



Teaching with AI, Not Against It: A Thinking Partner Framework for Working Adult Learners in Compressed Online Formats

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Abstract

Working adult learners in online graduate programs face challenges that make strict AI bans both impractical and unhelpful. This paper introduces the Thinking Partner Framework, a practical approach to AI integration developed and refined across six semesters of graduate research methods courses serving approximately 440 K-12 educators. Instead of treating AI as a problem to be detected, the framework positions AI as a Socratic partner that helps students learn while still requiring them to think for themselves. Five design principles—transparency, process documentation, authentic assessment, scaffolded autonomy, and metacognitive reflection—guide the framework's implementation. The paper includes practical tools such as sample prompts, documentation templates, and examples illustrating the difference between using AI for answers and using it as a thinking partner. Observations from

practice, including a 96% checkpoint completion rate and evidence of students transferring Socratic techniques to their own classrooms, suggest promise, though more rigorous research is needed. This framework gives distance education administrators a practical option beyond simply banning or allowing AI.

Keywords: artificial intelligence, adult learning, distance education, Socratic method, academic integrity, compressed courses

Introduction

When we talk about artificial intelligence in education, we often find ourselves trapped in a debate that misses the point. The conversation fixates on whether students will use AI to cheat, as if the key challenge is one of enforcement. But for working adult learners—the teachers, nurses, managers, and professionals who pursue graduate degrees while holding down full-time jobs and raising families—this framing is misguided.

For these students, AI tools serve a different purpose than they do for traditional undergraduates. Many working adults enroll to build real skills, even at personal cost, and limited time means they need to make every moment of learning count. When a professional uses an AI tool late at night after family responsibilities, it is often to make the most of their learning time, not to avoid work. The real issue is not whether people will use AI—they already do at work and in school. The challenge is whether we design learning experiences that help students use AI effectively, or leave them to figure it out alone.

This paper argues for a fundamental shift in the way we think about AI in education. It presents the Thinking Partner Framework, a practical approach developed and implemented across multiple course iterations that offers distance education administrators an alternative to the prohibition-versus-permission binary currently dominating institutional AI responses. When AI is used thoughtfully and guided by principles of adult learning, it can make education better, not worse. AI can help students learn more by providing explanations tailored to their specific knowledge gaps. It can prompt deeper thinking by asking follow-up questions that human instructors, constrained by class sizes and time pressures, cannot offer at scale. It can provide immediate, substantive feedback on drafts—the kind of formative feedback that research consistently shows accelerates learning but remains scarce in most school environments. But achieving these benefits requires intentional design. We cannot simply layer AI onto existing pedagogies and expect positive outcomes, nor can we rely exclusively on prohibition and detection. Instead, we must ask how AI can serve learning rather than subvert it.

Because disciplines, students, and institutions differ, a universal solution is not practical. Instead, we offer a process that can be adapted to local needs, starting with the key question: Who are our students, and what do they need? Too often, AI discussions emphasize administrative issues rather than students' real experiences. Our approach reverses this, beginning with students' constraints, motivations, and goals, and then considering policies.

AI in Education: Current Landscape and a Different Framework

The Current Landscape

ChatGPT's debut in November 2022 thrust generative AI into the educational spotlight, prompting institutional responses ranging from outright bans to cautious integration. The 2025 EDUCAUSE AI Landscape Study found that 57% of educators now view AI as a strategic priority, up from 49% in the prior year (Robert & McCormack, 2025). A recent study found that 94% of the top 50 U.S. universities had faculty guidelines emphasizing course-specific AI policies (An et al., 2025).

Academic integrity dominates institutional concern. Universities have classified submitting AI-generated content as violating honesty policies because it fails to constitute "original work" (Luo, 2024). Detection tools have

proliferated, though their reliability remains contested, leading instructors to seek alternative methods for verifying originality (Moore & Lookadoo, 2024). Beyond integrity, researchers have raised legitimate questions about skill development: Will students improve as writers if AI assists their drafting? Will they develop logical reasoning if AI handles corrections? These concerns deserve attention, but they rest on assumptions about student-AI interaction that may not hold universally.

