethical reviews have further emphasized concerns regarding fairness, privacy, transparency, accountability, and bias [17,18]. These issues are not peripheral to education. They are central learning demands. Physicians must be prepared to ask when AI is useful, when it is misleading, and how algorithmic outputs should be weighed against patient values and clinical experience.

CME research has shown that professional education can improve physician performance when instruction is interactive, relevant, and linked to practice [19] (Cervero & Gaines, 2015). Yet AI-focused CME can remain episodic, didactic, or tool-centered. Such approaches may introduce new terminology but fail to support the transfer of learning into complex clinical environments. HRD scholarship helps explain this limitation. Learning transfer depends on workplace support, opportunities for application, feedback, and organizational alignment [20]. Adult learners also require learning that is problem-centered, relevant to immediate responsibilities, and responsive to prior experience [21,22]. In AI-enabled clinical work, these principles suggest that CME should be case-based, workflow-embedded, interdisciplinary, and longitudinal.

UTAUT is useful because it organizes adoption-related beliefs into four constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions [8]. However, these constructs are often treated as individual attitudes that predict behavior. For AI-focused CME, they may be better understood as beliefs shaped by learning systems. CME can influence whether physicians perceive AI as clinically useful, whether AI feels manageable, whether peers and leaders legitimize its use, and whether organizational structures make responsible use possible. This study therefore uses UTAUT interpretively, not predictively, and integrates it with HRD to examine how professional education produces or constrains the conditions for AI integration.

3. CONCEPTUAL FRAMEWORK

The conceptual framework for the study integrates UTAUT with HRD to examine AI-focused CME as both a technology acceptance context and a professional learning system (Figure 1). This integration is important because AI adoption in clinical settings cannot be understood solely as a matter of individual preference. Physicians' decisions to use AI are shaped by perceived usefulness, perceived effort, peer and institutional norms, access to infrastructure, professional identity, and opportunities to practice judgment in real clinical conditions. UTAUT names the adoption-related domains, while HRD explains how those domains are produced through learning and organizational context.

Here, performance expectancy refers to how physicians come to understand AI's clinical value. The relevant issue is not whether AI is advertised as accurate, but whether physicians learn how AI can support attention, prioritization, diagnostic reasoning, or treatment planning without displacing accountability. Effort expectancy refers to the perceived cognitive, practical, and workflow demands of using AI. In AI-supported care, effort includes more than interface usability; it includes interpreting uncertainty, questioning outputs, documenting overrides, and communicating AI-informed decisions.

HRD adds an explanatory layer by treating CME as a mechanism of workforce development. From this perspective, physicians do not simply receive AI content and transfer it into practice. They interpret AI through experience, negotiate its implications for professional identity, and develop competence through formal and informal learning. The framework therefore positions CME as a mediating system that shapes expectations, effort, social legitimacy, and practical conditions for AI integration.

