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From AI Adoption to AI Pedagogical Transformation: Developing a Faculty AI Literacy Maturity Model for Higher Education

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ABSTRACT

Faculty members across higher education are increasingly using generative artificial intelligence for instructional design, assessment, feedback, and learning support, yet many institutional AI initiatives remain focused on basic technology adoption rather than on pedagogical transformation. Existing developmental models describe how educators progress with digital technologies in general, but limited work explains how faculty move from initial AI awareness toward pedagogically grounded and critically informed practice. This conceptual paper proposes a Faculty AI Literacy Maturity Model for higher education. Building on established stage-based and maturity models, and drawing on the Technological Pedagogical Content Knowledge framework, Transformative Learning Theory, the UNESCO AI Competency Framework for Teachers, and Communities of Practice, the model describes a six-stage developmental continuum: awareness, experimentation, pedagogical integration, critical reflection, collaborative transformation, and institutional leadership. Technical competency is treated as a moderating dimension across all stages rather than as a stage in itself. The paper presents the model visually, specifies provisional indicators, evidence requirements, and progression criteria for each stage, describes graduated settings in which faculty can experiment safely, and outlines a lean, credit-bearing implementation pathway. It concludes with a staged agenda for validation addressing content validity, reliability, construct validity, cross-institutional applicability, and longitudinal progression. The model is offered as a proposed framework for future empirical development, not as an established assessment instrument.

KEYWORDS AI literacy maturity model; faculty development; AI pedagogy; higher education innovation; instructional transformation; faculty AI readiness; ethical AI integration; professional development evaluation

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Introduction

Artificial intelligence is rapidly transforming higher education teaching and learning. Faculty members are increasingly experimenting with generative AI tools for instructional design, assessment, feedback, communication, and learning support. Many institutional AI initiatives, however, remain focused on basic technology adoption rather than deeper pedagogical transformation. As AI becomes more embedded in higher education, institutions need structured approaches that help faculty move beyond tool use toward ethical, reflective, and instructionally meaningful integration.

Institutional guidance has expanded quickly, but unevenly. Recent policy analyses indicate substantial year-over-year growth in the share of institutions issuing acceptable-use guidance for AI, alongside considerable variation in how far that guidance extends beyond writing tasks into assessment and disciplinary practice [1], [2]. Guidance alone, moreover, does not equate to capability. International survey evidence points to high rates of AI use among academic staff coupled with uneven confidence in applying these tools pedagogically [3]. This gap between availability and capability is the problem the present model addresses. Work on AI in education has long argued that instructional value depends on how tools are embedded in teaching rather than on the tools themselves [4], and recent analysis positions AI literacy, prompt engineering, and critical thinking as interdependent rather than sequential competencies [5]. Systematic review of critical thinking and AI in higher education similarly reports that studies frequently leave the target construct unspecified, which makes claims of instructional benefit difficult to evaluate or compare [6], and earlier work cautioned that the value of intelligent systems in education rests on whether they demand human reasoning rather than substitute for it [7].

Although AI literacy and faculty development have gained increasing attention, limited research has examined how faculty progress from initial AI awareness and experimentation toward pedagogically grounded, critically informed, and institutionally supported AI transformation. Existing discussions often emphasize AI adoption, tool training, or policy development. Established stage-based frameworks for educator digital competence and technology adoption offer useful precedents, but, as the literature suggests, none of them describes the specific progression that generative AI demands of faculty or connects that progression to teaching innovation, critical reflection, assessment redesign, and institutional leadership.

This paper makes three contributions. First, it proposes a six-stage Faculty AI Literacy Maturity Model, represented visually in Fig. 1, and positions it against existing developmental and maturity models. Second, it offers a provisional operational layer: observable indicators, evidence requirements, and progression criteria for each stage, guidance on how faculty with different levels of technical confidence can experiment and progress, and a lean, credit-bearing implementation pathway. Third, it sets out a staged agenda for implementing and empirically validating the model. Consistent with its conceptual nature, the model is presented as a proposed framework for future empirical development rather than as an established faculty evaluation or maturity-assessment instrument.