Research on AI detection tools illustrates the challenges of a surveillance-based approach. Weber-Wulff and colleagues (2023) tested fourteen tools and found they were not consistently accurate or reliable. They often missed AI-generated content, and the error rates were high enough to be concerning. Turnitin, seen as one of the better options, caught most unedited AI text, but still missed about a quarter. More concerning, Liang et al. (2023) found these tools often flagged writing by non-native English speakers and neurodivergent students, groups already facing extra challenges in higher education. These biases, combined with limited accuracy, suggest that detection-based approaches create an adversarial dynamic between students and institutions that is both unreliable and potentially harmful—particularly for already-marginalized populations. This evidence forms the basis for the transparency-centered alternative developed later in this paper.

Research synthesis reveals diverse applications of human-AI collaboration in higher education. Bond et al. (2024), in a meta-review of 138 secondary studies, identified key domains where AI facilitates learning: intelligent tutoring systems, adaptive learning environments, chatbots for engagement, and automated feedback approaches. These frameworks shift the conversation from “how do we stop AI use?” to “how do we design learning experiences that improve rather than replace student cognition?”

The Missing Population

Despite growing literature on AI in higher education, remarkably little addresses the distinctive situation of working adults in graduate programs. University policies, faculty integrity concerns, and pedagogical frameworks overwhelmingly assume a traditional undergraduate: young, full-time, primarily focused on learning in residential or synchronous settings, with ample time for extended engagement with course materials. Research indicates that students often remain uncertain about when they may use generative AI due to unclear or inconsistently communicated regulations (Jiang et al., 2025). These challenges may prove particularly acute for first-generation and minority learners, who face what researchers term an “AI literacy divide”—disparities in technological capital and prior exposure that create additional barriers (Hadar Shoval, 2025).

Working adult learners occupy a fundamentally different position regarding AI tools. Their motivation is often learning, not avoidance—many have already invested substantial time and money in the education they chose voluntarily. They want efficiency: strategies to maximize learning within limited time. They already use AI professionally and understand its capabilities and limitations from direct experience. And they possess professional judgment to critically evaluate AI outputs rather than accepting them uncritically. Policies designed to prevent undergraduate cheating may prove ill-suited for graduate programs serving working professionals. What remains missing is a framework for AI integration grounded in adult learning principles and the realities of distance education (Adarkwah, 2024). The framework proposed in this paper begins by rethinking what AI is for in educational contexts.

Answer Machine Versus Thinking Partner

Our argument rests on a distinction most institutions have yet to make: the difference between AI as an answer machine and AI as a thinking partner. The dominant view regards generative AI primarily as an answer provider. A student poses a question—“write this essay,” “solve this problem”—and receives a finished output. The student’s role reduces to formulating the query and accepting the response. This paradigm drives integrity concerns: if AI provides the answer, what does the student learn? (Bittle & El-Gayar, 2025). While this characterization describes genuine patterns of AI use, it represents only one possibility, and faculty concerns about AI dependency often encompass subtler forms of over-reliance than simple answer-seeking.

Another model positions AI not as an answer source but as a conversation partner, facilitating structured dialogue. In this mode, AI questions, challenges reasoning, surfaces assumptions, and guides learners toward their own conclusions. The outcome is not a finished product but a thinking process that leaves the learner better equipped to

handle similar problems independently. This distinction connects to the longstanding emphasis on questioning and dialogue in Socratic pedagogy. Recent research supports this approach: Fakour and Imani (2025) found that ChatGPT can function as a Socratic tutor engaging in dialogues that promote critical thinking. Favero et al. (2025) compared a Socratic chatbot, designed to pose thought-provoking questions rather than provide immediate answers, against conventional chatbots. Learners interacting with the Socratic tutor scored significantly higher than those using standard chatbots ($p < .001$), suggesting that structured questioning promotes deeper thinking even in brief AI interactions.

The Thinking Partner Framework

Theoretical Foundations

Building on the distinction between answer machine and thinking partner, we propose a framework positioning AI as a thinking partner for working adult learners. This framework draws on three interconnected theoretical traditions: social constructivism, adult learning theory, and reflective practice.

Illustration: Answer Machine vs. Thinking Partner

AI as Answer Machine	AI as Thinking Partner
<i>Student:</i> What’s the difference between qualitative and quantitative research?	<i>Student:</i> What’s the difference between qualitative and quantitative research?
<i>AI:</i> Quantitative research uses numerical data and statistical analysis to test hypotheses. Qualitative research uses non-numerical data like interviews and observations to explore phenomena in depth...	<i>AI:</i> Before I explain, I’d like to understand what you already know. Can you think of a question about your classroom that could be answered with numbers? And another that couldn’t?
Outcome: Student receives information to memorize.	<i>Student:</i> Like... how many students passed the test versus why some students struggle with fractions?
	<i>AI:</i> Exactly. You’ve just identified the core distinction. What kind of data would you need to answer each question? And what could each type of answer tell you that the other couldn’t?
	Outcome: Student constructs understanding through guided discovery.