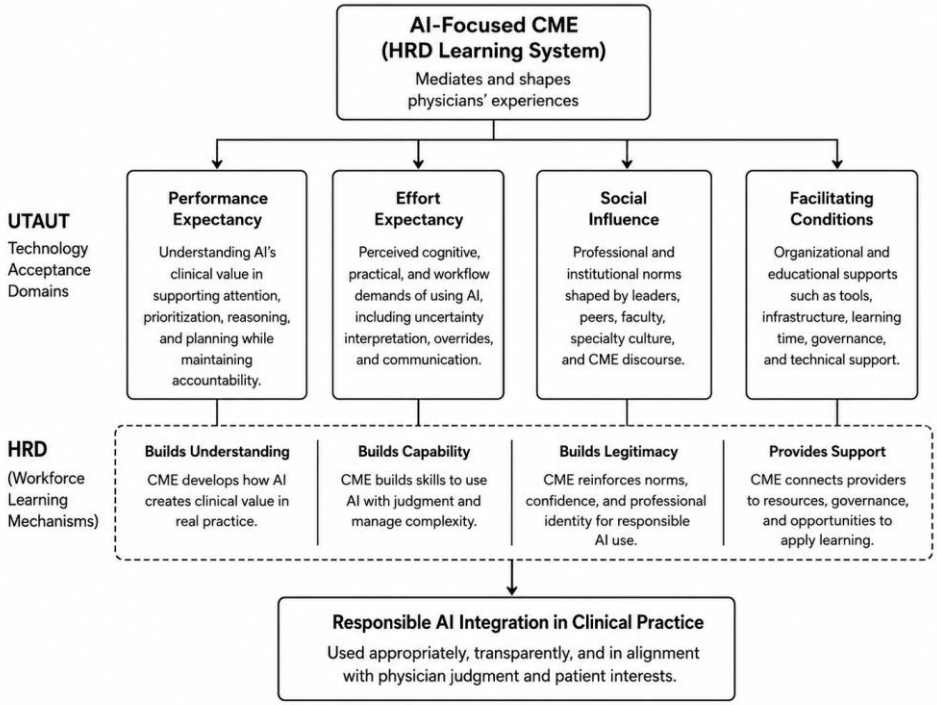

Figure 1. Integrated UTAUT-HRD framework for AI-focused continuing medical education and responsible ai integration in clinical practice

4. METHOD

The present article reports one component of a larger doctoral dissertation study [23]. The dissertation examined physician learning, continuing medical education, and artificial intelligence integration within a large academic health system. This manuscript focuses specifically on the portion of the dissertation concerned with AI-focused CME as both a technology acceptance context and a professional learning system.

The study used an interpretive qualitative case study design with a phenomenological orientation. The case was a large metropolitan academic health system in Texas with an established CME infrastructure and emerging AI-related educational activities. This design was appropriate because the inquiry examined a contemporary educational and organizational phenomenon within its real-world context and sought to understand how physicians interpreted AI-focused CME rather than measure adoption outcomes.

Participants were 14 practicing physicians representing diverse specialties (Table 1). Participants varied in years of practice and in their exposure to AI tools, including ambient documentation, monitoring systems, clinical decision support, image recognition, triage algorithms, population analytics, surveillance tools, risk modeling, and treatment-planning platforms. This variation allowed the study to examine AI-related CME across multiple clinical workflows and specialty contexts.

Data were collected through semi-structured interviews and organizational artifacts. Interviews focused on physicians' experiences with AI-related CME, perceptions of AI in clinical practice, perceived barriers and supports, ethical and professional concerns, informal learning, workflow alignment, and recommendations for CME design. Organizational artifacts included internal

emails, CME announcements, evaluation forms, and materials related to AI-focused professional education. These documents were analyzed to understand how the organization framed AI, what learning objectives were emphasized, and how formal messages aligned or diverged from physicians' lived experiences.

Analysis proceeded in three stages. First, transcripts were read repeatedly to identify meaning units close to participants' language. Initial open codes captured issues such as AI reshaping attention, informal learning, interpretive judgment, workflow burden, trust calibration, and accountability. Second, related codes were grouped into axial categories that described broader patterns in how CME influenced AI integration. Third, the resulting themes were interpreted through UTAUT and HRD concepts. This interpretive use of theory did not force data into predefined categories; instead, it clarified how empirically derived themes related to technology acceptance and workplace learning.

Trustworthiness was supported through triangulation across interviews and documents, analytic memoing, attention to discrepant cases, and preservation of participant language in theme development. Because the study focused on physician meaning-making rather than measurement of adoption behavior, the analysis emphasized the relationship between what physicians said they learned in CME, how they described applying or resisting AI in practice, and how organizational materials framed AI-related education. Ethical procedures included informed consent, de-identification of participants and the organization, secure storage of interview data, and reporting practices designed to prevent deductive disclosure in highly specialized roles.

Table 1. Participant characteristics and AI exposure context.

