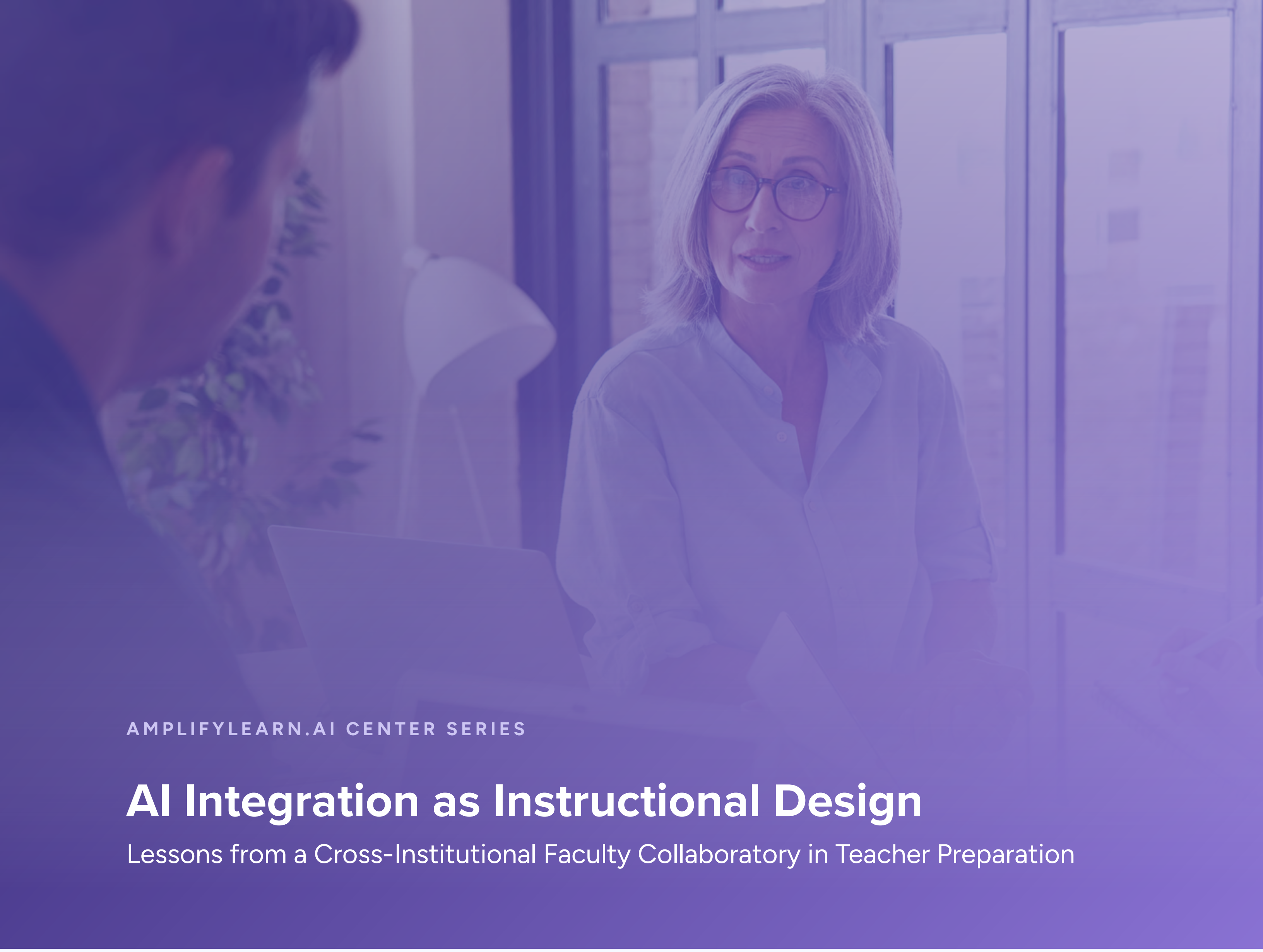

AMPLIFYLEARN.AI CENTER SERIES

AI Integration as Instructional Design

Lessons from a Cross-Institutional Faculty Collaboratory in Teacher Preparation

PRODUCED BY

Educator Preparation Program Faculty Collaboratory on AI in Teacher Education, facilitated by the AmplifyGAIN Research & Development Center at the University of Washington College of Education

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DISCLOSURE

Colleague AI, Inc. developed the platform provided to collaboratory participants. Authors Alex Liu and Min Sun are affiliated with Colleague AI. Platform adoption in the collaboratory was voluntary, and the conclusions reported here are not restricted to any single GenAI platform.

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Executive Summary

In a classroom assessment course at Gonzaga University, teacher candidates (also known as pre-service teachers; hereafter, candidates) who had initially judged their feedback substantively useful devalued that same feedback once they learned AI had been involved in producing it. The instructor, Dr. Suzann Girtz, termed this the “balloon popping” effect. Disclosure of AI authorship altered how candidates valued feedback whose content was otherwise unchanged.

This episode reflects a broader challenge in teacher education. Generative AI (GenAI) adoption has been expanding among K-12 teachers. Two waves of nationally representative surveys of U.S. public school math and science teachers documented this growth. In 2026, 58% of surveyed math and science teachers reported using GenAI in their teaching, and 31% reported using it weekly or more. Both figures represent growth from 2025 (50% and 21%, respectively) (Liu et al., 2026; Esbenshade et al., 2025). Yet across the full 2026 sample, only 11% of teachers reported that their districts had established formal guidelines, 58% reported receiving no formal AI training, and 48% cited insufficient training as a barrier to adoption. Professional practice is changing more rapidly than the institutional structures responsible for guiding it, and this gap is directly relevant to educator preparation programs (EPPs), which prepare the teachers who will enter these institutions.

> ***Disclosure of AI authorship altered how candidates valued feedback whose content was otherwise unchanged.***

EPPs occupy a pivotal position in closing this gap. They must prepare teacher candidates not only to use AI tools but to exercise professional judgment and develop pedagogical reasoning about when AI supports or undermines classroom instruction and student learning, how to evaluate AI outputs critically, and how to navigate school contexts where policies are absent, emerging, or conflicting. In a 2024 survey of over 500 education school leaders, Weiner et al. (2024) found that teacher preparation programs lagged behind K-12 districts in integrating AI, and more than half of the surveyed leaders reported that their faculty lacked confidence in bringing AI into instruction. Given the pace of change since then, current conditions may differ, though systematic guidance for EPPs remains limited. This white paper suggests that a central task for EPPs is the design of learning experiences that develop professional reasoning in AI-mediated environments, which involves more than the adoption of new tools.