Vygotsky’s Zone of Proximal Development offers a central lens. Cai, Msafiri, and Kangwa (2025), in a systematic review of 158 empirical studies, found that AI tools assist learners in individualizing self-assessment, improving motivation, and providing learning support that leads to better academic performance. An AI designed as a thinking partner operates precisely in this zone: providing sufficient support to keep students engaged with challenging material while requiring them to perform the cognitive work of constructing knowledge. The thinking partner model also corresponds to constructivist principles, positioning students as active builders of knowledge (Wibowo et al., 2025). Social constructivism’s emphasis on human interaction raises important questions about AI as a learning partner; human discourse includes emotional attunement and shared cultural understanding that AI lacks. Yet for working adults with limited access to peers or study groups, AI may offer cognitive engagement otherwise unavailable. One pilot study found that students receiving both AI and human tutoring scored higher on critical thinking assessments than those with AI alone (Gurung et al., 2025).

Adult learning theory provides additional grounding. Knowles’s (1984) foundational principles of andragogy emphasize that adults are self-directed, bring substantial prior experience to learning, are motivated by relevance to their professional lives, and prefer problem-centered over content-centered approaches. Adarkwah (2024) extends these principles into the generative AI era, arguing that AI-infused adult learning must honor adult learners’ autonomy and experience while leveraging technology to support self-directed engagement. The Thinking Partner

Framework aligns with each of these principles: it respects learner autonomy by offering AI as a resource rather than a requirement, leverages professional experience through context-specific prompts, connects learning to workplace application, and centers on real problems rather than abstract content delivery. The framework also draws on the broader tradition of transformative learning, which suggests that dialogue—including dialogue with AI—can prompt the critical reflection necessary for perspective transformation, particularly when learners encounter ideas that challenge their existing frames of reference.

This scaffolding is especially valuable for adults managing demanding schedules. Consider a K-12 teacher pursuing her Master’s degree who encounters unfamiliar statistical concepts. Without support, she might spend hours struggling with textbook explanations ill-suited to her background. A thinking partner enables conversations that pinpoint specific misunderstandings and connect new concepts to her existing knowledge—not by providing answers, but by presenting a clearer path to figuring things out herself.

Reciprocal Transparency

A core mechanism of the Thinking Partner Framework is reciprocal transparency—the recognition that documentation of AI use creates learning opportunities flowing in both directions. When students document their AI interactions, they develop metacognitive awareness of their own learning processes. When instructors review these documented interactions, they gain unprecedented insight into student thinking—where misconceptions arise, how understanding develops, and which concepts require additional instructional attention.

This reciprocity distinguishes the Thinking Partner Framework from simple disclosure requirements. Traditional AI policies ask students to acknowledge AI use; reciprocal transparency asks them to show their learning. A student who documents how a Socratic dialogue helped clarify the distinction between correlation and causation has done more than comply with a policy; they have created evidence of genuine learning while simultaneously helping their instructor understand how similar students might struggle with similar concepts.

For working adult learners, reciprocal transparency matches professional practice. These students already document their work in professional lives—lesson plans, patient notes, project reports. Documenting learning processes extends this professional habit into academic work.

Five Design Principles for AI-Integrated Learning

The thinking partner framework carries direct implications for course design. This section presents five interconnected principles that guide instructors in building courses where AI integration supports rather than undermines learning. These principles translate the theoretical foundations above into concrete design choices: they specify how students should be taught to engage AI as a Socratic partner, how learning processes become visible and assessable, and how assessments are structured so that AI-as-answer-machine cannot succeed.