Related work and theoretical foundations

Developmental and Maturity Models in Educational Technology

Stage-based accounts of educator change long predate generative AI. The Concerns-Based Adoption Model (CBAM) describes how educators' concerns about an innovation move from initial unconcern and information-seeking through personal and management concerns toward concerns about consequences for students, collaboration with colleagues, and refocusing, and pairs these Stages of Concern with behaviorally defined Levels of Use [8]. The European Framework for the Digital Competence of Educators (DigCompEdu) specifies six proficiency levels, from Newcomer and Explorer through Integrator and Expert to Leader and Pioneer, across six competence areas [9]. The UNESCO AI Competency Framework for Teachers organizes its competencies into three progression levels: acquire, deepen, and create [10]. At the institutional level, the e-Learning Maturity Model adapted capability-maturity logic from software process improvement to assess the quality of university e-learning processes [11]. Research on technology integration further shows that progression is constrained both by external, first-order barriers such as access, time, and support and by internal, second-order barriers such as pedagogical beliefs and confidence [12], [13].

These models supply the structural precedent for a staged account, and the present model draws on each. Its sequence parallels the movement in CBAM from self-oriented concerns toward collaboration and refocusing, its six-level granularity is comparable to DigCompEdu, in which the Explorer, Integrator, and Leader levels correspond closely to the experimentation, integration, and leadership stages proposed here, and its stages can be read against the three UNESCO progression levels (Section II-D). None of these models, however, addresses the specific demands that generative AI places on faculty. DigCompEdu treats digital competence generically, CBAM describes responses to any innovation, the e-Learning Maturity Model assesses institutional processes rather than individual practice, and the UNESCO framework, written for teachers broadly, specifies competencies at each level rather than the transitions between levels. Reviews of AI in higher education have also noted the scarcity of educator perspectives and of critical reflection on the pedagogical and ethical implications of AI [14]. The present model responds to this gap in two ways: it treats critical reflection on AI as a distinct developmental stage rather than a cross-cutting attitude, and it links individual faculty progression to the institutional conditions that enable it.

Four further bodies of work supply the model's internal logic. Technological Pedagogical Content Knowledge supplies the integration logic, Transformative Learning Theory supplies the mechanism of change, the UNESCO AI Competency Framework for Teachers supplies the competency vocabulary, and Communities of Practice supplies the social structure through which practice becomes shared.

Technological Pedagogical Content Knowledge

The TPACK framework holds that effective technology integration arises from the intersection of technological, pedagogical, and content knowledge rather than from technical skill alone [15]. Applied to AI, this positions the central question not as whether faculty can operate a generative tool but as whether they can align its use with disciplinary content and instructional purpose. Recent extensions of the framework address generative AI directly, arguing that its breadth and unpredictability strain the original construct [16]. Related work proposes Intelligent-TPACK to capture the ethical and pedagogical knowledge required to integrate AI-based tools responsibly [17], and empirical study of AI-TPACK has begun to map relationships among its knowledge components [18]. TPACK grounds the experimentation and pedagogical integration stages of the model.

Transformative Learning Theory

Mezirow describes transformative learning as beginning with a disorienting dilemma that prompts critical examination of previously unquestioned assumptions [19]. Generative AI functions as such a dilemma for many faculty, particularly where it unsettles established assessment practices. The critical reflection stage of the present model is grounded in this account.

UNESCO AI Competency Framework for Teachers

The UNESCO framework establishes a shared vocabulary for teacher AI competencies spanning human-centered mindset, ethics of AI, AI foundations and applications, AI pedagogy, and AI for professional development [10]. It sits alongside a broader literature defining AI literacy as a set of competencies for evaluating and interacting with AI systems [20], [21], which grounds the awareness stage. Read against the UNESCO progression levels, stages 1 and 2 of the present model correspond broadly to acquiring, stages 3 and 4 to deepening, and stages 5 and 6 to creating (Fig. 1). This alignment is the author's interpretation rather than part of the UNESCO framework. The present model complements the framework by describing progression between levels rather than specifying competencies at a given level.

