AI as Muse, Sparring Partner, or Ghostwriter? Comparing AI Use in Public Education vs. Professional Development

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Artificial intelligence (AI) tools like ChatGPT are creating both challenges and opportunities in learning environments. In public education, AI poses a dilemma: it can tempt students to bypass academic rigor, yet it can also enhance their intellectual engagement if applied purposefully. In contrast, learning and development (L&D) and human resources (HR) professionals in workplace environments often approach AI from a production-centered perspective to increase efficiency, automate content creation, and streamline workflows. Comparing these two settings highlights a philosophical and functional fork in the road: education emphasizes cognitive depth and skill-building, while workplace learning often prioritizes speed, efficiency, and practical outcomes. *Keywords: AI-supported learning, artificial intelligence, ChatGPT, educational technology, instructional design, learning and development*

Introduction

Artificial intelligence is rapidly transforming how we generate, evaluate, and interact with information. In public education and professional development — specifically in the learning & development (L&D) and human resources (HR) environments — we are seeing two divergent trends. In both arenas, AI tools are being integrated into writing, training, and assessment tasks — but not always in the same way, or for the same reasons. This article explores how AI is being used on both fronts:

- In public education, the emphasis is on cognitive skill development and academic integrity.
- In professional development, the emphasis often centers on efficiency, speed, and ease of content production.

By contrasting these settings, we can begin to unpack not just what AI is doing in each context, but how and why the goals, risks, and best practices diverge. The resulting insights may help educators and training professionals better define their expectations — as well as their own roles — in a world increasingly shaped by intelligent tools.

This paper presents a conceptual analysis, or position paper, comparing the ways in which public education and professional development contexts are integrating AI. The goal is to interpret these divergent practices through a theoretical and practical lens rather than report empirical findings.

Theoretical Framework

Understanding how artificial intelligence is being adopted in both educational and workplace settings requires a grounding in long-established learning theories. More recent research on instructional design and cognitive processes further underscores and expands on the classic literature. The goal is to connect contemporary AI practices with frameworks that explain how people learn, process information, and perform in complex environments.

Constructivist Roots

Constructivist theorists assert that learners actively build their own knowledge by engaging with content, contexts, and peers, rather than simply absorbing information from educators. Beyond instructional objectives, savvy learners construct knowledge at their own pace, aligned with their interests and learning styles (Brown, Collins, & Duguid, 1989; Perkins & Salomon, 1989). From this perspective, AI has the potential to expand the realm of learner control. It offers adaptive prompts, customized feedback, and Socratic tutoring opportunities that help them independently explore a topic beyond a fixed curriculum. For example, conversational AI can function as a “thinking partner” by encouraging students to test ideas, pose questions, and refine arguments. In this way, AI aligns with the constructivist emphasis on learners assembling their own knowledge frameworks and taking ownership of their learning.

Cognitive Load and Working Memory

Cognitive load theory (Sweller, 1988; Sweller, van Merriënboer, & Paas, 2019) offers another framework for understanding AI’s instructional potential. Because working memory is limited in both capacity and duration, instructional designers must carefully weigh every aspect of how information is presented. Poorly structured or overly redundant material can overwhelm learners by increasing cognitive load. By extension, badly designed AI may mirror this effect by flooding learners with disorganized or irrelevant content. In contrast, carefully chunked information reduces cognitive load and supports learners’ ability to build vivid and durable mental models. Likewise, a well-designed AI tutor can facilitate schema-building by simplifying complex explanations or supplying visual examples.

Learning Taxonomies

Classic taxonomies such as Bloom’s (1984) and Gagné’s (Gagné, Briggs, & Wager, 1992) still serve as useful frameworks for categorizing educational objectives and outcomes. Bloom’s hierarchy graduates from recalling basic facts at the lowest level to analyzing, synthesizing, and evaluating new knowledge at the highest levels. In contrast, Gagné proposes a three-part cognitive taxonomy that distinguishes between declarative knowledge, intellectual skills, and cognitive strategies.