Principle	Core Concept	Implementation
1. Transparency	Make AI use visible and productive rather than banned or hidden	Clear syllabus language; assignment-level guidance; reciprocal documentation
2. Process Documentation	Assess how students think, not just what they produce	Checkpoint submissions; AI dialogue transcripts; reflection prompts
3. Authentic Assessment	Connect to professional practice where AI collaboration is the norm	Context-specific applications; real-time defense of reasoning; workplace problems
4. Scaffolded Autonomy	Progressively develop independent judgment about AI use	Early prompting templates; fading structure; culminating autonomous work
5. Metacognitive Reflection	Build awareness of learning processes and AI collaboration strategies	Learning journals; AI use analysis; transfer planning

Transparency over prohibition makes AI use visible and productive. Research on AI policymaking consistently shows that clarity about expectations works better than ambiguity or punishment (Chan, 2023; Moore & Lookadoo, 2024). At the assignment level, transparency means specifying what kind of AI interaction is expected. Students need explicit instruction in how to engage AI as a Socratic partner rather than an answer source. The ability to use AI tools as cognitive scaffolds rather than shortcuts represents exactly the kind of AI literacy professionals will need throughout their careers.

Process documentation shifts assessment focus from products to processes. When students engage with AI thinking partners, their interactions can be recorded and evaluated, providing richer insight into learning than final products alone. Research on AI-resistant assessment emphasizes “Process-Product Assessment Models” that evaluate decisions students make during human-AI interaction (Awadallah Alkouk & Khlaif, 2024). Black and Tomlinson (2025) found that when students documented their AI use, most distinguished clearly between AI-assisted editing and their own contributions.

Authentic assessment designs tasks resembling professional work, where AI collaboration is becoming the norm. Research demonstrates that contextualization provides real protection for assessment integrity, connecting course concepts to specific professional situations that generic AI cannot address (Balducci, 2024). When students must apply learning to their own contexts or defend reasoning in real-time dialogue with instructors, generic AI responses fall short.

Scaffolded autonomy recognizes that effective AI use is a skill requiring development. Early AI interactions receive substantial instructor guidance, while later work demands increasingly independent decision-making. Research indicates that unstructured use may not foster deep engagement, while structured implementation paired with reflective practices may enhance analytical and reasoning skills (Cai et al., 2025).

Metacognitive reflection makes explicit that AI-integrated education should include reflection on learning itself. Research shows that students skilled in metacognition use AI tools more effectively, maintaining an appropriate balance between AI assistance and independent thinking (Xu et al., 2025).

The five principles work together as a system. Transparency sets clear expectations. Process documentation shows evidence of learning and builds reflection. Authentic assessment links AI use to real professional tasks. Scaffolded autonomy helps students develop good judgment over time. Metacognitive reflection ensures learning goes beyond the course. Together, these principles also redefine academic integrity: when learning processes are visible and documented, integrity becomes alignment between claimed and actual processes rather than a matter of surveillance and detection. A student who accurately documents AI use and demonstrates genuine understanding maintains integrity even if AI provided substantial assistance. A student who claims independent work while concealing AI use lacks integrity regardless of product quality.

These design principles cannot stop all misuse. A student who wants to use AI just for answers will still find ways. The goal is not perfect enforcement, but to create learning experiences where using AI as a thinking partner is the best and most effective choice.

Implementation: Graduate Research Methods for K-12 Educators

The framework comes to life through a series of graduate research methods courses designed for K-12 educators pursuing Master’s degrees. These courses operate under constraints that shape every design decision: they run for just six weeks, they are entirely asynchronous, and the students are simultaneously full-time teachers and graduate students.

The Six-Week Compressed Format

The six-week format is not a pedagogical preference but an institutional reality for working adults. These students cannot commit to fifteen-week semesters without experiencing strain that leads to withdrawal. Research on compressed formats yields generally positive findings. Price (2024) found that students in accelerated courses

perform at least as well as those in traditional-length courses on effort-based assessments, though topic mastery assessments showed performance decline. Holzweiss, Polnick, and Lunenburg (2019) reported positive outcomes in online compressed programs, noting that the format creates focused intensity beneficial for highly motivated adult learners. The key insight is that compressed formats require purposeful redesign rather than mere compression (Vlachopoulos et al., 2019).

AI integration supports this redesign by extending instructional presence into spaces traditional instruction cannot reach. Teachers who have been grading their own students' papers until 10 PM do not bring optimal cognitive resources to learning new research methods. AI dialogue can support learning through patient, non-judgmental questioning—available whenever the student can work, adapting to their pace, and never showing impatience with repeated questions. This support supplements instruction rather than replacing it.