To begin building evidence from practice, the AmplifyGAIN Center, a national R&D center at the University of Washington College of Education funded by the Institute of Education Sciences, organized an EPP Faculty Collaboratory that convened 15 faculty members (also known as teacher educators; hereafter, faculty) from 13 higher education institutions across the United States to design, implement, and document AI-integrated activities in teacher preparation courses from January to June 2026. Twelve faculty completed the full design-implementation cycle and contributed the use cases synthesized here. Participants represented mathematics education, educational technology, assessment, multilingual education, clinical practice, elementary education, and AI literacy. Institutional contexts ranged from R1 research universities to regional comprehensives, an HBCU, and urban public universities. Rather than prescribing a single model of AI integration, the collaboratory asked each faculty member to develop an implementation suited to their course, discipline, and candidate population.

Despite this variation, the implementations yielded consistent lessons. Together they suggest that AI integration is an instructional design problem rather than a tool adoption problem, and five cross-cutting themes emerged.

FIVE CROSS-CUTTING THEMES

- **AI works best when positioned as support for professional judgment, not an answer provider.** Across cases, faculty positioned AI as a thinking partner, critique generator, or rehearsal tool while candidates retained responsibility for evaluating, adapting, and justifying instructional decisions.
- **Bounded and sequenced use protects core learning.** Faculty who protected independent disciplinary analysis before introducing AI found that candidates could evaluate AI outputs more critically. When AI entered too early, it bypassed the reasoning skills the course was designed to develop.
- **Critical evaluation requires explicit scaffolding.** Candidates did not critique AI outputs spontaneously. Faculty had to build requirements for auditing, comparing, and revising AI-generated content into the assignment itself.
- **Context shapes what responsible use looks like.** No single implementation model held across disciplines, course types, and candidate populations. Programs need shared principles with course-specific boundaries.
- **Implementation takes iteration, and responsible integration requires more course design work, not less.** Every faculty member adjusted between initial design and classroom practice, and all needed to write clearer directions, model prompting and inspection, define boundaries, and develop assessments that capture candidates' thinking processes.

This paper provides a high-level synthesis, practical strategies, and program-level recommendations for EPP leaders, faculty, curriculum designers, and accreditation stakeholders seeking to integrate AI into teacher preparation responsibly. The companion use case library provides detailed implementation cases, and the R&D agenda translates practitioner experience into priorities for researchers and technology partners. The central recommendation is that EPPs start small, design intentionally, make human judgment visible, and treat AI literacy as an integrated dimension of professional teacher preparation rather than a standalone technology skill.

1. Introduction: The EPP Challenge

1.1 The AI Moment in K-12 Education

Generative AI (GenAI) has moved rapidly from an emerging technology to a substantive presence in K-12 educators' work routines. Between 2023 and 2025, GenAI adoption among U.S. math and science teachers more than doubled, rising from 19% to 50% (Diliberti et al., 2024; Esbenshade et al., 2025). Among adopters, teachers report using these tools primarily for instructional planning (76%), creating assessments (61%), and supporting classroom instruction (50%), though only 13% report using AI for grading or feedback (Esbenshade et al., 2025). Much of this use is self-directed. Among teachers who use GenAI, 88% rely on ChatGPT, often without district-endorsed alternatives or formal guidelines (Esbenshade et al., 2025).

Even though AI is present in more than half of teachers' professional routines, teachers remain hesitant to introduce AI to their students or bring it into the classroom, as they perceive that students would encounter AI in ways that complicate authorship, assessment, independent practice, and school policy. Results from a 2026 nationally representative survey of K-12 math and science educators indicate that teachers' concerns regarding student AI use are intensifying. Teachers identified the potential negative impact on human creativity (67%), student over-reliance (66%), and academic integrity (60%) as primary risks (Liu et al., 2026). Notably, each of these figures reflects an increase in concern compared to the preceding year (Esbenshade et al., 2025). The data indicate that self-directed teacher AI adoption has outpaced institutional guidance and training. Even among frequent users[1], a group we might expect to be best supported, 32% reported that their districts have no AI guidelines, only 18% reported established formal policies, and 61% had received no district-provided formal training.

1.2 Why EPPs Need Specific Guidance

For EPPs, the challenge extends beyond deciding whether to allow or prohibit AI in coursework. Candidates occupy a dual position. They are simultaneously learners still developing disciplinary and pedagogical knowledge and judgment, and emerging professionals who will soon make independent instructional decisions in K-12 institutions where AI is already present. EPP faculty therefore must protect the development of core professional capacities (noticing student thinking, making instructional decisions, designing assessments, building relationships, reflecting on practice) while also preparing candidates to navigate AI-mediated schools in future field placements, where they will need to model responsible and effective AI use for K-12 students.

This dual responsibility poses a challenge for EPPs, since faculty must evaluate not only the quality of AI-assisted outputs but also the reasoning candidates use to reach them. The importance of the latter also surfaced in the collaboratory faculty's classrooms. A candidate who can produce a polished AI-assisted lesson plan but cannot explain why that plan fits the learners, standards, and instructional purpose has not demonstrated the professional judgment expected of practicing educators. Several faculty observed exactly this gap. Candidates produced materials quickly but struggled to justify their pedagogical appropriateness, suggesting a disconnect between the quality of the artifacts candidates produced and their ability to reason about them.

Prior work has documented the limits of existing guidance for AI use in teacher preparation. Weiner et al. (2024) reported that, as of 2024, teacher preparation programs lagged behind K-12 districts, with most AI instruction folded into existing coursework and centered on plagiarism prevention rather than pedagogical integration, though the field has continued to evolve since that assessment. Sperling et al. (2024) reviewed 34 studies on AI literacy in teacher education and found that the field lacked consensus on what AI literacy means for professional educators, as distinct from general digital literacy. UNESCO's AI Competency Framework for Teachers (2024) defines 15 competencies across five dimensions, but it was designed as a global policy reference rather than as implementation guidance grounded in faculty practice. The gap this white paper addresses is the translation from such frameworks to field-tested implementation in EPP courses.