Communities of Practice

Wenger characterizes communities of practice as groups bound by mutual engagement, joint enterprise, and a shared repertoire [22]. This account grounds the collaborative transformation stage, in which individual experimentation becomes shared departmental practice, and informs the institutional leadership stage, in which that shared practice shapes policy and culture.

Method of model development

This is a conceptual paper. The model was developed through interpretive synthesis of interdisciplinary literature rather than through systematic review, and no new empirical data were collected for this paper.

The development process followed the phase logic common to maturity-model design, which proceeds through scoping, design, population, testing, deployment, and maintenance [23], and the related requirement that a proposed model be compared with existing models before iterative development and planned evaluation [24]. This paper completes the scoping, design, and population phases. It defines the domain and audience (faculty in higher education), compares the model with existing developmental and maturity models as discussed in Related work and Theoretical Foundations, and populates each stage with orientations, institutional supports, indicators, and evidence requirements. The testing, deployment, and maintenance phases are specified as future work.

The synthesis drew on three literatures: technology integration frameworks in teacher education, adult and transformative learning theory, and emerging AI literacy competency frameworks. It was additionally informed by the author's qualitative case study of critical thinking instruction in a hybrid, AI-enhanced undergraduate education course [25]. That study found that development of critical thinking reflected deliberate instructional design more than delivery modality, and that AI functioned as a conditional scaffold whose value depended on the critical literacy of the user. Both findings shaped how the present model distinguishes tool use from pedagogical intention. The synthesis also drew on the author's related work on AI integration with preservice teachers, including a mixed-methods examination of the pedagogical, cognitive, and ethical implications of AI integration for creative and critical thinking [26], an account of promoting critical thinking in hybrid learning [27], and a case study of AI-enhanced game-based learning in hybrid education [28].

Six stages, rather than a smaller number, follow from a single criterion: each boundary must mark a qualitative shift in what a faculty member can do, not a quantitative increase in how much AI they use. Two boundaries derive from the author's Instructional Critical Thinking Model, which was itself constructed inductively from case evidence rather than imposed on it [25]. That model holds that development requires visibility before extension, since practitioners cannot deliberately extend a practice they cannot yet name. Applied to faculty AI literacy, this separates integration, where AI is used with instructional intent, from critical reflection, where the practice itself becomes nameable and therefore examinable. The remaining boundaries follow the frameworks in the Related Work and Theoretical Foundations section of this article, each of which marks a transition the others leave implicit.

The faculty AI literacy maturity model

The model conceptualizes faculty AI literacy as more than technical proficiency. It positions AI literacy as a developmental and transformative process that includes ethical awareness, pedagogical decision-making, critical thinking, assessment redesign, and collaborative innovation. Faculty are understood to move through progressive stages, beginning with awareness of AI tools and risks, proceeding through experimentation with instructional applications, and then to intentional pedagogical integration. More advanced stages involve critical reflection on AI ethics, bias, academic integrity, and student learning, followed by collaborative transformation through communities of practice and, finally, institutional leadership. Fig. 1 represents the model visually.

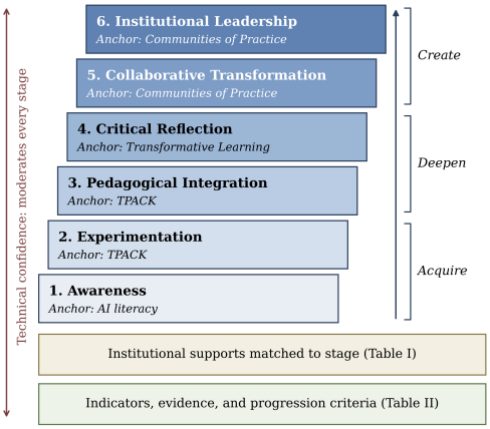


Fig. 1. The Faculty AI Literacy Maturity Model. Stages are grouped by the author against the UNESCO acquire, deepen, and create progression levels, and each stage names its anchoring framework; institutional supports (Table 1) and operational criteria (Table 2) form the base; technical confidence moderates progression across all stages.