The Relevance Challenge in Required Courses

Research methods is a required course, not an elective, and this distinction shapes every design decision. Working adults who voluntarily enroll in graduate programs do not necessarily see research methods as relevant to their professional goals—many enter expecting a hurdle to endure rather than a skill to acquire. This motivational challenge is well documented in adult learning theory: Knowles (1984) emphasized that adults engage most deeply when they perceive direct relevance to their work, yet required courses impose content that students have not chosen and may not immediately value. The thinking partner framework addresses this challenge directly. Because Socratic prompts are designed to begin from the student's own professional context—"I'm developing a research question about [topic] in my classroom"—students encounter course concepts through problems they already care about rather than through abstract textbook exercises. A teacher exploring whether a reading intervention works in her classroom is learning research design, even if she enrolled expecting the course to be irrelevant. AI as a thinking partner amplifies this effect: it can tailor every exchange to the student's specific situation, making a required course feel personally applicable in ways that generic lectures or discussion boards cannot. The student feedback reported later in this paper—teachers using evaluation frameworks in IEP meetings, applying critical analysis to district mandates, adopting Socratic techniques with their own students—demonstrates that when required courses are designed around professional relevance, students do not merely endure them; they carry the learning forward.

The Research Consumer Orientation

The fundamental pedagogical shift becomes clear from the first module: students are learning to become intelligent research consumers, not researchers. This distinction matters because conventional research methods instruction carries assumptions borrowed from doctoral education—sampling theory, design controversies, epistemological frameworks—that serve aspiring scholars while burdening practitioners who want to evaluate and apply published research in their classrooms. The consumer orientation redefines competence. Students need to locate relevant literature, judge study quality and significance, understand methodological strengths and limitations, and apply findings to practice.

The contested research on AI detection tools illustrates precisely why the research consumer orientation matters. When institutions adopt detection-based policies, they make consequential decisions affecting students' academic futures. Yet the research base is nuanced. An educator who cannot critically evaluate these studies—who cannot assess methodological limitations, recognize when findings may not generalize, or weigh conflicting evidence—is poorly equipped to advocate for appropriate policies in their own institutions. The K-12 teachers in our courses will sit in faculty meetings where administrators propose AI detection mandates. They will hear vendor claims about accuracy rates. The capacity to read the primary research, identify its strengths and limitations, and translate findings into context-appropriate practice is not a lesser form of research competence. It is the form of research competence these professionals most urgently need.

AI integration supports this reorientation in three interconnected ways:

AI-Assisted Literature Exploration. Working teachers rarely have access to comprehensive research databases at their schools. AI assistance can reduce the time required to identify relevant literature from hours to minutes. But efficiency gains mean little if students accept AI-generated summaries uncritically. The course design pairs

exploration opportunities with structured critical evaluation: students locate sources and compare AI summaries against actual abstracts and methodology sections, documenting discrepancies.

Socratic Dialogue for Research Paradigms. The Socratic protocols developed for these courses feature extended conversations beginning with what students already know. Rather than defining qualitative research abstractly, dialogue prompts students to consider questions from their own experience: What kinds of questions can numbers answer? What can’t numbers tell you? A student wrestling with validity concepts at 11 PM can engage in a clarifying conversation rather than waiting for an instructor’s response.

Progressive Feedback on Student Work. The six-week timeline creates challenges around revision cycles. AI-assisted feedback addresses this compression problem. Escalante, Pack, and Barrett (2023) found no significant difference in learning outcomes between students receiving AI feedback and those receiving human tutor feedback. Students receive rapid structural feedback on drafts while instructors provide evaluative feedback requiring disciplinary judgment. Crucially, the design requires students to document feedback received, actions taken in response, and reasoning behind accepting or rejecting suggestions.

Sample Socratic Prompts

Purpose	Prompt Template
Concept Clarification	“I’m trying to understand [concept]. Instead of defining it for me, help me figure it out by asking me questions about what I already know and where I’m confused. Start by asking what I think [concept] means.”
Research Design Thinking	“I’m developing a research question about [topic] in my classroom. Guide me through thinking about methodology by asking questions—don’t tell me what approach to use. Help me discover which approach fits my question.”
Article Evaluation	“I just read a study about [topic]. I want to evaluate its quality. Ask me questions that help me think critically about the methodology, sample, and conclusions. Challenge my initial impressions.”
Application to Practice	“I want to apply [research finding] to my [grade level/subject] classroom. Help me think through implementation by asking about my specific context, potential obstacles, and how I might know if it’s working.”