Participant	Gender	Primary Specialty	Years in Practice	Educational Involvement	AI Exposure or Use Context
P01	Female	Family Medicine	3	UME	Ambient AI documentation
P02	Female	Anesthesiology	14	GME	Monitoring systems
P03	Male	Cardiology	22	GME	Clinical decision support
P04	Male	Critical Care, Neonatal	12	UME	Real-time analytics
P05	Male	Dermatology	6	GME	Image recognition
P06	Female	Emergency Medicine	9	UME/GME	Triage algorithms
P07	Female	Endocrinology	11	GME	Population analytics
P08	Female	Geriatrics	20	UME	Limited AI exposure
P09	Male	Hospital Medicine	2	UME	Order-set guidance
P10	Female	Infectious Disease	17	GME	Surveillance tools
P11	Male	Nephrology	19	GME	Risk modeling
P12	Female	Psychiatry	18	UME	Limited or skeptical AI exposure
P13	Male	Radiology	5	GME	High AI integration
P14	Male	Oncology	13	GME	Treatment planning

UME = undergraduate medical education; GME = graduate medical education. AI = artificial intelligence.

5. FINDINGS

Seven interrelated themes explain how CME influenced AI integration in clinical practice. The themes show that physicians did not experience AI-focused CME as simple technical training. Instead, CME shaped how they interpreted AI's role, developed judgment, calibrated trust, and located professional responsibility within AI-supported workflows. The themes also show that AI-focused CME was never experienced apart from the clinical environment. Participants assessed CME through the lens of actual practice: whether the content matched the tools they used, whether the instruction accounted for workflow constraints, and whether it helped them act responsibly when AI recommendations were unclear or incomplete.

The first theme was that CME shaped how clinicians learned to use AI to support clinical attention rather than replace decisions. Physicians described AI as a tool that surfaces risks, prioritizes information, and prompts closer attention. When CME framed AI as attentional support, it helped preserve clinician agency. When CME presented AI as a tool to be followed, physicians reported more uncertainty about the proper relationship between algorithmic output and clinical judgment.

The second theme was that CME shaped the development of interpretive judgment for AI use. Participants emphasized that safe AI integration requires the ability to reason with AI outputs, especially when recommendations conflict with clinical intuition. Effective CME did not merely show physicians how a system worked; it gave them opportunities to interpret uncertain outputs, consider edge cases, and justify decisions. This type of learning was especially important because AI outputs are probabilistic and context-dependent.

The third theme was that CME reinforced professional accountability and clinical responsibility in AI-supported decisions. Participants repeatedly stated that responsibility remains with the physician. AI may inform, prompt, or organize information, but it does not carry liability or moral responsibility. CME was therefore important when it clarified documentation expectations, decision ownership, and ethical responsibility. When CME left these issues implicit, physicians relied on informal norms that varied by specialty and team.

The fourth theme was that CME interacted with informal and experiential learning to build competence for AI integration. Physicians often learned AI use through peer discussion, observation, case conferences, tumor boards, and practical experimentation. Formal CME functioned best when it supported this ongoing workplace learning by providing shared language, conceptual framing, and opportunities for follow-up. It functioned poorly when it attempted to replace experiential learning with one-time instruction.

The fifth theme was that misalignment between CME and clinical practice constrained effective AI integration. Participants described gaps between idealized CME scenarios and the realities of time pressure, alert fatigue, incomplete data, patient complexity, and team-based decision making. When CME did not simulate real clinical conditions, physicians found it less useful for practice. This misalignment increased cognitive burden and reduced the likelihood that learning would transfer into daily work.

The sixth theme was that CME influenced how trust in AI was developed and recalibrated over time. Trust was not static. Physicians described it as provisional, shaped by repeated use, model errors, institutional messaging, and peer interpretation. CME supported appropriate trust when it acknowledged model limitations, bias, false positives, false negatives, and the need for questioning. CME undermined trust when it emphasized performance claims without discussing uncertainty.

The seventh theme synthesized the preceding findings: effective CME built interpretive competence for AI use rather than tool compliance. Participants distinguished meaningful learning from checkbox training. They did not want CME that told them what to click or when to obey an alert. They wanted CME that strengthened professional reasoning with AI. In this sense, AI-focused CME was most valuable when it developed clinicians' ability to think with the tool, question the tool, explain the tool, and remain accountable for decisions.