The six stages ascend from individual adoption to collective and institutional transformation and are grouped against the three UNESCO progression levels. The theoretical framework anchoring each stage is shown within it, institutional supports and operational criteria form the base on which progression rests, and technical confidence is shown as a dimension that moderates progression at every stage rather than as a stage in itself. Table 1 summarizes the faculty orientation and institutional support associated with each stage.

Table 1. Faculty ai literacy maturity model

Stage	Faculty Orientation	Institutional Support
1. Awareness	Recognizes AI tools and associated risks; forms initial views of relevance to own teaching.	Introductory sessions; plain-language guidance on institutional policy.
2. Experimentation	Trials generative tools for instructional applications; evaluates usefulness case by case.	Sandbox environments; peer rehearsal; low-stakes pilot support.
3. Pedagogical Integration	Moves from incidental use to intentional integration into course design and assessment.	Instructional design consultation; course redesign time.
4. Critical Reflection	Examines AI ethics, bias, academic integrity, and effects on student learning.	Structured reflective forums; policy and integrity guidance.
5. Collaborative Transformation	Works with colleagues to develop shared practice through communities of practice.	Faculty learning communities; cross-disciplinary networks.
6. Institutional Leadership	Shapes departmental and institutional AI strategy, policy, and culture.	Governance roles; strategic investment in sustained development.

Progression is not assumed to be uniform or strictly linear. Faculty may occupy different stages across different courses, may return to experimentation when new tools or new courses appear, and move through the stages as much because of institutional conditions as because of individual disposition.

Stage Indicators and Progression Criteria

A maturity model becomes usable only when its stage boundaries can be applied consistently to individual faculty members. Table 2 therefore proposes, for each stage, observable indicators of practice and the evidence a faculty member would provide to demonstrate readiness to move to the next stage. The indicators are written as observable practices rather than attitudes so that they can be verified from artifacts, and each evidence requirement corresponds to the qualitative shift that defines the next boundary.

A conjunctive placement rule is proposed: a faculty member is placed at the highest stage for which the indicators are met and for which evidence exists at each preceding stage. This rule reflects the developmental claim of the model, and it prevents a faculty member from being placed at an advanced stage, for example on the basis of a governance role, without evidence of the integration and reflection that the model assumes precede it. Because practice can differ across courses, placement is made per course and summarized as a profile rather than as a single score.

Table 2. Provisional stage indicators and progression evidence

Stage	Observable Indicators	Evidence for Progression
1. Awareness	Describes what generative AI tools do and their main limitations (fabrication, bias, data privacy); knows institutional AI policy.	Brief written statement on AI relevance and risk in own discipline.
2. Experimentation	Has tried AI on at least one instructional task in a sandbox, peer rehearsal, or bounded pilot; can say what worked and what failed.	Experimentation log of tasks, outputs, problems, and judgments of usefulness.
3. Pedagogical Integration	AI use is tied to stated learning outcomes; syllabus sets AI expectations; at least one activity or assessment is redesigned.	Annotated course artifact with an alignment rationale.
4. Critical Reflection	Examines AI's effects on assessment validity, equity, integrity, and student reasoning; revises practice accordingly.	Reflective analysis grounded in student work or feedback, with documented revision.
5. Collaborative Transformation	Co-develops and shares AI-informed practice; contributes to a community of practice.	Shared resource reviewed or adopted by peers; record of community participation.
6. Institutional Leadership	Shapes departmental or institutional AI policy, curriculum, or professional development.	Documented contribution to policy, governance, or program design (terminal stage).