1.3 About This White Paper

The EPP collaboratory began from the premise that AI integration in teacher preparation is a design problem involving instructional intent, candidate learning goals, professional judgment, authorship, disclosure, access, assessment integrity, clinical placement expectations, and program coherence. The goal was to learn from varied implementations and synthesize practical guidance for the field, rather than to standardize AI use across institutions.

This white paper is written for the following audiences:

- EPP program leaders developing program-wide expectations for AI use in teacher preparation;
- EPP faculty redesigning syllabi, assignments, and assessments to address AI;
- Curriculum designers and clinical coordinators aligning coursework with field placement realities;
- Policy and accreditation stakeholders considering how AI literacy fits teacher preparation standards;
- R&D and technology partners designing AI tools for teacher education contexts.

This document is intended as a translational synthesis from practitioner implementation rather than a research report, policy mandate, or product endorsement. Detailed cases, materials, and faculty-specific examples are housed in the companion online use case library. This paper synthesizes what those cases, taken together, suggest for the field.

2. The AmplifyGAIN EPP Collaboratory

2.1 About the AmplifyGAIN Center

The AmplifyGAIN (Amplify Generative AI Innovations in Math and Science Education) Center at the University of Washington College of Education is a National Research and Development Center funded by the Institute of Education Sciences, U.S. Department of Education (Grant R305C240012). The center focuses on the use of GenAI to enhance mathematics and science teaching and learning in K-12 schools.

The collaboratory documented in this paper is one strand of a coordinated research-practice program. The center has fielded nationally representative surveys of K-12 teacher GenAI adoption (N = 1,011, Liu et al., 2026; N = 979, Esbenshade et al., 2025), conducted large-scale qualitative and quantitative studies on AI use and implementation in K-12 contexts (e.g., Liu et al., 2025b; Esbenshade et al., 2026), and carried out co-design and design-based research for AI-powered technology development (e.g., Sarkar et al., 2025; Liu et al., 2025a). These strands provide complementary perspectives from K-12 settings, and their implications for teacher preparation informed how the center facilitated the EPP collaboratory. Meanwhile, the participating EPP faculty grounded the implementations within teacher education literature and their own program contexts.

2.2 Collaboratory Design and Structure

The EPP Faculty Collaboratory convened 15 faculty members (not counting the center facilitators) from 13 institutions across the United States to explore responsible AI integration in teacher preparation courses. The collaboratory ran from January through June 2026, structured as a practitioner-led, cross-institutional learning community.

The collaboratory membership was heterogeneous by design. Participating faculty represented mathematics education, classroom assessment, educational technology, multilingual education, elementary education, clinical practice, and AI literacy. Institutional contexts included R1 research universities, regional comprehensive institutions, an HBCU, and urban public universities. Programs ranged from undergraduate initial licensure to graduate professional certification. Lessons that held across such varied contexts were expected to be more transferable to the broader field than lessons drawn from a single setting.

The collaboratory asked each faculty member to design and implement at least one course task or activity that integrated AI. Faculty selected their own tools, timing, boundaries, and assessment approaches. The center provided structure, access to an AI platform, design consultation, and shared reflection spaces. Implementation decisions remained local. Colleague AI, a research-backed AI platform for K-12 teaching and learning, was provided free of charge as the GenAI tool. Adoption of Colleague AI was voluntary and based on faculty and candidates' choices. Colleague AI served as the primary shared platform rather than an exclusive requirement, and some courses allowed candidates to select a platform for their own use. Therefore, although the use cases generated from the collaboratory concentrated on Colleague AI, the results and lessons learned are not restricted to any single GenAI platform.

The collaboratory arc moved through six sessions from orientation to future directions:

JAN 2026	FEB 2026	MAR 2026
Session 1 · Orientation	**Session 2 · Design sharing**	**Session 3 · Evaluation**
AI landscape, goal-setting, platform introduction	Design presentations, peer feedback, planning	Assessment frameworks, evaluation approaches
APR 2026	**MAY 2026**	**JUN 2026**
Session 4 · Mid-implementation	**Session 5 · Final deliverables**	**Session 6 · Future directions**
Progress reports, troubleshooting, design revision	Use case compilation, white paper planning	R&D agenda generation, network formation

Figure 1. The six-session arc of the EPP Faculty Collaboratory, January through June 2026.

2.3 Participants

Twelve faculty completed the design-implementation cycle within the collaboratory period and contributed to this white paper.

Table 1. Participating faculty, institutions, and EPP focus areas.

Faculty	Institution	EPP Focus Area
Dr. Amanda Zeller	University of Tennessee, Knoxville	Educational Technology
Dr. Anne Traynor	Purdue University	Assessment & Evaluation
Dr. Brenda Sarmiento-Quezada	Purdue University	Linguistics & Multilingual Education
Dr. Candace Walkington	Southern Methodist University	AI Literacy / Mathematics Education
Dr. Emily Holtz	University of Tennessee, Knoxville	Elementary Education
Dr. Grace Pai	Queens College, CUNY	Mathematics Education
Dr. Hea-Jin Lee	The Ohio State University at Lima	Mathematics Education
Dr. Li Sun	Augustana University	Educational Technology
Dr. Liza Bondurant	Mississippi State University	Mathematics Education
Dr. Shirley Burnett	Jackson State University	Mathematics Education
Dr. Stephanie Casey	Eastern Michigan University	Mathematics Education
Dr. Suzann Girtz	Gonzaga University	Assessment & Evaluation

2.4 Outputs

The shared work produced three related outputs. First, the companion online use case library indexes 11[2] detailed faculty implementations, each documenting course context, activity design, AI role, do/do-not guidance, evidence and reflections, and materials reviewed. Second, this white paper synthesizes cross-case lessons and translates them into actionable guidance for the field. Third, an R&D agenda translates practitioner experience into priorities for researchers and technology partners.

3. What We Learned Across Cases

Although the 11 AI implementations were designed independently, cross-case comparison at the collaboratory's final sessions revealed recurring themes across markedly different settings. The use cases present five dominant themes, described in the following sections.

3.1 AI Should Support Professional Judgment, Not Bypass It

The strongest common theme across all implementations was that AI should not be treated as a substitute for teacher thinking. Faculty used different framings depending on their disciplinary context. These included AI as a "thinking partner" or "pedagogical mirror" (Dr. Sarmiento-Quezada), a "reflective rehearsal partner" (Dr. Holtz), a "peer" or "co-pilot" (Dr. Burnett), a critique generator (Drs. Traynor, Girtz), and a planning scaffold (Drs. Zeller, Sun). The underlying structure was consistent across these framings. Candidates remained responsible for evaluating, revising, adapting, rejecting, and explaining AI-generated suggestions.