Triangulation with organizational artifacts strengthened these findings. CME announcements often framed AI as decision support, which aligned with physicians' preference for augmentation rather than replacement. However, evaluation forms and follow-up communications revealed persistent requests for more specialty-specific cases, clearer guidance about liability, and more realistic instruction on workflow burdens such as alert fatigue. Internal communications also showed that much AI learning occurred after formal CME, through clarifications, peer exchanges, and problem solving during implementation. These documents confirmed that formal CME functioned as an entry point into AI integration, while sustained competence developed through ongoing organizational learning.

Table 2. Summary of themes for AI-focused CME.

Theme	Meaning for CME Design
AI as support for clinical attention	CME was effective when AI was framed as augmenting attention and prioritization rather than replacing decisions.
Interpretive judgment	Physicians needed opportunities to reason with probabilistic outputs, disagreement, and uncertainty.
Professional accountability	CME clarified that responsibility for AI-supported decisions remains with the clinician.
Informal and experiential learning	Formal CME worked best when connected to workplace learning, peer discussion, and real cases.
CME-practice alignment	Misalignment with workflow, alert fatigue, and time pressure reduced learning transfer.
Trust calibration	Trust in AI developed through repeated use, reflection, transparency, and attention to limitations.
Interpretive competence	The central goal of CME was not compliance with tools but competent judgment with tools.

5. FINDINGS

Figure 2 provides the interpretive structure for this discussion by showing how AI-focused CME operates at the intersection of three interrelated problems: an educational problem, an organizational problem, and a technology integration problem. The central claim of the study is that responsible AI integration in clinical practice is not achieved through tool exposure or technical instruction alone. Rather, it requires the development of interpretive competence: the physician's capacity to evaluate AI-generated information, situate that information within patient-specific clinical reasoning, recognize uncertainty and limitations, and remain accountable for decisions made in AI-supported environments. In this sense, AI-focused CME is not simply a mechanism for transferring information about AI. It is a professional learning system through which physicians learn how AI should and should not enter clinical judgment [24].

The findings therefore challenge a narrow conception of AI education as literacy, awareness, or procedural training. AI literacy remains necessary because physicians need basic knowledge of AI terminology, capabilities, risks, and limitations. However, the findings suggest that literacy is insufficient when physicians must make decisions under conditions of uncertainty, incomplete data, time pressure, competing recommendations, and patient-specific complexity. Participants

did not describe their primary educational need as learning what AI is or how to operate a discrete tool. They described a need to understand how to reason with AI, when to question AI, how to explain AI-informed decisions, and how to preserve professional accountability when AI becomes embedded in clinical workflow. This distinction is central: the movement from AI-focused CME to responsible AI integration is not direct or automatic. It is mediated by physicians' developing capacity to interpret AI outputs within real clinical contexts.