Merrill’s performance–content matrix (1994) organizes types of information (content) versus levels of task difficulty (performance). Similar to Bloom’s taxonomy, Merrill’s model depicts the activity of remembering (recall) as less difficult than applying or creating information.

When mapped against these taxonomies, AI’s role varies. At the lower end of each spectrum, AI reduces the need for routine comprehension and recall tasks, decreasing cognitive load and saving time. By freeing learners’ bandwidth for higher-order activities, AI can help them move quickly to more sophisticated tasks. AI can also provide examples and practice scenarios that support skill transfer.

Implications for Instructional Design

For instructional designers, the integration of AI underscores the continuing relevance of principles articulated by scholars such as Mager (1997) and Clark (1994). These include setting clear objectives, defining performance-based criteria, and evaluating performance against the standards and conditions required in actual practice.

AI may accelerate content generation, but the underlying instructional intent cannot be outsourced to AI. Human instructional designers (IDs) should specify who the learners are, what they need to do, under what conditions, and to what standard. Recent literature on AI in education reinforces the idea that AI is most effective when guided by thoughtful pedagogy, a multidisciplinary approach, and robust ethical guidelines — not when treated as a shortcut to learning (Holmes et al., 2022; Zawacki-Richter et al., 2019).

Implications for Professional Development

Regarding workplace training, adult learning theory reminds us that learners gravitate toward self-direction. A succinct way to explain this is: "As people mature, their self-concept evolves from being dependent to becoming more self-directed" (Knowles, 1984, as cited by Pappas, 2025). Baldwin & Ford (1988) noted, "The conditions of transfer include both the generalization of learned material to the job and the maintenance of trained skills over a period of time on the job." These views of self-directed learning help explain why AI is valued as an efficient, personalized, job-relevant tool. But again, there are significant risks in bypassing careful instructional design. Unless AI is guided by ID best practices, any gains in efficiency could occur at the expense of depth or accuracy.

Bridging Theory and Practice

This dual emphasis on education and professional development underscores the paradox researchers have noted: AI holds promise in both settings. Yet the criteria for "success" diverge depending on whether the goal is formative growth or performance efficiency.

Taken together, these perspectives help explain why AI requires setting different priorities in education and workplace learning. In education, constructivist and cognitive theories encourage the use of AI as a tool for exploration, reflection, and intellectual growth. In the workplace, performance-focused models highlight its benefits for helping professionals acquire skills more quickly and generate content more efficiently. Both purposes remain firmly tied to instructional design theory.
AI should not be used to replace established principles. Instead, it should interact with them — sometimes reinforcing, sometimes challenging — the balance between efficiency and rigor.

AI in Public Education

The emergence of ChatGPT has generated both concerns and opportunities within public education, notably in English composition. While teachers are grappling with the challenges of academic integrity and the potential impact on original thinking, many are also exploring ways to use this technology to enhance the learning experience.

On the con side, when ChatGPT made its education debut in late 2022, many teachers worried that it would interfere with deeper learning and make writing assignments more formulaic and superficial. As Blose (2023) noted, a K-12 teacher surveyed by Study.com commented, "I think ChatGPT is a crutch that will prevent students from actually needing to learn content. Although I can see its use for small tasks, like how to email a teacher with questions, it also prevents students from developing the soft skills that completing those small tasks allows." Other critiques included increased opportunities for cheating (via AI plagiarism), and concerns about AI errors and inaccuracies.

On the pro side, a growing number of educators have come to the conclusion that ChatGPT's benefits outweigh the risks. Many are embracing AI to revitalize their lesson plans and instructional strategies, such as by enabling students to:

- Generate different ideas, angles, and perspectives.
- Enhance writing skills by using AI's personalized feedback.
- Spark their creativity and imagination using AI's writing prompts.