This theme bears directly on the purpose of teacher education, which is to develop pedagogical reasoning rather than simply to produce artifacts such as lesson plans, rubrics, reflections, or feedback comments. The collaboratory repeatedly observed cases in which artifact production outpaced the underlying reasoning. For example, one faculty member observed that candidates could produce materials quickly using Colleague AI but struggled to justify why those materials were instructionally appropriate. Another faculty member tested AI-assisted grading, found it “not great,” and returned to human-only grading. The “balloon popping” observation described at the opening of this paper further suggests that perceptions of authorship affect how feedback is received. Candidates’ valuation of feedback changed substantially when they learned AI had been involved, even though the feedback content was unchanged.

In a comparative study of 529 source-blinded lesson plan pairs evaluated by 16 experienced mathematics educators, Sarkar et al. (2025) found that human-authored plans were preferred overall (58.7% vs. 41.3% for GPT-4), particularly for student discourse facilitation, group work, and developmentally appropriate scaffolding at the elementary level. AI plans were competitive at the high school level and preferred for structured reflective summaries, but they lacked the contextual depth educators valued. Read alongside the observations from EPP courses, these results suggest that although AI can generate structurally competent materials, the quality of instructional materials still relies on teachers bringing their own professional judgment about context, learners, and instructional purpose. Developing that judgment therefore remains a central purpose of teacher education in the digital era.

3.2 Bounded and Sequenced Use Protects Core Learning

At Purdue University, Dr. Brenda Sarmiento-Quezada’s class began the semester with fully independent work. Candidates recorded an English Learner’s speech, transcribed it, analyzed its linguistic features and cross-linguistic transfer patterns, and constructed an initial instructional plan entirely without AI. Only after completing that independent disciplinary analysis could candidates optionally use AI to generate instructional strategies, scaffolds, equity considerations, or alternative approaches. When candidates did use AI, they documented what they accepted, adapted, rejected, or chose not to use.

Her Linguistic Analysis and Instructional Planning Project offered an explicit example of a pattern that recurred across the collaboratory’s implementations, namely a deliberate distinction between the work candidates had to complete independently and the work AI could later support. This distinction does not require splitting a course into an independent first half and an AI-supported second half. It can instead operate iteratively, alternating independent and AI-supported work within smaller tasks. Dr. Burnett’s implementation at Jackson State illustrates this iterative structure. Her candidates first created a baseline algebra lesson plan without AI, then used Colleague AI to request modifications aligned with the Mississippi Mathematics Instructional Observation Protocol (MIOP), and finally evaluated the AI output for mathematical accuracy and classroom realism before submitting. The independent-then-AI sequencing also extended beyond content generation. Dr. Holtz structured AI use around Tennessee TEAM rubric topics only after candidates had completed authentic field experience and initial reflective writing.

Sequencing matters because candidates cannot critically evaluate AI output without an independent foundation for judgment. When AI is introduced too early, it can bypass the very noticing, analysis, planning, and reflection skills the course is meant to develop. When AI enters after candidates have produced an initial human-generated baseline from their own reasoning, it supports connection, comparison, critique, and refinement rather than substitution.

This does not mean that discussion of AI must always be delayed. In Dr. Walkington’s course, where GenAI literacy was itself the learning goal, structured and required AI use across all assignments was appropriate. The broader principle is that faculty need to identify which learning goals require independent practice, which goals benefit from AI-mediated practice, and which goals involve learning to evaluate and use AI itself.

3.3 Critical Evaluation Requires Explicit Scaffolding

AI can produce seemingly high-quality materials, which makes spontaneous critique of AI outputs feel unnecessary. One faculty member observed that some candidates accepted the first AI response without questioning it, while another reported that some candidates initially viewed AI as either wholly helpful or wholly problematic, lacking nuanced criteria for evaluating specific outputs. Faculty also commonly observed that candidates could generate materials quickly but struggled to explain why those materials were pedagogically appropriate. Across cases, critical evaluation appeared to be a skill that faculty must deliberately cultivate rather than a disposition candidates bring with them.

The most effective designs made critique an explicit requirement. Dr. Traynor found that asking candidates to compare multiple AI-generated outputs, rather than evaluating a single output in isolation, helped them distinguish stronger from weaker options and develop evaluative criteria. Dr. Walkington found that explicit requirements prompted her students to reliably audit hallucinations and iterate with AI. Dr. Sarmiento-Quezada observed that requiring candidates to document their reasoning process led them to reflect on and identify both benefits, such as brainstorming and alternative strategies, and limitations, such as lack of learner specificity, developmental inappropriateness, and insufficient context sensitivity.

The most useful designs made critique visible and assessable. Approaches included the following:

- Preserving original AI outputs alongside revised versions (Drs. Zeller, Burnett, Bondurant & Casey)
- Documenting prompt history with iterative refinement (Drs. Walkington, Sun, Burnett)
- Annotating revisions to explain what was accepted, adapted, or rejected and why (Drs. Sarmiento-Quezada, Burnett)
- Requiring hallucination and bias audits as assignment components (Dr. Walkington)
- Comparing AI output against candidates' own prior work (Drs. Pai, Sarmiento-Quezada)
- Defending choices orally in final presentations (Drs. Burnett, Sun)
- Writing reflection essays connecting the AI process to professional judgment development (Drs. Zeller, Holtz, Sun, Bondurant & Casey)

These process requirements made it harder for AI to become a shortcut and made candidates' reasoning visible for faculty to assess. The design implication is clear. AI literacy in EPPs must include explicit instruction, practice, and assessment of critical evaluation, not merely exposure to tools.

3.4 Context Shapes What Responsible Use Looks Like

Whereas the first three themes reflect convergence across cases, the fourth concerns variation. There was no single implementation model across the collaboratory, and this variation was itself informative. Faculty worked with undergraduate candidates (Drs. Pai, Lee, Sarmiento-Quezada, Girtz, Bondurant & Casey), graduate interns (Dr. Holtz), in-service educators pursuing advanced credentials alongside EPP students (Dr. Walkington), and students in both face-to-face and asynchronous course formats (Dr. Traynor). Some courses were explicitly about AI (Dr. Walkington). Others were methods courses (Drs. Lee, Pai, Bondurant & Casey, Burnett), assessment courses (Drs. Traynor, Girtz), linguistics courses (Dr. Sarmiento-Quezada), technology courses (Drs. Zeller, Sun), or internship seminars (Dr. Holtz) where AI was a selective support.