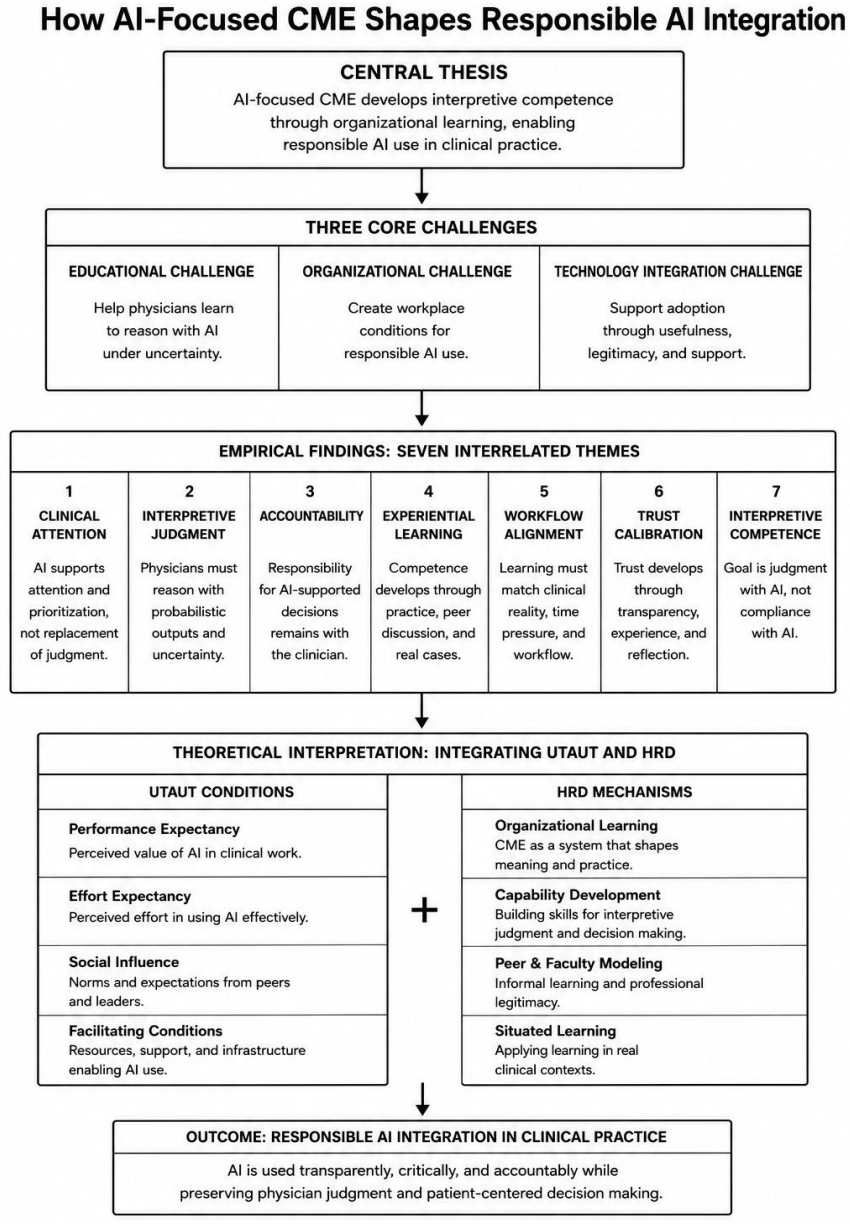

Figure 2. An Interpretive Framework of How AI-Focused CME Shapes Responsible Artificial Intelligence Integration in Clinical Practice

The first consideration here is the education problem. AI integration requires more than exposure to new digital tools because AI changes the conditions under which physicians attend, interpret, decide, and justify clinical action [25]. The theme of AI as support for clinical attention illustrates this point. Participants were most receptive to AI when CME framed it as augmenting attention,

prioritization, and clinical reasoning rather than replacing physician decision-making. This finding is important because it reframes performance not as automation efficiency alone, but as clinically meaningful support for human judgment [26]. AI became educationally acceptable when physicians could see how it helped them notice risk, organize complex information, or prompt further inquiry while leaving final responsibility with the clinician. When CME presented AI as something to follow rather than something to interrogate, the educational relationship between physician and tool became less clear.

The second theme, interpretive judgment, deepens this point. Physicians did not need CME merely to demonstrate that an AI system could generate recommendations. They needed CME to help them practice reasoning with outputs that may be probabilistic, incomplete, biased, context-insensitive, or in tension with clinical intuition. This finding suggests that the core educational task is not simply knowledge acquisition but judgment formation. In AI-supported care, the physician's competence lies partly in knowing how to interpret ambiguity. CME becomes meaningful when it creates opportunities to examine uncertain outputs, discuss edge cases, compare algorithmic recommendations with clinical reasoning, and justify decisions when AI and physician judgment diverge.

The third theme, professional accountability, shows that AI integration is also an ethical and professional problem. Participants repeatedly emphasized that responsibility remains with the physician. AI may assist with pattern recognition, risk stratification, documentation, triage, or treatment planning, but it does not assume moral, professional, or legal accountability for patient care. CME was therefore most useful when it made accountability explicit through discussion of documentation, decision ownership, escalation, override practices, and communication with patients or teams. When these matters were left implicit, physicians relied on informal norms that varied by specialty, team, and local practice. This finding is significant because it shows that responsible AI integration depends not only on what physicians know about AI, but also on how professional responsibility is socially organized and educationally reinforced.