- Receive immediate access to information from a wide range of sources.

Yet even teachers who are proactively experimenting with AI (in essay generation, for example) are scoping out its pitfalls. Dominguez (2023) describes how some teachers preemptively encourage their students to recognize AI's limitations for themselves. As a before-and-after-ChatGPT-debut experiment, she "asked students to enter the same essay prompt they'd written back in October into ChatGPT, then compare their work to ChatGPT's instant essay. They scored ChatGPT's work using the same College Board rubric their essays were evaluated against. Once they were done scoring, the students determined that the computer [AI] was no match, confirming that it lacked the specificity, musicality, and soul that their [own] writing exhibits."

Turning Shallow Thinking into True AI Collaboration

But what if students themselves can "train" AI to match their own "specificity, musicality, and soul"? How would that change the equation?

Instead of educators banning ChatGPT out of fear that it will "do the thinking" for their students, they can require learners to use an intensely interactive approach — where every thought becomes an in-depth, back-and-forth conversation. Only after considerable debate and deliberation — sentence by sentence and paragraph by paragraph — would a student arrive at an outcome that represents his or her own authentic thought processes and voice.

A New Pedagogical Approach for Writing Assignments

After all, AI tools are not the problem; the task design is. To rethink their approach, educators can:

- Redesign lesson plans to allow, or even require, the use of AI.
- Model the disciplined use of AI as a:
    - Muse to aid in brainstorming ideas.
    - Interlocutor and sparring partner to interrogate, co-create, and refine, but strictly avoid using it as a ghostwriter on which to offload the writing assignment.
- Require students to show their cognitive journey by submitting both the finished assignment and the AI chat transcript that clearly demonstrates a high level of interaction, creativity, and analysis. This task redesign helps educators realign their expectations to reward the quality of learners' exchanges with AI over superficially generated compositions. In this way, instructors can compel students to use AI in a much more sophisticated fashion.

Using the model above, Table 1 shows an AI-integrated writing assignment process that could involve these steps:

Table 1

Steps in an AI-Integrated Writing Assignment Process

Step	Activity	Description
1	Compose a first pass	Students write an independent draft before using AI.
2	Collaborate iteratively	Students interact with AI to explore and refine ideas.

3	Provide evidence of original thinking	Students submit the essay plus a ChatGPT transcript that shows their iterative conversation and reasoning.

Example of an AI-Supported Writing Assignment

Instructors can apply this framework to student assignments, as illustrated below.

Assignment Description:

“Use an AI tool like ChatGPT to help compose your essay on [topic]. However, you must:

1) Begin with your own outline or brainstorm.

2) Use the AI chat to challenge, expand, or clarify your ideas — not write the essay for you.

3) Submit both your final essay and the full transcript of your AI interaction. Your conversation thread should reflect the ideas you accepted, changed, or rejected — and why.”

Evaluation Criteria:

Using the three-part assessment model pioneered by Dr. Robert F. Mager in Preparing Instructional Objectives (1997), educators can evaluate student writing assignments with clear, precise criteria. The three elements of the model are:

- Performance (usually expressed as a performance objective)
- Conditions
- Criteria

As expanded further in Table 2, a sample assignment could be constructed as follows:
“Given a writing assignment on [a topic] that requires AI interaction, the student will...”

Table 2

Sample Evaluation Criteria for AI-Supported Writing Assignments

Element	Definition	Example
Performance objective	The skills, knowledge, or behaviors that the student must demonstrate.	“Demonstrate original reasoning, precision, and coherence in the final submitted essay.”