Checkpoint Documentation Template

Students submit checkpoint documentation at key points during each module:

AI Interaction Checkpoint

1. What concept or task were you working on?
2. What did you ask the AI? (Paste your initial prompt)
3. What was confusing or unclear before the conversation?
4. How did your understanding change during the dialogue?
5. What follow-up questions emerged? What remains unclear?
6. How might you apply this understanding in your classroom?

Observations from Practice

The framework has been implemented and progressively refined across six semesters of graduate research methods courses, serving an average of 73 students per semester (approximately 440 students total). Earlier iterations established the core Socratic approach and transparency principles; later iterations added the structured scaffolding, prompt templates, and checkpoint documentation described in this paper. What follows represents systematic observations drawn from instructor field notes, review of student checkpoint submissions, and analysis of course evaluations rather than formal research findings. These observation methods, while not constituting controlled research, provide a structured basis for the patterns reported below.

Students vary considerably in how they approach AI assistance. Some engage with Socratic dialogue as intended: wrestling with questions, documenting confusion, and returning to concepts multiple times before achieving understanding. Others optimize for efficiency, finding the fastest path through required interactions. This pattern is neither surprising nor necessarily problematic. Adults managing full-time teaching, families, and graduate school engage in rational triage, allocating limited cognitive resources to meet competing demands.

Instead of trying to predict which students will fully engage, we design for a wide range of engagement. The framework aims to make deeper engagement clearly more rewarding, so students who use Socratic dialogue learn more than those who just want quick answers. Even students focused on efficiency still learn something. We cannot force every student to go deep, but we can make it appealing.

Across the six semesters, checkpoint documentation completion rates averaged 96%, though the depth and reflectiveness of submissions varied. Student responses on checkpoint assignments ranged from 300 to 600 words, with later iterations—which included more explicit scaffolding and prompt templates—tending toward the higher end of that range and producing noticeably more substantive reflections. Average grades across all assignment attempts ranged from 57% to 96%. The most common pattern of AI interaction observed in checkpoint submissions was an initial direct question followed by increasingly dialogic exchange—suggesting that many students naturally shifted toward the thinking partner mode once they experienced its value.

Final grades may appear inflated because the course design allows students to correct and resubmit assignments as many times as needed to achieve the highest possible score. This policy is intentional: it prioritizes mastery over penalty and aligns with the framework's emphasis on process over product. Additionally, the increasing accuracy of student work across resubmissions suggests that AI use—while not formally tracked—likely contributes to improved performance. From a learning standpoint, this is not problematic: repeated engagement with the material, regardless of whether the student consults AI, a textbook, or a peer, results in greater exposure to course content and deeper understanding.

The most encouraging observations involve students connecting course learning to their work. One special education teacher described using AI-assisted literature searches to find research supporting a specific intervention she wanted to recommend at an IEP meeting. A middle school science teacher applied the critical evaluation framework to assess a district-mandated curriculum program, ultimately presenting her analysis to her principal. Several students have reported using Socratic questioning techniques with their own students.

Student Feedback

Direct student feedback, gathered through course evaluations and informal written reflections, has been mixed in instructive ways. Students appreciate that AI assistance is available at 10 PM when they can finally work after putting their children to bed. They value AI dialogue's non-judgmental quality—they can ask "basic" questions without embarrassment.

Representative student comments from course evaluations:

"I can ask the same question five different ways without feeling stupid. That's not something I'd do in a discussion board where everyone can see."

— Elementary teacher, first-generation graduate student

"The Socratic approach was frustrating at first. I just wanted to know what validity meant. But by the end, I actually understood it instead of just memorizing a definition."

— High school English teacher

“I used this same approach with a student who was struggling with thesis statements. Instead of telling her what was wrong, I asked questions. It worked.”

— Middle school reading specialist

Critical responses reveal legitimate concerns. Some students express frustration that the Socratic approach “won’t just give me the answer”—surfacing precisely the tension between efficiency and learning the methodology is designed to foreground. Others worry about AI accuracy, having encountered fabricated citations in other contexts. This skepticism represents exactly the critical AI literacy the course aims to develop.

Challenges and Adaptations

Implementation has required ongoing adjustment. Early iterations provided insufficient structure for AI interactions, resulting in shallow engagement. Students uncertain what “productive” AI use looked like defaulted to direct questions and accepted direct answers—precisely the pattern the course design sought to prevent. Subsequent versions introduced more explicit scaffolding: specific question stems, required follow-up sequences, and checkpoint prompts clarifying expectations.