Context shaped where each faculty member set boundaries on AI use.

- **Multilingual education.** Dr. Sarmiento-Quezada protected linguistic analysis and learner-specific reasoning before allowing AI-supported instructional planning because candidates needed to develop their own analytical competence in identifying cross-linguistic transfer patterns.
- **Clinical internship seminars.** Dr. Holtz protected reflective writing grounded in lived classroom experience and connected AI use specifically to Tennessee TEAM observation rubric domains.
- **Assessment courses.** Dr. Traynor and Dr. Girtz used AI outputs as material for candidates to evaluate and critique rather than as authoritative models, developing assessment literacy through critical analysis of AI-generated tasks and rubrics.
- **AI-focused coursework.** Dr. Walkington's full-semester course on GenAI for educators required broad AI use with disclosure, iterative prompting records, and hallucination and bias audits because the course itself was about developing GenAI literacy.
- **Elementary mathematics for multilingual learners.** Dr. Pai framed AI use around questions of trust (mathematical and pedagogical), adaptation needs, and whether AI supports student mathematical thinking, explicitly respecting candidates' autonomy in deciding whether to use AI in their own future practice.
- **Mathematics education.** Dr. Burnett positioned AI as a "peer/co-pilot" for brainstorming and revision while protecting candidates' original intellectual work and requiring oral defense of choices.

This variation matters for program policy. A single broad rule ("AI is allowed" or "AI is prohibited") does not give faculty or candidates sufficient guidance. EPPs need shared principles at the program level and course-specific implementation decisions that account for disciplinary goals, candidate development stage, and clinical context.

3.5 Implementation Takes Iteration

Every implementation required adjustment between initial design and classroom practice. Initial designs drew on faculty members' prior teaching experience, pedagogical and content knowledge, and familiarity with earlier technologies. However, GenAI did not behave like the technologies that informed these designs. Rather than executing instructions, it generated content and participated in instructional decisions, which unsettled assumptions built from prior experience. The opportunities and obstacles this created varied across individuals.

Faculty reports surfaced predictable frictions alongside unexpected learning. Some faculty discovered that candidates needed more help with prompting than expected, that candidates experienced cognitive overload when platform navigation competed with pedagogical learning, and that candidates who used AI fluently for personal purposes did not automatically transfer those skills to professional instructional contexts. In addition, some candidates remained strongly opposed to AI throughout the semester. One faculty member reflected that a one-on-one conversation earlier in the process might have helped address those concerns. AI integration in teacher education is therefore not just a matter of tool adoption but a matter of personal belief, pedagogical value, and professional judgment. Faculty are responsible for supporting candidates in establishing these values before they enter the K-12 field and work independently in classrooms.

Faculty adjusted their designs in response to implementation experience.

- Dr. Burnett would introduce AI earlier in the project sequence, after candidates have an initial plan and research base, rather than waiting until late in the semester.
- Dr. Sun would give more time for candidates to explore AI for classroom discourse facilitation, UDL choice boards, and cognitively varied instructional explanations.

- Dr. Holtz would provide more structured guidance on critical evaluation earlier and create more collaborative analysis of AI-generated responses.
- Dr. Walkington would address ethical concerns earlier in the semester, based on issues that surfaced in early project work.
- Dr. Bondurant and Dr. Casey cited the collaboratory model itself as a sustainability factor, noting that ongoing peer consultation supported their iterative design process.

These adjustments should not be read as evidence that AI integration failed. Rather, they indicate that responsible integration requires iterative design, faculty learning communities, and institutional patience. Multiple faculty converged on the same recommendation to start small, with one assignment, one bounded activity, one clear purpose, and one cycle of reflection before scaling. Dr. Holtz further recommended that programs begin with faculty conversations about AI before moving to policy conversations.

4. Practical Strategies for EPP AI Integration

The following six strategies emerged from the collaboratory implementations. Each is grounded in specific faculty practice and suited to different course contexts and learning goals. Faculty are encouraged to select the strategy that matches the learning goal at hand rather than to adopt all six.

1 Bounded Activity With Clear Purpose

A single bounded activity with a clear instructional purpose offers a more manageable starting point than a course-wide AI redesign. A bounded activity identifies when AI may be used, when it may not be used, what candidates must document, and what counts as successful learning.

WHEN TO USE. Faculty integrating AI into an existing methods, assessment, or clinical course for the first time.

EXEMPLARS. Dr. Zeller's single-session lesson plan critique (Weeks 11-12 of an existing educational technology course); Dr. Traynor's two-part activity within a 15-week asynchronous assessment course; Dr. Pai's single asynchronous interactive activity within an elementary mathematics methods course.

KEY FEATURES. Defined scope (e.g., one to two weeks), existing course goals preserved, documentation requirements built in, and the task tested by faculty first.

2 Generate-Inspect-Critique-Revise Workflow

Candidates generate or receive an AI output, inspect and critique it against professional criteria, revise it for their specific context and learners, and reflect on the process. This model applies to lesson planning, assessment design, feedback writing, differentiation, and instructional material adaptation.

WHEN TO USE. Any assignment where candidates are developing instructional design skills and the learning goal includes professional judgment about quality.

EXEMPLARS. Dr. Zeller (lesson plan generation, critique via comments and highlighting, revision, reflection); Dr. Burnett (baseline plan, AI-enhanced version using MIOP criteria, critique for mathematical accuracy, follow-up prompting, reflection); Dr. Bondurant and Dr. Casey (existing lesson, trial of AI-suggested modifications, revision, reflection).

KEY FEATURES. Generation is only the first step. Faculty assess critique quality and revision rationale, not just the final product. Candidates explain what they changed and why.

3 Sequence AI After Independent Analysis

When a course goal depends on disciplinary reasoning, candidates must be able to demonstrate that reasoning independently. The timing of AI's entry is therefore crucial. This strategy introduces AI only after an initial human analysis. The sequence is particularly important for linguistic analysis, student work analysis, assessment evaluation, and professional reflection.

WHEN TO USE. Courses where the learning goal is disciplinary competence that could be bypassed if AI generates the analysis first.