Conditions	The circumstances under which the performance should occur.	“Given access to a laptop with a ChatGPT account and text editing software such as TextEdit or Word, the student will compose an essay of 500–1,000 words in a 90-minute writing session under supervised conditions.”
Criteria	Observable, measurable standards for evaluating the final (or interim) performance. These are usually pass/fail mastery levels that show whether a learner has met the standards — rather than a system of comparing students to each other by grading on a curve.	“A. Submit the following: 1) A final essay of 500–1,000 words, to be delivered as a TextEdit or Word file. 2) A ChatGPT transcript that reflects the student’s initial notes — plus at least three rounds of prompting that show accepted, rejected, or refined ideas. Students should ‘think aloud’ by narrating their reasoning throughout the chat thread. To submit the transcript, learners should copy the entire conversation and paste it into a TextEdit file to retain original formatting and dialog labels. B. Demonstrate original reasoning using: • A clear, distinct perspective • Well-structured arguments • Analysis and synthesis of evidence • Unique insights and conclusions C. Demonstrate precision using: • Specific, accurate language • Relevant terminology and data • Exclusion of unnecessary details D. Demonstrate coherence using: • A clear structure and logical flow • A consistent style and tone • Effective topic sentences • Logical transitions between ideas”

To recap, in public education, the challenge isn’t whether to use AI, but how to use it meaningfully. By designing assignments that require thoughtful interaction with AI — as both a brainstorming aid and editorial sparring partner — educators can turn the risks of misuse into opportunities for rigorous, in-depth scholarship.

Just as the introduction of calculators into schools decades ago didn’t eliminate the need to understand math, AI doesn’t have to replace critical thinking. Instead, by designing assignments that align with AI’s strengths, educators can have confidence that robust learning is occurring.

To position these debates within a broader instructional design context, it’s helpful to consider recent classroom studies that illuminate both the promise and the pitfalls of AI integration.

AI in Education: Emerging Practices and Challenges

In educational settings, AI is emerging as both a potential aid to intellectual development and a source of new challenges. Much of the current debate centers on whether AI undermines academic rigor, or, alternatively, whether integrating it into the curriculum can help learners develop more advanced reasoning and critical thinking skills. Recent studies suggest that the outcome largely depends on how AI is adapted for each instructional process.

For instance, one classroom study on AI-supported writing instruction found that “ChatGPT can guide students’ practice on standard writing processes, such as brainstorming and outlining ideas” (Söğüt, 2024, p. 8). When used this way, generative AI tools can provide low-risk opportunities for students to experiment with different approaches to expression. Such uses align with constructivist principles, encouraging learners to explore a subject and iteratively refine their thinking in dynamic — and sometimes unexpected — ways.

A 2025 MIT study (“Your Brain on ChatGPT,” Kosmyna et al.) found that students who began writing using ChatGPT exclusively — like a ghostwriter — showed reduced neural engagement and critical thinking when they later switched to writing without AI. In contrast, those who started by writing on their own — and only later switched to AI — showed stronger cognitive activation when they returned to writing without AI. These results suggest that students engaging with AI only after initially working through their own ideas demonstrate deeper cognition.

At the same time, concerns exist about a potential over-reliance on AI. A systematic review of artificial intelligence in education (AIEd) noted a “lack of critical reflection of challenges and risks of AIEd, [and] the weak connection to theoretical pedagogical perspectives” (Zawacki-Richter et al., 2019, p. 1). This observation reinforces the idea that AI activities should accompany careful lesson design, such as explicit performance expectations and structured opportunities for reflection.

Similarly, cognitive load research cautions that instructional design must avoid overwhelming working memory with excessive or unstructured material. Sweller, van Merriënboer, and Paas (2019) observed that “cognitive load is increased when unnecessary demands are imposed on the cognitive system. If cognitive load becomes too high, it hampers learning and transfer” (p. 2). Unguided or unchecked AI-generated content can fall into this trap, increasing complexity instead of clarifying meaning.

Access considerations also factor into the AI conversation. As Luckin (2018) points out, educational technologies risk amplifying disparities if equity barriers remain unaddressed. Inconsistent access to reliable AI tools across schools and districts raises pressing questions about who benefits and who is left behind. Such disparities call for educators to find ways to compensate, for example, by challenging students to scrutinize and evaluate their sources, remain alert for bias, and reflect on the quality of their AI interactions.