Students arrive with widely varying AI experience. Some use ChatGPT daily; others have never engaged with generative AI. This variance requires differentiated support, challenging to provide within compressed timelines. AI integration can also inadvertently diminish perceived instructor involvement. When students receive immediate AI responses, instructor feedback may seem unnecessary or delayed. Sustaining clear distinctions between AI and instructor roles requires explicit communication—students must understand not only what AI can do but what it cannot, and why instructor expertise remains essential.

Limitations

These observations carry major limitations. They emerge from routine teaching practice rather than systematic research, lack comparison groups or standardized measures, and reflect courses taught by one instructor at one institution. They may be subject to bias, as the instructor who designed AI integration is also evaluating its effects. All data were collected from existing course records without student identification; because the data were de-identified and drawn from normal educational practice, Institutional Review Board approval was not required.

Access equity represents a limitation we have not adequately addressed. While working adults generally have smartphones and internet access, the quality of that access varies considerably. A student completing coursework on a phone screen during a lunch break faces different constraints than one with a laptop and reliable home internet. We have not collected data on how access differences affect engagement with AI-integrated assignments. Future implementations should examine these questions directly, building equity assessment into course design rather than hoping the problem does not exist.

Implications for Distance Learning Administrators

Policy: From Prohibition to Purposeful Integration

The dominant institutional response to generative AI has been prohibition, framing AI use as an integrity threat requiring detection and punishment. For programs serving working adults, prohibition-focused policies create three interrelated problems. First, they prove unenforceable—working professionals use AI routinely in their careers and will continue to do so. Second, prohibition prevents learning—when AI use is forbidden, students cannot develop the competencies they need professionally. Third, detection-focused approaches carry the documented biases discussed earlier, disproportionately harming non-native English speakers and other already-marginalized populations.

Alternative policy frameworks emphasize transparency over prohibition. These policies ask not “Did you use AI?” but “How did you use AI, and what did you learn from it?” Clear guidance on prohibited uses remains important—submitting AI-generated work without documentation, using AI for assessments designed for independent completion, and misrepresenting AI contributions all violate integrity. But the offense is deception, not tool use.

Actionable Recommendations for Administrators

- 1 Replace prohibition-focused AI policies with transparency-focused alternatives.** Shift from “Did you use AI?” to “How did you use AI, and what did you learn?” Require documentation rather than ban usage.
- 2 Invest in faculty development that includes hands-on AI experience.** Faculty cannot teach effective AI use without having used AI themselves. Provide time, resources, and communities of practice for ongoing development.
- 3 Redesign assessment to emphasize process documentation.** When AI can produce polished products, product-only evaluation provides less information about learning. Require students to show their work and explain their reasoning.
- 4 Create communities of practice for ongoing peer learning.** AI capabilities evolve rapidly. Training appropriate for 2024 will be outdated by 2026. Establish ongoing structures for faculty to share successes, troubleshoot challenges, and develop collective expertise.
- 5 Discontinue reliance on AI detection tools.** These tools are unreliable, biased against non-native speakers, and pedagogically counterproductive. They position faculty as investigators rather than partners in learning.
- 6 Address equity considerations proactively.** Students in rural areas or low-income communities may have unequal access to AI tools. Consider institutional AI access, orientation resources, and differentiated support structures.

Practical mitigation strategies for equity exist but require institutional commitment. Programs might provide institutional AI access through site licenses, ensuring all students can use the same tools regardless of personal resources. Orientation modules can assess students’ technology situations and provide differentiated onboarding for those less familiar with AI tools. Assignments can be designed around freely available AI platforms rather than premium features. In our implementation, we have relied on freely available tools and avoided assignments requiring paid features, but we have not systematically assessed whether access disparities affect engagement or outcomes. Administrators adopting similar approaches should build equity assessment into their implementation from the start rather than treating it as an afterthought.

Faculty Development and Scaling

Policy changes without faculty support produce paper compliance rather than pedagogical transformation. Faculty need AI literacy themselves—understanding what AI can and cannot do, recognizing common failure modes like hallucination, and developing effective prompting skills. Faculty cannot teach students to use AI well without having used it themselves. They need pedagogical redesign support through instructional design consultation, course development grants, or reduced teaching loads during redesign phases. Faculty benefit from communities of practice, sharing successful approaches, troubleshooting challenges, and developing collective expertise. Development must be ongoing rather than one-time; AI capabilities evolve rapidly, and training appropriate for 2024 will be outdated by 2026.