EXEMPLARS. Dr. Sarmiento-Quezada (linguistic analysis and instructional planning completed independently before optional AI use); Dr. Burnett (baseline lesson plan completed before AI enhancement); Dr. Lee (student work analysis written before AI simulation); Dr. Holtz (reflective writing connected to field experience before AI-supported rehearsal).

DESIGN QUESTION. What must candidates be able to notice or decide independently before AI can be helpful rather than substitutive? Once that baseline is clear, AI can enter as a second opinion, alternative generator, or critique partner.

4 Make AI Interaction Auditable

If candidates use AI, faculty need visibility into how it was used. Documentation serves two purposes. It provides evidence for assessment of professional judgment, and it scaffolds candidates' own metacognitive awareness of their AI interaction patterns.

WHEN TO USE. Any assignment where AI is permitted and professional reasoning is a learning goal.

EXEMPLARS. Dr. Walkington (full prompting records with iteration, hallucination audits, and bias audits required for every assignment); Dr. Burnett (chat transcripts submitted alongside final work, with oral defense); Dr. Sun (mini-lesson presentations including descriptions of original prompts, critique of the first output, and the prompt refinement process); Dr. Sarmiento-Quezada (documentation of accepted, adapted, and rejected suggestions with rationale).

DOCUMENTATION APPROACHES. Prompt histories, disclosure statements, annotated revisions, accepted/adapted/rejected logs, hallucination audits, comparison with candidates' prior independent work, and reflective narratives on the process.

5 AI-Simulated Teaching Practice

AI can create opportunities for low-stakes rehearsal with simulated students, instructional decision scenarios, feedback conversations, or practice responding to mathematical misconceptions. These uses extend practice opportunities beyond what faculty or field placements can provide in real time.

WHEN TO USE. Courses focused on developing responsive teaching moves, feedback skills, or instructional decision-making.

EXEMPLARS. Dr. Lee (multi-turn AI simulations responding to student mathematical thinking, connected to prior written student work analysis); Dr. Holtz (simulated student work analysis, questioning and feedback simulations, and instructional decision-making scenarios connected to the Tennessee TEAM rubric); Dr. Pai (scenarios involving ELL students in elementary mathematics discussions).

CAUTION. Simulations require structure. Faculty should define roles, rounds of interaction, expected candidate moves, reflection prompts, and limits on what AI should simulate. AI-mediated rehearsal should supplement, not replace, authentic interaction with students, mentors, peers, and instructors. Bondurant and Shaughnessy (2026) frame this as AI supporting "approximations of practice" while preserving the necessity of authentic human interaction for developing relational teaching skills.

6 Instructor-Mediated AI (Behind the Scenes)

Not every AI integration requires candidates to use AI directly. Faculty can use AI to generate examples, assessment materials, flawed drafts, or contrasting cases for candidates to analyze and critique. This approach develops critical AI literacy without requiring every candidate to adopt the tool themselves.

WHEN TO USE. Faculty want to introduce AI-generated materials as objects of analysis without requiring student-facing AI interaction, or institutional barriers limit student access.

EXEMPLAR. Dr. Girtz used AI-generated assessment examples as objects of candidate critique in equity-centered redesign tasks. She emphasized transparency about her own AI use and modeled the evaluation and revision process for candidates.

KEY CONSIDERATION. If faculty use AI-generated materials, they should consider when and how to disclose that use. Dr. Girtz's experience with the "balloon popping" effect, in which students' perceptions of feedback changed once they learned AI was involved, suggests that transparency and modeling are essential parts of instructor-mediated approaches.

5. Do and Do-Not Guidance

The following guidance synthesizes faculty deliverable forms, implementation reflections, and midpoint synthesis discussions. Each item is grounded in at least one faculty member's documented implementation experience.

DO

- ✓ **Do align AI use with a specific learning goal.** AI should solve or illuminate an instructional problem, not simply be added because it is available. Every faculty member who reported successful implementation had a clear pedagogical rationale connecting AI use to existing course outcomes.
- ✓ **Do try the tasks yourself before assigning them.** Faculty who tested tasks identified navigation issues, unclear prompts, platform constraints, and likely points of candidate confusion before candidates encountered them. One faculty team emphasized this as their top recommendation.
- ✓ **Do provide clear, concise, candidate-facing directions.** One faculty member found that candidates experienced cognitive overload when platform navigation competed with pedagogical learning. Screenshots, examples, structured prompts, and step-by-step instructions reduce unnecessary friction.
- ✓ **Do require candidates to document AI use.** Disclosure, prompt history, accepted and rejected suggestions, and reflections make professional judgment visible and assessable.
- ✓ **Do teach candidates to critique AI outputs.** Accuracy, bias, standards alignment, learner specificity, developmental appropriateness, and feasibility should be explicit evaluation criteria. Candidates do not develop these skills from exposure alone.
- ✓ **Do preserve human agency.** Candidates should make and defend final decisions. Faculty approaches included requiring oral defense of choices, requiring documentation of why suggestions were accepted or rejected, and positioning AI as a supporting partner rather than the lead thinker.
- ✓ **Do address privacy and confidentiality directly.** Candidates should not enter identifying student, family, school, clinical placement, or protected information into AI tools.
- ✓ **Do honor different dispositions toward AI.** One faculty team found that a candidate remained strongly opposed throughout the semester, and reflected that an earlier one-on-one conversation may have helped this candidate become more open to the potential benefits of AI. Another faculty member explicitly respected candidates' autonomy in deciding whether to use AI in their future practice. Skepticism may reflect legitimate ethical, environmental, relational, or equity concerns.
- ✓ **Do connect AI activities to authentic teaching work.** Faculty anchored AI use in state observation rubric domains, instructional observation protocols, real ELL mathematics scenarios, and lesson planning. Lesson planning, student thinking, feedback, assessment, and clinical reflection are stronger anchors than generic tool exploration.
- ✓ **Do plan for iteration.** Every faculty member reported gaps between initial design and actual implementation. First implementations should be treated as pilots that generate design learning.

DO NOT

- ✕ **Do not assume candidates already know how to use AI well.** Multiple faculty found that everyday AI use does not automatically transfer to professional instructional use, and that candidates who used AI fluently for personal purposes did not transfer those skills to instructional contexts.
- ✕ **Do not use one policy for every course and task.** AI boundaries should vary by learning goal, student population, discipline, and clinical context. As one faculty member emphasized, one AI rule does not work for every person, task, or circumstance.