Self-report is likely to be adequate for screening at stages 1 and 2, but stages 3 to 6 are defined by changes in practice and should be confirmed through portfolio evidence. These indicators are provisional. They are intended as the item pool and scoring framework for the instrument development described in Evaluation Agenda and Future Work Section, not as a validated assessment.

Experimentation: From Sandbox to Live Classroom

Experimentation is the stage at which faculty first take visible risks, and where that experimentation happens matters. Three graduated settings are distinguished. The first is a sandbox: an institutionally approved, privacy-compliant environment in which faculty try tools on their own materials, such as past assignments, anonymized or synthetic student work, and draft rubrics, without students present and without student data. The second is peer rehearsal, in which an AI-supported activity is trialed with colleagues, for example within a faculty learning community, before it reaches students. The third is a bounded live pilot: a single low-stakes activity in a live class, such as an AI-enhanced game-based task of the kind examined in [28], announced to students in advance, with a non-AI alternative available and a planned fallback if the tool fails. Because mastery experiences are the most influential source of self-efficacy [29], this sequence allows faculty to accumulate successful experience before the stakes rise.

Live pilots will still produce problems: fabricated or inaccurate output, uneven student access to tools, students who outpace the instructor technically, and uncertainty about academic integrity. The model treats these not only as risks to manage but as material for later stages. An inaccurate output examined openly with students becomes an exercise in evaluative judgement [30], and a short post-session log of what happened, how the instructor responded, and what will change supplies the evidence that Table 2 requires for progression to integration and, later, the raw material for critical reflection. Institutional support at this stage therefore includes not only access to tools but explicit permission to fail in bounded ways, together with clear guidance on data privacy and academic integrity.

Technical Competency as a Moderating Dimension

Faculty arrive with different levels of technical confidence, and some approach AI with anxiety rather than curiosity. Research on technology integration identifies confidence and self-efficacy, alongside knowledge, pedagogical beliefs, and institutional culture, as central to whether teachers change practice [13]. The model treats technical competency as a moderating dimension that runs across all stages rather than as a stage in itself (Fig. 1). This choice is deliberate. If technical skill defined the stages, faculty with low technical confidence would be held at the bottom of the continuum regardless of their pedagogical expertise, and faculty with high technical confidence would be credited with a maturity they may not have.

Two implications follow. First, faculty with lower technical confidence can progress to the higher stages, because what distinguishes those stages is pedagogical and critical judgement rather than technical sophistication. An experienced teacher who uses a single tool cautiously but interrogates its effect on assessment validity is operating at stage 4. For these faculty, entry supports should reduce first-order barriers [12] through guided templates, paired mentoring with a more confident colleague, and extended sandbox time. Second, faculty with high technical confidence face a different risk: moving quickly from experimentation into widespread use while bypassing critical reflection. For these faculty, the appropriate support is structured reflection rather than further tool training. Placement should therefore record technical confidence separately, so that support can be differentiated within, as well as across, stages.

The Transition from Integration to Critical Reflection

The transition from stage 3 to stage 4 warrants particular attention, since both involve deliberate use. At stage 3, the faculty member asks whether an AI-supported activity serves the instructional purpose. At stage 4, the question turns back on the tool itself: what the model encodes, whose knowledge it represents, and what it does to the validity of the assessment it supports. Evidence from a case study of critical thinking instruction in an AI-enhanced hybrid course supports this distinction, finding that AI functioned as a conditional scaffold whose instructional value depended on whether users brought critical literacy to it [25]. Design-principles work on scaffolding critical thinking with large language models describes the stage 3 orientation [31], while scholarship on evaluative judgement in a time of generative AI [30] and on the risk of metacognitive offloading [32] describes the questions that characterize stage 4. At this stage, critical thinking is better understood as a human-AI partnership in which the instructor retains evaluative authority than as a capacity that AI either supports or replaces [33]. Case evidence from an AI-mediated undergraduate course reinforces the caution: although critical engagement appeared across student interactions with generative systems, the authors declined any causal claim absent a comparison condition [34]. The distinction also has a professional-identity dimension, since naming one's own instructional practice is bound up with how teachers understand their role [35]. The author has examined this mechanism directly, finding that Socratic questioning in AI-enhanced higher education functions to surface assumptions and make reasoning available for examination rather than to supply conclusions [36].

