ARTIFICIAL INTELLIGENCE COMPETENCY IN TEACHER EDUCATION: A PEDAGOGICAL MODEL FOR PREPARING FUTURE TEACHERS

Hasan Olimjonov
Jizzakh state pedagogical university
hasanolimjonov@jdpu.uz

Abstract. Teacher preparation programs increasingly face a mismatch between widespread access to artificial intelligence and novice teachers' ability to judge its pedagogical value. This conceptual article synthesizes teacher-knowledge theory, AI literacy research, and UNESCO's teacher competency guidance to propose an integrated model for pre-service teacher education. The Teacher AI Pedagogical Readiness (TAPR) model combines foundational AI literacy, subject-specific design, critical evaluation, ethical and inclusive practice, and reflective professional judgment. A staged teacher education pathway is proposed, progressing from analyzing AI limitations to designing, simulating, and critically reflecting on lessons. Assessment is based on defensible pedagogical decisions rather than prompt fluency alone. The article provides a sample analytic rubric and researchable propositions for program evaluation. It does not claim that the model has been experimentally validated. Its contribution is a curriculum-oriented account of how to prepare teachers to use AI as a bounded professional resource while safeguarding student learning, privacy, and teacher autonomy.

Keywords: teacher education; AI literacy; pedagogical competence; pre-service teachers; technological pedagogical content knowledge; professional ethics

1. Introduction

The rapid diffusion of generative AI creates a new problem for teacher education: candidates may be able to obtain plausible lesson plans without knowing how to evaluate them. Technical familiarity with a chatbot is not the same as professional readiness to teach with AI. Teachers must decide whether a generated explanation is accurate, whether a learning activity supports the intended cognitive demand, whether examples respect learner diversity, and whether data handling is appropriate.

The technological pedagogical content knowledge (TPACK) tradition argues that effective technology integration requires interaction among content, pedagogy, and technological affordances (Mishra & Koehler, 2006). Shulman's account of teacher knowledge further highlights the transformation of subject matter into teachable representations (Shulman, 1986). These perspectives help explain why generic AI tutorials are insufficient as a stand-alone preparation strategy. UNESCO's AI competency framework for teachers (2024) also emphasizes human-centered values, ethics, foundations, pedagogy, and professional learning. This article turns those ideas into a sequenced program model.

2. Methodological Approach

The study uses conceptual synthesis to connect three literatures: teacher knowledge and instructional design (Shulman, 1986; Mishra & Koehler, 2006), AI literacy competencies (Long & Magerko, 2020), and policy-oriented teacher AI competencies (UNESCO, 2024). Selected research on large language models and educational risks provides contextual support (Kasneci et al., 2023; UNESCO, 2023).

The procedure involved identifying common competence domains, distinguishing technical procedures from professional decisions, mapping competence development onto teacher-education activities, and defining observable assessment evidence. Source selection was purposive rather than exhaustive. No survey, participant observation, or intervention took place. The model should be treated as a curriculum proposal pending local co-design and empirical assessment.

3. Results: The Teacher AI Pedagogical Readiness Model

Dimension 1, foundational AI literacy, covers what generative models can and cannot do. Candidates explain probabilistic text generation in accessible terms, distinguish fluent language from established evidence, recognize hallucinations, and identify situations where automated output must not be trusted. The expected product is not a technical examination of machine learning mathematics but an informed explanation of capabilities and limitations relevant to classroom decisions.

Dimension 2, subject-specific pedagogical design, requires candidates to align AI-supported activities with curriculum objectives, disciplinary epistemology, and learner developmental stages. A science teacher should judge the validity of a model-generated explanation of a physical process; a language teacher should judge whether suggested corrections support communicative competence rather than merely stylistic conformity. Candidates must show that they can construct a suitable non-AI alternative.

Dimension 3, critical evaluation, asks candidates to verify factual statements against credible references, test prompts with intentionally ambiguous cases, and detect fabricated citations or overconfident answers. Dimension 4, ethical and inclusive practice, addresses privacy, intellectual property, learner consent where appropriate, bias, accessibility, and differences in connectivity. Dimension 5, reflective professional judgment, requires candidates to document why an AI-assisted intervention was selected, modified, or rejected and what evidence would justify changing the decision.

These dimensions should be taught as mutually reinforcing rather than isolated software skills. A candidate can demonstrate sophisticated prompting and still fail to notice that an activity excludes students with low connectivity; conversely, an ethically aware candidate may need more guidance in disciplinary accuracy checking. Program assessment therefore requires multiple forms of evidence.