Next, the organizational problem. AI-focused CME does not occur in isolation from the workplace. Physicians interpreted CME through the conditions of actual clinical practice, including workflow constraints, peer expectations, leadership messages, documentation requirements, patient complexity, alert fatigue, and access to technical support. The theme of informal and experiential learning demonstrates that competence developed through a combination of formal CME and workplace-based learning. Participants described learning through peer discussion, observation, case conferences, tumor boards, practical experimentation, and follow-up conversations after implementation. Formal CME was most valuable when it provided shared language, conceptual framing, and an initial structure for inquiry. It was least effective when it attempted to substitute one-time instruction for the iterative learning that occurs in practice.

This finding is important for the HRD interpretation of the study. From an HRD perspective, CME is not merely an educational event; it is part of an organizational learning system. The development of AI-related competence requires repeated application, feedback, reflection, peer exchange, and reinforcement within the conditions where the technology is actually used. The study captures this by positioning HRD interpretation in parallel with UTAUT interpretation in terms of importance. This suggests that technology acceptance and workforce learning are mutually implicated. Physicians' beliefs about usefulness, effort, legitimacy, and support are not formed only in their individual minds. They are produced through organizational experience, workplace discourse, faculty modeling, policy structures, and opportunities to practice.

The theme of CME-practice alignment help to expand this argument. Participants reported that CME was less effective when it relied on idealized scenarios that did not reflect the realities of clinical care. AI integration occurs amid time pressure, incomplete information, interruptions, alert fatigue, team-based decision-making, and patient-specific nuance. When CME did not account for these realities, participants experienced a gap between what was taught and what was usable. This misalignment increased cognitive burden and weakened transfer into practice. The implication is that AI-focused CME must be designed as situated learning rather than abstract content delivery. Specialty-specific cases, simulations of workflow constraints, discussion of documentation and liability, and opportunities to compare AI outputs with clinical reasoning are not peripheral design features. They are conditions for learning transfer.

The theme of trust calibration adds another dimension to the organizational problem. Trust in AI was not described as a stable attitude or a simple decision to accept or reject a tool. Participants described trust as provisional, evolving, and dependent on repeated use, transparency, peer interpretation, model performance, institutional messaging, and visible limitations. CME supported appropriate trust when it acknowledged uncertainty, false positives, false negatives, bias, and the need for questioning. CME undermined trust when it emphasized performance claims without helping physicians understand when those claims might fail in practice. This finding is important because it reframes trust as a developmental and organizational achievement rather than a precondition for adoption. Trust is calibrated through experience, dialogue, feedback, and responsible institutional framing.

Next, the technology integration problem. Through the UTAUT lens, the findings suggest that performance expectancy, effort expectancy, social influence, and facilitating conditions were not fixed individual beliefs that physicians brought unchanged into CME. Instead, these domains were shaped by the educational and organizational environment. Performance expectancy was shaped by whether CME helped physicians see AI as clinically valuable for attention, prioritization, reasoning, and planning. Effort expectancy was shaped by whether CME reduced or intensified the cognitive and workflow demands of using AI. Social influence emerged through peer modeling, faculty expectations, leadership communication, specialty norms, and shared discourse about accountability. Facilitating conditions included infrastructure, governance, protected learning time, technical support, workflow alignment, and opportunities to apply learning.

This interpretation extends UTAUT by placing technology acceptance within a professional learning context. In many technology adoption studies, the central question is whether users trust and intend to adopt or use a system [3,27,28]. The present findings suggest that this question is too limited for AI in clinical practice. For physicians, responsible AI adoption is not only a matter of intention or frequency of use. It is a matter of how AI is incorporated into professional reasoning, how uncertainty is handled, how accountability is preserved, and how organizational conditions support or constrain safe use. CME can therefore shape UTAUT domains by making AI appear clinically useful, cognitively manageable, socially legitimate, and practically supported. Conversely, poorly designed CME can weaken these same domains by presenting AI in generic, decontextualized, or overly promotional ways.