- ✕ **Do not let AI replace disciplinary analysis or professional reflection.** Protect the parts of the assignment where candidates must develop their own thinking. As one faculty member framed the principle, independent thinking should come first.
- ✕ **Do not assess only polished final products.** AI can produce fluent artifacts, so EPP assessment must capture reasoning, critique, and the revision process.
- ✕ **Do not send AI-generated content into classrooms without inspection.** Faculty and candidates should review accuracy, appropriateness, bias, and alignment first. AI-generated materials require verification before use with K-12 students.
- ✕ **Do not use AI grading or feedback as a replacement for human evaluation.** Candidates in one course found AI-assisted grading "not great" and time-consuming, and the course returned to human-only grading.
- ✕ **Do not overuse AI in every activity.** One faculty member warned against letting AI crowd out peer dialogue, instructor feedback, lived reflection, and independent practice. Another faculty member recommended against encouraging student-facing chatbots for teachers of children below eighth grade.
- ✕ **Do not frame AI as a shortcut.** The goal is stronger professional reasoning, not faster completion. One faculty member explicitly prohibited submitting final graded work fully created by AI unless that was the specific assignment purpose.
- ✕ **Do not write overly long directions.** One faculty team found that lengthy instructions overwhelmed candidates. Clear, concise task descriptions with focused goals were more effective.
- ✕ **Do not ignore candidates' dispositions toward AI.** Resistance may signal productive professional reasoning that deserves engagement rather than dismissal.

6. Program-Level Recommendations

Course-level design is a necessary starting point for AI integration, but program-level coherence requires coordination beyond individual courses. The recommendations that follow move from the course level to the program level.

6.1 Build Shared Principles Before Mandates

Programs should begin with faculty conversations about what they want candidates to learn about teaching in AI-mediated contexts. Shared principles should address professional judgment, privacy, equity, authorship, disclosure, clinical placement expectations, and appropriate tool use. Dr. Holtz specifically recommended that programs start with faculty conversations before policy conversations, and the collaboratory's experience is consistent with that ordering.

Mandates are risky when they arrive before faculty have developed shared language. The collaboratory experience suggests that faculty need flexibility to design course-specific AI policies that fit disciplinary goals and candidate development levels. A shared set of principles can anchor program coherence while preserving the contextual variation documented in Section 3.4. This aligns with broader findings that effective professional development must be sustained, collaborative, and connected to instructional priorities rather than imposed through top-down mandates (Darling-Hammond et al., 2017; Nucci et al., 2026).

6.2 Sequence AI Literacy Across the Program

AI preparation should not be isolated in one technology course. Candidates need repeated, developmental opportunities to encounter AI across foundations, methods, assessment, clinical practice, and capstone experiences. The collaboratory demonstrated that AI integration looks different at each stage because it serves different learning goals, which suggests that programs can sequence those encounters deliberately.

One possible program-level sequence follows.

- **Foundations.** Basic AI literacy, ethics, privacy, bias, authorship, and school policy variation. Candidates learn what GenAI is, how it works at a conceptual level, and why professional judgment matters. (Connects to established AI competency frameworks.) (Exemplar: Dr. Walkington.)
- **Methods courses.** AI-supported lesson planning, differentiation, student work analysis, and instructional material critique. Candidates practice the generate-inspect-critique-revise workflow within their discipline. (Exemplars: Drs. Zeller, Burnett, Bondurant & Casey, Pai, Lee, Sun.)
- **Assessment courses.** AI-generated assessment tasks, rubric critique, feedback analysis, and validity questions. Candidates evaluate AI outputs against professional standards. (Exemplars: Drs. Traynor, Girtz.)
- **Linguistics and content courses.** Bounded AI use after independent disciplinary analysis. Candidates develop the baseline competence needed to evaluate AI suggestions critically. (Exemplar: Dr. Sarmiento-Quezada.)
- **Clinical and internship seminars.** AI-supported rehearsal, problem-of-practice inquiry, reflection boundaries, and field-site policy navigation. (Exemplars: Drs. Holtz, Lee.)
- **Program completion.** Evidence that candidates can explain responsible AI use, evaluate AI outputs, protect student data, navigate district policy variation, and justify instructional decisions with and without AI support.

6.3 Assess Professional Judgment, Not Tool Fluency Alone

Tool fluency is necessary but insufficient. Candidates should be assessed on whether they can decide when AI is appropriate, identify flawed outputs, adapt suggestions to specific learner contexts, explain tradeoffs, and preserve human relationships and responsiveness. The center's research on AI-generated lesson plans found that AI outputs increasingly compete with human-authored plans on structural dimensions but lack the contextual depth, discourse facilitation, and developmental nuance that distinguish professional teaching (Sarkar et al., 2025).

In an AI-rich environment, the ability to produce a lesson plan is less informative than the ability to explain why that plan fits the standards, learners, context, and instructional purpose. Programs may need to revise rubrics to value reasoning and decision-making more explicitly. Assessment approaches from this collaboratory that capture professional judgment include oral defense (Dr. Burnett), annotated revision documentation (Dr. Sarmiento-Quezada), prompt refinement narratives (Drs. Sun, Walkington), and comparative analysis (Drs. Pai, Traynor).

6.4 Provide Access, Infrastructure, and Faculty Support

Responsible AI integration requires institutional investment in access to approved tools, faculty development time, technical support, and protected time for assignment redesign. Uneven access can create inequity among candidates and across programs.

Programs should take the following steps.

- Identify privacy-compliant, institutionally approved AI tools for instructional use.
- Provide faculty with support and time for iterative course redesign. The collaboratory experience confirms this work takes more time, not less.
- Support faculty learning communities where peer consultation, shared problem-solving, and iterative refinement can occur. The collaboratory model itself served this function.
- Provide alternatives when candidates have ethical, accessibility, or technical concerns about AI use.

- Address institutional approval processes early. One faculty member spent considerable time navigating data privacy agreements for an AI platform, a delay that earlier coordination could have reduced.

6.5 Coordinate With Clinical Partners

Clinical placements add a final layer of complexity because district and school AI policies vary dramatically. In the nationally representative survey, 42% of teachers reported that their districts have no AI guidelines, and among teachers reporting formal or informal guidelines, 87% indicated that AI use is permitted with specific restrictions (Liu et al., 2026). As a result, candidates may move between university coursework where AI is integrated thoughtfully and field placements where AI is banned, undefined, or ubiquitous without guidance.

Programs should prepare candidates to do the following.