A lean, credit-bearing implementation pathway

The indicators in Table 2 make it possible to translate the conceptual stages into a faculty-development system. The proposed pathway is built on lean principles, which in higher education emphasize defining value from the perspective of those served, removing activities that do not contribute to that value, and improving processes through short, evidence-informed cycles [37]. Applied here, value is defined as change in faculty practice that benefits student learning, and the principal source of waste is provision mismatched to stage: introductory tool training offered to faculty who already integrate AI, or governance roles offered to faculty who have not yet experimented.

Entry by Placement

Rather than enrolling all faculty in a common sequence, the pathway begins with placement after which faculty draw on the support matched to their stage in Table 1. This allows faculty to enter at the stage their existing practice warrants, and it is consistent with evidence that teacher change often follows, rather than precedes, successful change in classroom practice [38].

Credit-Bearing Recognition

Each stage transition is associated with a micro-credential defined by three elements: the competencies addressed, mapped to the five UNESCO dimensions [10]; the evidence requirement in Table 2; and a peer or faculty-developer review of that evidence. In U.S. higher education, credentials at the earlier stages could carry recognition as documented professional-development hours, while credentials at stages 4 to 6 could be recognized in annual review and promotion and tenure dossiers, or supported through course release and stipends for facilitating communities of practice. Tying recognition to evidence of changed practice rather than to attendance keeps the credential aligned with the qualitative shifts that define the stages. Specific credit values are institutional decisions and are deliberately left open.

Implementation Cycles and Measurable Outcomes

Implementation would proceed in semester-length Plan-Do-Study-Act cycles of the kind used in improvement science [39]. Each cycle begins with placement, delivers stage-matched support, collects evidence, and reviews results before the next cycle begins. Measurable outcomes can be organized by the five levels of professional development evaluation: participants' reactions, participants' learning, organizational support and change, participants' use of new knowledge and skills, and student learning outcomes [40]. Operationally, these include the proportion of participants completing a stage transition within a cycle, the quality of submitted artifacts scored against a rubric, change in the institutional distribution of faculty across stages, and course-level indicators of student learning where AI-supported designs have been introduced. Cohort structures drawn from faculty learning community practice [41] provide the social infrastructure for stages 4 and 5.

Evaluation agenda and future work

Because the model is conceptual, its stages, boundaries, and indicators should be treated as hypotheses. Table 3 sets out a staged agenda for implementation and validation, organized around the sources of validity evidence identified in the Standards for Educational and Psychological Testing: test content, response processes, internal structure, relations to other variables, and consequences of use [42].

Two findings would count against the model as proposed. If item-response or latent class analyses showed that adjacent stages, particularly integration and critical reflection, could not be distinguished empirically, the six-stage structure would need to be collapsed or redefined. If longitudinal data showed that faculty routinely reached the collaborative or leadership stages without evidence of critical reflection, the claim of ordered progression would need to be revised. Stating these conditions in advance is intended to make the model testable rather than merely illustrative. The portfolio rubric in Phase 2 can build on prior work on measuring critical thinking in hybrid classrooms with emerging technologies, which favors evidence of reasoning processes over final products [47]. A practical first step would be a one-year pilot with a small, cross-disciplinary faculty cohort at a single institution, combining the draft instrument with stage-matched support and design-based refinement of both, before multi-site validation.