The HRD interpretation complements this UTAUT analysis by explaining how these adoption-related perceptions are developed. CME functions as an organizational learning system, a capability development mechanism, a site of faculty and peer modeling, and a form of situated learning. These HRD processes matter because AI competence cannot be produced through information delivery alone. Physicians must have opportunities to apply AI in context, receive feedback, observe responsible use, discuss uncertainty, and refine judgment over time. The study therefore positions CME as a mediating system between technology availability and responsible

clinical integration. AI tools may be introduced by vendors, health systems, or institutional leaders, but physicians learn what those tools mean for practice through organizationally situated learning.

The integrative contribution of the study lies in bringing UTAUT and HRD together. UTAUT clarifies the technology-in-education challenge: physicians must perceive AI as useful, manageable, socially legitimate, and supported. HRD clarifies the workforce learning challenge: those perceptions are cultivated through organizational learning, capability development, peer modeling, and situated practice. These perspectives show that responsible AI integration is not the endpoint of technology adoption alone. It is the outcome of a learning system that develops physicians' capacity to use AI critically, transparently, and accountably. This is the central logic is that AI-focused CME shapes empirical learning experiences, those experiences influence UTAUT domains and HRD processes, and together they support responsible AI integration in clinical practice.

The findings also complicate the assumption that AI adoption improves when physicians are simply exposed to more AI content. Participants were not asking for more content in the abstract. They were asking for more relevant, situated, and professionally meaningful learning. They wanted specialty-specific cases, realistic workflow scenarios, clearer guidance about liability and documentation, greater visibility into model limitations, and opportunities to compare AI recommendations with physician reasoning. This suggests that the design problem for AI-focused CME is not primarily one of volume, access, or coverage. It is a problem of educational architecture. CME must be designed to develop capability, not merely transmit information.

The study further suggests that responsible AI integration requires a shift in evaluation. If CME is assessed only by participation, satisfaction, or self-reported confidence, the most important forms of learning may remain invisible. The relevant question is not simply whether physicians completed AI-focused CME or whether they felt more familiar with AI afterward. The more consequential question is whether CME improved their capacity to interpret AI outputs, recognize limitations, document decisions, communicate uncertainty, calibrate trust, and maintain accountability in practice. Evaluation models for AI-focused CME should therefore attend to judgment, transfer, and organizational reinforcement rather than only knowledge gain or adoption intent.

6. IMPLICATIONS

Several practical implications follow. First, AI-focused CME should be case-based and specialty-specific. Physicians need to practice interpreting AI outputs in realistic scenarios that include uncertainty, conflicting evidence, incomplete data, and patient-centered constraints. Second, CME should address accountability directly. Learners need clear guidance on documentation, patient communication, liability, bias, and the boundaries of AI authority [29]. Third, CME should be longitudinal. One-time AI sessions may raise awareness, but trust calibration and judgment development occur over time. Fourth, CME should connect formal instruction to informal workplace learning. Grand rounds, tumor boards, morbidity and mortality conferences, simulation sessions, peer coaching, and interdisciplinary case reviews can become sites for AI sensemaking. Fifth, CME evaluation should move beyond attendance, satisfaction, and short-term knowledge checks. Better indicators include changes in reasoning quality, appropriate override behavior, documentation practices, team communication, and confidence in questioning AI outputs. Finally, organizational leaders should treat AI-focused CME as part of implementation infrastructure. Without protected time, accessible tools, clear governance, and workflow support, education alone cannot produce responsible AI integration [30,31]. This means that CME planners should be included early in AI implementation decisions rather than

asked to educate clinicians after tools have already been deployed. When education is separated from implementation, CME becomes reactive. When education is integrated into implementation, it can surface clinician concerns, identify workflow barriers, and create feedback loops between users, educators, and system leaders.