Administrators reasonably ask whether these approaches can scale. Faculty expertise and readiness vary; scaled implementation requires differentiated approaches, with institutions identifying and supporting early adopters, then facilitating diffusion as successful examples emerge. Assessment at scale creates challenges—process documentation generates work that instructors must review, creating workload challenges that institutions must address through appropriate course sizes, grading support, or technology-assisted evaluation. Some elements require instructor customization, particularly the Socratic prompts, which work best when fitted to specific course content. Other elements, such as checkpoint templates and transparency language, could be standardized across programs. Initial adoption requires significant investment—approximately 15–20 hours for course redesign plus regular adjustments based on student feedback.

The fundamental point remains: adult learners in distance education need preparation for AI-integrated professional practice. That preparation comes through thoughtful integration, not prohibition.

Conclusion and Future Research Directions

This paper has presented the Thinking Partner Framework as a practical alternative to the prohibition-versus-permission binary that dominates institutional AI responses. Drawing on six semesters of implementation with approximately 440 working adult learners, the framework demonstrates that AI can be integrated into graduate education in ways that support rather than undermine learning—when guided by clear design principles and grounded in adult learning theory. Surveys consistently show that AI tool adoption is widespread among working professionals across fields (Robert & McCormack, 2025), and graduate education should prepare students to use these tools thoughtfully rather than pretending they do not exist.

The framework presented here offers a different perspective. Rather than viewing AI as a threat requiring detection and punishment, it positions AI as a thinking partner to be leveraged and evaluated. Rather than designing assessments that AI cannot complete, it creates learning experiences helping students develop competencies for working with AI effectively. Rather than demanding students pretend AI does not exist while completing academic work, it invites them to document their AI use and reflect on what they learn from it.

The initial observations presented here suggest promise but do not provide evidence sufficient for confident recommendation. More rigorous research is needed across several dimensions. Learning outcome comparisons should examine whether students in AI-integrated courses learn as much or more than those in traditional formats, using controlled comparisons with validated assessments focused on outcomes most relevant for working adults—research application, critical evaluation, and professional transfer. The checkpoint submissions students complete generate rich data about how students interact with AI tools; systematic analysis could reveal patterns of effective versus ineffective AI use, common misconceptions in AI interaction, and developmental trajectories in AI literacy. Longitudinal studies following graduates through their careers would provide evidence about long-term professional impact that course-level assessment cannot capture.

Equity and access questions are particularly urgent. Our implementation has not systematically examined whether students with limited internet access, older devices, or less AI experience engage differently with the framework. The assumption that working adults have sufficient technology connectivity may mask significant variation: reliable home internet versus mobile-only connectivity, current devices versus aging hardware, familiarity with AI tools versus first-time exposure. For programs serving first-generation graduate students, students from under-resourced school districts, or students in rural communities, these questions are not academic—they determine whether AI integration expands opportunity or reinforces existing inequities. Research examining differential outcomes across student populations and comparative studies of faculty development models would help institutions allocate resources effectively.

The challenge AI brings to education is not mainly about technology. It is about our beliefs on the purpose of education. If education is only about proving students can work alone, then AI is a significant problem. But if education is about helping people think critically, creatively, and ethically in any situation, then AI is an opportunity.

Working adult learners already live and work in a world full of AI. Graduate education should help them think well in this environment, rather than ignoring the reality they face. This study invites distance learning administrators to

shift their focus: instead of asking how to stop AI use, ask how to encourage good thinking in a world where AI is everywhere. The framework shared here is just one approach—imperfect and still developing. As more institutions and disciplines take on this challenge, better solutions will appear. Finding these answers is the task ahead.

Author's Note on AI Use

Consistent with the transparency this paper advocates, Claude (Anthropic) served as a thinking partner throughout the development of this manuscript, helping refine organization and prose. The authors drafted all sections, developed the framework and its theoretical foundations, and formulated all substantive claims, interpretations, and conclusions. AI assistance was used primarily for structural feedback on draft sections and for improving sentence-level clarity. No substantive content—including the framework design, literature review analysis, observations from practice, or recommendations—was generated by AI.

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