4. A Four-Stage Preparation Pathway

Stage 1, inspect: teacher candidates compare AI-generated and human-authored instructional resources, annotate at least three content or pedagogical concerns, and explain their significance. Stage 2, design: candidates create a lesson sequence with an explicit objective, expected misconceptions, a justified role for AI, a non-AI fallback, and a student-data protection plan.

Stage 3, simulate: in a microteaching session, peers enact diverse learner responses while the candidate adapts instruction. The evaluator can introduce an erroneous AI-generated suggestion to observe whether the candidate verifies it before classroom use. Stage 4, reflect: candidates collect structured peer feedback, inspect whether the intended reasoning actually occurred, and submit a revision memo with specific improvements. The cycle repeats in disciplinary methods courses and supervised practicum.

A workable assessment rubric uses five criteria: subject accuracy, pedagogical alignment, critical AI evaluation, inclusion and data safeguards, and reflective justification. Each criterion can be rated on a four-level scale from 1 (unsupported or unsafe decisions) to 4 (well-justified, verified, and responsive decisions). The total is descriptive rather than a validated psychometric score. Institutions should test inter-rater agreement and revise descriptors before using the rubric for high-stakes certification.

5. Discussion and Institutional Implementation

The TAPR model rejects an instrumental view in which teacher readiness is measured by the number of AI tools known. Professional competence requires knowing when not to use an AI system, how to recognize misleading outputs, and how to maintain a classroom culture of inquiry. UNESCO (2024) offers a useful foundation for situating these skills within broader teacher development, but implementation must be adapted to subjects, age groups, institutional infrastructure, and national requirements.

Teacher education institutions can begin by mapping existing course assignments onto the five dimensions, training supervisors to apply the same evaluation criteria, and providing safe practice environments with synthetic rather than real student data. Faculty development is essential: candidates are unlikely to learn critical oversight if instructors themselves use automated outputs uncritically. Procurement and policy processes should include privacy assessment and accessibility considerations, alongside educational usefulness.

Future studies can examine changes in lesson-plan quality, error-detection accuracy, and microteaching performance before and after the pathway. Longitudinal follow-up during teaching practice would be particularly valuable because confidence with tools may not predict competent classroom action. Cross-disciplinary analysis could establish where subject differences require specialized indicators and where a common competency foundation is appropriate.

6. Curriculum Integration Across Teacher Education

A teacher-education program should not isolate AI competence in a single technical elective. Foundational coursework can introduce model limitations, data literacy, and critical verification; subject-methods courses can examine how AI changes lesson design in specific disciplines; practicum seminars can require students to justify real instructional choices. This distributed model helps candidates connect technical capabilities to theories of learning, curricular purposes, and professional obligations. It also prevents competence from being reduced to memorizing prompt templates that may quickly become obsolete as interfaces change. Faculty teams can map program-level outcomes to existing courses and identify places where explicit assessment evidence is missing.

In a language-teaching methods course, for example, a candidate might examine AI-generated speaking prompts for communicative authenticity, age appropriateness, and cultural representation. A science-teaching candidate could test whether generated analogies distort an underlying mechanism. A history-teaching candidate could evaluate citations and the presentation of contested interpretations. Across these tasks, candidates should report their verification strategy, revision decisions, and a meaningful alternative when AI is not suitable. Such disciplinary cases make the connection between AI literacy and pedagogical content knowledge concrete.

7. Performance Assessment and Quality Assurance

An assessment portfolio could contain an annotated AI response, a lesson plan, evidence from microteaching, an ethical-risk review, and a reflection on student learning. Reviewers would assess accuracy of subject content, alignment with objectives, the quality of verification, accessibility, and the clarity of professional judgment. A shared rubric supports consistency, but its scores must not be described as validated measures without empirical study. Moderation sessions can help instructors agree on what constitutes adequate evidence and what kinds of errors indicate a need for further training. The portfolio should emphasize decisions and revisions rather than the volume of tool use.

Quality assurance also needs an explicit feedback loop. Candidates who fail to identify an invented reference should be given a new verification challenge, targeted feedback, and an opportunity to demonstrate improvement. Instructors should periodically replace examples because model behavior changes over time. To study rubric quality, institutions can collect independently rated samples and examine agreement, discriminability, and differences across subjects. Such activities constitute a program-evaluation plan, not results of the present conceptual study. High-stakes decisions must remain explainable and open to review.