The findings and their interpretation through UTAUT and HRD suggest that the challenge of AI integration is fundamentally a learning design challenge rather than a technology deployment challenge [32]. As illustrated in Figure 2, responsible AI integration emerges when physicians develop interpretive competence, calibrate trust appropriately, understand the boundaries of professional accountability, and receive ongoing organizational support for learning. These outcomes are unlikely to result from traditional CME approaches that emphasize information transmission or tool familiarization alone. Instead, the findings indicate that AI-focused CME should be intentionally designed as a developmental process that supports physicians before, during, and after AI enters clinical workflow [33]. Drawing from the seven themes identified in this study, a four-part design logic is proposed to guide the development of AI-focused CME. The model translates the study's empirical findings into actionable educational principles by organizing learning around four interdependent functions: orientation, interpretation, accountability, and reinforcement. These functions provide a practical framework for designing CME that supports not only AI adoption, but the development of responsible, context-sensitive, and professionally accountable AI use in clinical practice (Table 3).

Table 3. AI-Focused CME Design Framework for Responsible Clinical AI Integration

Design stage	CME design purpose	Physician learning target	Evidence of transfer
Orientation	Define the AI tool's purpose, limits, and clinical boundaries.	Explain what the tool supports, what it does not do, and where it may fail.	Physician identifies appropriate and inappropriate use cases and describes AI as decision support, not decision replacement.
Interpretation	Teach physicians to reason with AI outputs under uncertainty.	Evaluate AI recommendations against clinical judgment, patient context, and alternative explanations.	Physician justifies when to accept, modify, question, or override an AI output.
Accountability	Clarify professional, ethical, and documentation responsibilities.	Maintain decision ownership, communicate uncertainty, monitor bias, and follow escalation pathways.	Physician documents AI-supported reasoning, explains decision ownership, and recognizes ethical or equity risks.
Reinforcement	Extend AI learning into ongoing workplace practice.	Calibrate trust, learn from errors, discuss cases, and adapt as tools and workflows evolve.	Physician participates in follow-up learning, reports workflow issues, adjusts use based on feedback, and contributes to improvement.

7. LIMITATIONS AND FUTURE RESEARCH

This study has limitations. It was conducted within one academic health system, which limits transferability to smaller hospitals, community settings, or organizations with different levels of AI maturity [34]. The study relied on physicians' self-reported experiences rather than direct observation of AI use. It also focused on physicians, although AI integration involves nurses, pharmacists, information technology specialists, administrators, learners, patients, and other

stakeholders. Finally, AI tools and policies evolve rapidly; findings should be interpreted as situated within a transitional period of AI adoption.

Future research should examine AI-focused CME across multiple institutions and specialties. Longitudinal studies could investigate how physicians' trust, judgment, and use patterns change after repeated CME and workplace exposure. Mixed-methods research could develop measures of interpretive competence, trust calibration, and AI learning transfer [35]. Comparative studies could also examine how different CME designs, such as simulation, peer coaching, case conferences, and online modules, shape responsible AI integration. Importantly, future work should include interprofessional teams because AI-supported care is rarely an individual activity. Research should also examine patient-facing communication about AI, because physicians increasingly need to explain how algorithmic information enters clinical decisions without undermining patient trust.

8. CONCLUSION

AI integration in clinical practice is not simply a technical transition; it is a professional learning challenge. For practicing physicians, responsible AI use requires more than familiarity with tool functions. It requires the capacity to interpret probabilistic outputs, question limitations, explain AI-informed reasoning, and preserve accountability within patient care. This study shows that CME can support that capacity when it is designed as an organizational learning system rather than a one-time content-delivery event. Effective AI-focused CME develops interpretive judgment, clarifies professional responsibility, connects formal instruction to workplace learning, aligns with clinical realities, and supports trust calibration over time. The central implication is that CME should not aim to produce compliant users of AI tools. It should develop clinicians who can think critically with AI while maintaining human judgment, ethical responsibility, and patient-centered care. More broadly, the study suggests that successful technology integration in education depends less on the sophistication of the tool itself than on the quality of the learning system built around it.

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