- Ask about local school and district AI expectations during field placement orientation.
- Avoid entering student data, identifying information, or protected records into AI systems regardless of setting.
- Understand that appropriate AI use in university coursework may not automatically transfer to field settings.
- Navigate contexts where policies are absent, emerging, or conflicting, a condition the center's survey suggests describes the majority of current school settings.

7. Recommendations by Audience

FOR EPP PROGRAM LEADERS

- **Start with a program-level vision for responsible AI in teacher preparation.** Articulate what your program wants candidates to know, do, and value regarding AI in teaching before developing specific policies.
- **Invest in faculty learning communities.** The collaboratory model demonstrates that cross-institutional, cross-disciplinary peer consultation supports iterative design in ways that isolated individual effort does not.
- **Provide designated support and time for assignment redesign.** This work requires more design effort, not less. Protect course instructors' time for testing, revising, and reflecting on AI-integrated activities.
- **Clarify privacy, disclosure, and data expectations at the program level** so individual faculty do not have to navigate institutional compliance alone.
- **Avoid overly rigid policies that prevent course-specific judgment.** Shared principles with local flexibility, as described in Section 6.1, are more sustainable than one-size-fits-all mandates.
- **Expect iteration.** First implementations are pilots. Programs should treat the first year of AI integration as generating design knowledge rather than demanding polished results.

FOR EPP FACULTY

- **Start with one bounded, meaningful activity.** Define what candidates must do before AI, what AI may support, what must be documented, and how final work will be evaluated.
- **Try the task yourself first.** Every faculty member who did this reported better-designed activities and fewer implementation problems.
- **Model critical AI use.** Show candidates your own process of prompting, evaluating, rejecting, and revising. Transparency about instructor AI use is instructive.
- **Assess process alongside product.** Require documentation that makes professional reasoning visible, such as prompt histories, revision annotations, reflections, and oral defense.
- **Honor candidate dispositions.** Resistance to AI may signal productive professional reasoning. Create space for conversation rather than mandating compliance.
- **Connect AI to authentic teaching tasks within your discipline** rather than generic tool exploration.

FOR POLICY AND ACCREDITATION STAKEHOLDERS

- **Frame AI literacy as an integrated dimension of professional teacher preparation,** not a standalone technology skill or a single course requirement.
- **Write standards that emphasize professional judgment, ethical decision-making, equity, and instructional reasoning** rather than proficiency with particular tools, which will change faster than accreditation cycles.
- **Accommodate disciplinary and contextual variation.** The collaboratory demonstrates that responsible AI use looks different in assessment courses, multilingual education, clinical practice, and AI literacy courses. One standard cannot capture this variation.
- **Recognize that teacher candidates need preparation for schools where AI policies are absent, emerging, or conflicting.** Standards should address navigation of ambiguity, not only compliance with existing guidelines.

FOR R&D AND TECHNOLOGY PARTNERS

- **Design AI tools that keep teacher thinking visible.** EPP faculty need platforms that support documentation, instructor oversight, and process assessment, not only final product generation.
- **Prioritize short, interpretable outputs that candidates can evaluate** rather than comprehensive materials that discourage critique. The center's research found that teachers valued AI most when it produced bounded, actionable artifacts rather than lengthy generic responses (Liu et al., 2025a).
- **Support the generate-inspect-critique-revise workflow at the platform level.** Tools should make it easy to preserve original outputs, annotate revisions, and export interaction records.
- **Partner with faculty and candidates in iterative co-design.** The most useful tools emerge from sustained collaboration with practitioners who understand the pedagogical goals AI should serve, not from assumptions about what educators need.

8. Looking Ahead

8.1 Unresolved Questions for the Field

The collaboratory surfaced questions that no single implementation could resolve but that should guide future research, policy, and program design.

- **Readiness thresholds.** When do candidates know enough to use AI without it substituting for the reasoning the course is designed to develop? Multiple faculty grappled with this boundary without reaching a generalizable answer.
- **Authentic versus simulated practice.** Which aspects of teaching expertise can be meaningfully rehearsed with AI-simulated interactions, and which require authentic human interaction with K-12 students, families, mentors, and peers? Drs. Lee and Holtz both used AI simulations productively, but neither claimed simulations could replace field experience.
- **Assessment of AI-supported competence.** How should programs evaluate whether a candidate who demonstrates competence with AI support can also demonstrate competence independently? What does "competent to teach" mean when AI is permanently available as a cognitive partner?
- **Long-term effects.** What happens when AI-prepared candidates enter classrooms? Does AI-integrated preparation produce teachers who exercise stronger professional judgment, or does it produce dependence on tools that may not be available or appropriate in their schools?
- **Policy navigation.** How do we prepare candidates for a 30-year career in which school AI policies will evolve unpredictably? Current conditions, in which 42% of teachers report no district guidelines and only 11% report formal policies, represent a transitional state rather than a stable one (Liu et al., 2026).
- **Equity by design.** How can AI integration in teacher preparation reduce rather than reproduce inequity across candidates (differential access, prior AI experience, institutional resources), across schools (urban versus rural, well-resourced versus under-resourced), and across the students those teachers will serve?

8.2 Invitation to the Field

Dr. Girtz's observation that candidates re-evaluated feedback after learning of AI involvement illustrates the stakes of this work. Candidates attend to the source of professional thinking, and cultivating that attentiveness deliberately is part of what preparation programs are designed to do.

This work is ongoing and collaborative. The companion use case library and this white paper are intended as starting points rather than final answers. We invite EPPs to take part in the following ways.

- Adapt use cases and strategies from the companion library to their own institutional and disciplinary contexts.
- Contribute additional use cases from their own implementations.
- Contact the AmplifyGAIN R&D Center (amplifylearn@uw.edu) for collaboration on research, resource development, or expanded participation.

The broader task is to build shared professional judgment about when AI helps teacher learning, when it interferes, and how EPPs can prepare candidates for classrooms that are still changing. That task belongs to the field, not to any single center or collaboratory.

COMPANION RESOURCE

The detailed use cases are indexed in the companion online use case library. Each page includes faculty, institution, course, AI integration overview, activity description, do/do-not guidance, evidence and reflections, materials reviewed, and library tags.

Notes

[1] Frequent users are teachers who reported that they use generative AI tools daily or weekly for professional tasks.

[2] Two of the 12 faculty collaborated on a single shared use case.

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EPP COLLABORATORY

https://www.amplifylearn.ai/epp-collaboratory/