8. Equity, Professional Responsibility, and Institutional Capacity

Preparation for AI use is incomplete unless candidates can work under diverse infrastructure conditions. Rural placements, schools with shared devices, and learners who need assistive formats may require different strategies. Candidates should show how learning objectives can be achieved without automated assistance and how teaching materials can be checked for accessibility. They should also understand when data protection rules or institutional policy prohibit the submission of student records to external services. The ability to decline a tool on defensible grounds is a positive demonstration of professional competence rather than a failure to innovate.

University leaders can support these practices through faculty workshops, vetted examples, approved data-handling procedures, and partnerships with schools that expose candidates to realistic constraints. Teachers need time to compare tools and audit errors; otherwise AI integration may add hidden workload. Continuous professional development should monitor emerging risks without assuming that every new feature has educational value. Partnerships should include mentor teachers, accessibility specialists, and student representatives so that implementation reflects the classroom community rather than solely the priorities of technology providers.

9. Directions for Empirical Validation

The proposed model invites research at three levels. At the candidate level, studies can assess error detection, lesson-plan quality, and the articulation of ethical reasoning before and after a designed learning sequence. At the classroom level, observations can examine whether teachers actually preserve student participation and verify generated material during instruction. At the institutional level, researchers can assess faculty workload, equitable access, and the durability of professional learning. Mixed-methods designs are especially appropriate because survey confidence is an incomplete proxy for responsible teaching behavior. Comparative studies should document the exact tasks and safeguards used.

An additional priority is contextual adaptation. The relative importance of instructional design, verification, and data governance may vary across early childhood education, secondary subjects, special education, and university teaching. Cross-context validation would help distinguish a common competence core from necessary local extensions. Future publications should report limitations transparently, including convenience samples, differences in digital access, and rapidly evolving software capabilities. Such evidence could refine the proposed pathway into a practical, testable teacher-preparation curriculum rather than a generic declaration that teachers should become AI literate.

6. Conclusion

AI-ready teachers need more than prompt-writing proficiency: they require integrated knowledge of subject matter, pedagogy, technical limitations, ethics, and reflective decision-making. The TAPR model offers five complementary domains and a four-stage instructional pathway suitable for adaptation in teacher education programs. Its usefulness and fairness should be tested through transparent, locally grounded empirical evaluation.

References

Miao, F., & Cukurova, M. (2024). AI competency framework for teachers. UNESCO. https://www.unesco.org/en/articles/ai-competency-framework-teachers

Miao, F., & Holmes, W. (2023). Guidance for generative AI in education and research. UNESCO. https://www.unesco.org/en/articles/guidance-generative-ai-education-and-research

Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. Teachers College Record, 108(6), 1017–1054. https://doi.org/10.1111/j.1467-9620.2006.00684.x

Shulman, L. S. (1986). Those who understand: Knowledge growth in teaching. Educational Researcher, 15(2), 4–14. https://doi.org/10.3102/0013189X015002004

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, 1–16. https://doi.org/10.1145/3313831.3376727

Kasneci, E., et al. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. Learning and Individual Differences, 103, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial intelligence in education: Promises and implications for teaching and learning. Center for Curriculum Redesign.

Selwyn, N. (2019). Should robots replace teachers? AI and the future of education. Polity Press.

Saranya, E., Sethuraman, P., Olimjonov, H., Nagendram, S., Ganesh, M., & Sapaev, I. (2026, August). Deep Reinforcement Learning for Cloud Resource Allocation and Energy-Efficient Data Center Operations. In *2026 International Conference on Next-Gen Intelligent Computing and Applications (ICONICA)* (Vol. 1, pp. 1-11). IEEE.

Kannan, N., Kollinal, R. K., Olimjonov, H., Ahammad, S. H., Kanagaraju, M., & Sapaev, I. (2026, August). Intelligent Ensemble Learning for Climate-Aware Agricultural Planning and Resource Allocation. In *2026 International Conference on Next-Gen Intelligent Computing and Applications (ICONICA)* (Vol. 1, pp. 1-10). IEEE.

Guru, K. V., Rajan, C., Olimjonov, H., Lakshmi, N. V., Joseph, A. V., & Nazarova, S. (2026, August). Capsule Network-Based Historical Document Digitization for Intelligent Knowledge Organization and Digital Archiving. In *2026 International Conference on Next-Gen Intelligent Computing and Applications (ICONICA)* (Vol. 1, pp. 1-9). IEEE.