Table 3. Proposed implementation and validation agenda

Phase	Guiding Question	Proposed Methods
1. Content validation	Are stages and indicators complete, distinct, and correctly ordered?	Delphi panel of faculty developers, instructional designers, and AI-in-education researchers [43]; content validity indices.
2. Instrument development	Do faculty interpret items and evidence requirements as intended?	Items written from Table 2 indicators; cognitive interviews; pilot of the portfolio rubric.
3. Reliability and structure	Do items form a coherent scale with distinct, ordered stages?	Multi-institution survey; internal consistency; Rasch analysis of stage ordering [44]; inter-rater agreement on portfolio scoring.
4. Cross-institutional applicability	Does the model hold across institution types, disciplines, and countries?	Multi-site sampling; tests of measurement invariance across groups.
5. Longitudinal progression	Do faculty move through the stages, and in this order?	Two- to three-year panel data; latent transition analysis [45].
6. Implementation impact	Does stage-matched provision change practice and student learning?	Design-based research iterations [46]; evaluation at the five levels in [40].

Discussion and implications

Once operationalized and validated, the model is intended to be usable. A center for teaching and learning could apply it diagnostically, placing faculty at a stage and matching them to appropriately tiered programming rather than offering a single general workshop. Faculty at the awareness and experimentation stages need low-stakes exposure, safe experimentation environments, and clear institutional guidance. Faculty at the integration and reflection stages need design consultation and time for course redesign. Faculty at the collaborative and leadership stages need convening structures and governance roles rather than further training. Designing workshop provision around this kind of staged intent, rather than around tool coverage, has been explored in earlier work on professional development for critical thinking in hybrid higher education settings [48], and translated into workshop training on strategies for fostering critical thinking in hybrid and AI-enhanced learning environments [49]. A finding from that program of work bears directly on how such provision should be sequenced: a professional development workshop deepened instructors'

practice where they were already intentional, giving intuitive practice a shared vocabulary rather than introducing technique to those without one [25]. Tiered programming should therefore be designed to make existing practice nameable before attempting to extend it.

The model also clarifies where institutional effort tends to be misallocated. Development programs frequently concentrate resources at the earliest stages, where demand is most visible, while providing little structure for faculty who have already integrated AI and now face harder questions about assessment validity and disciplinary epistemology.

Limitations

The model is conceptual and has not been empirically validated. It was derived from literature synthesis rather than from observation of faculty practice, and the six stages are proposed rather than demonstrated. The indicators, evidence requirements, and progression criteria in Table 2 and the implementation pathway in discussion related to a Lean, Credit-Bearing Implementation Pathway are provisional; no instrument yet exists for reliably placing a faculty member on the continuum, and there is not yet evidence that faculty progress through the stages in the order proposed or that the stages represent distinct levels of maturity. Self-report placement may be affected by social desirability, which is one reason portfolio evidence is proposed for the higher stages. The credit-bearing pathway reflects U.S. institutional structures, and the model as a whole reflects the conditions of well-resourced higher education systems; it may transfer poorly to contexts with different infrastructure, governance, or recognition systems. The validation agenda in Section Evaluation Agenda and Future Work is designed to address these limitations.

Conclusion

Higher education institutions need developmental frameworks that support faculty AI literacy and pedagogical transformation, not only tool adoption. This paper has proposed a six-stage Faculty AI Literacy Maturity Model, positioned it against existing developmental and maturity models, and represented it visually. It has also offered a provisional operational layer of indicators, evidence requirements, and progression criteria; guidance on safe experimentation and on supporting faculty with different levels of technical confidence; a lean, credit-bearing implementation pathway; and a staged agenda for validation. The model is a proposed conceptual framework for future empirical development rather than an established assessment of faculty AI readiness. Its value will depend on whether its stages can be distinguished in practice and whether stage-matched provision helps faculty move from adopting AI toward ethical, reflective, and human-centered AI pedagogy.

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Conflict of interest

The author declares no conflicts of interest.

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