In short, AI’s utility in education is neither inherently “weak” nor “strong.” Its effectiveness depends on how well instructors combine AI with instructional best practices. When grounded in learning theory and coupled with opportunities for learners to exercise judgment, creativity, and responsibility, AI can achieve its greatest potential as an academic tool.

Universal Design for Learning: A Framework for Purposeful AI

Universal Design for Learning (UDL) offers a powerful means of aligning AI use with instructional intent. It emphasizes designing learning around purpose and task rather than allowing technology to drive the process. In this model, educators start with learner goals — the activities and skill sets learners need to master — and then select AI tools that serve those goals. Technology then becomes a flexible ally that addresses learner variability, sustains engagement, and offers multiple pathways for success (AIPilot SG, 2024; Lynch, 2023). This contrasts with a tech-first approach, in which the tool leads and pedagogy follows. That method can result in force-fitting instruction without first considering which skills and goals it should be serving.

UDL's three core principles entail multiple means of engagement (the "why" of learning), representation (the "what" of learning), and action and expression (the "how" of learning). Together, they provide a practical way to integrate AI after having identified learner goals (Learning Technology Center of Illinois [LTCI], n.d.). For instance, to support the "why," an instructor might use a conversational AI chatbot to simulate a historical figure, thereby connecting the lesson goals to students' curiosity. To vary the "what," AI tools such as text-to-speech or translation engines can help students access challenging material in ways that match their strengths. And to support the "how," AI-powered multimedia platforms can give learners alternative ways to demonstrate understanding beyond traditional essays or tests.

The common thread across all three principles is intentionality — start with the goal, not the tool. AI should act as a scaffold, not a shortcut. For example, a writing assistant might help students brainstorm and organize ideas for a research paper without producing the finished work. This positions AI as a partner in critical thinking rather than a substitute for it. Equally important, UDL encourages co-design — inviting students to help define when and how AI supports their learning. Such shared design reinforces learner agency and helps educators anticipate barriers before they arise (Schwartz, 2024).

When viewed through a UDL lens, AI becomes a catalyst for personalization and inclusion rather than a one-size-fits-all solution. By grounding AI use in learning goals and human variability, instructional designers can ensure that technology amplifies — rather than replaces — purposeful pedagogy.

Learning Theories and AI: Constructivism and Cognitive Load

Constructivist Perspectives on AI Use

AI technologies both enhance and challenge constructivist approaches to learning. Constructivism emphasizes that learners actively build understanding through experience, reflection, and interaction. When used thoughtfully, AI supports these processes by personalizing learning environments, providing adaptive feedback, and enabling hands-on exploration. This dynamic scaffolding operates within a learner's "zone of proximal development" (ZPD) and reflects a social, collaborative approach to learning — emphasizing peer dialogue, guided participation, and shared construction of knowledge (Grubaugh et al., 2023). Similarly, AI-powered simulations and chatbots can create experiential learning opportunities that allow students to "learn by doing" — an essential aspect of knowledge construction in both academic and workplace settings (Tran et al., 2025).

AI can also foster the metacognitive reflection that constructivists regard as key to deep learning. Adaptive platforms can prompt learners to evaluate their understanding, identify misconceptions, and revisit concepts until new schemas are formed. A recent study on AI-based educational datasets found that constructivist methods were particularly effective for connecting learners' existing knowledge with real-world practice (Choi et al., 2025). These findings underscore that, when guided by purposeful pedagogy, AI can extend constructivism by scaling individualized and active learning.

Yet AI's alignment with constructivism is not without tension. Overreliance on automated assistance can inadvertently weaken the learner's role in building knowledge. Scholars caution that excessive automation may promote passive engagement — reducing the "germane" effort that leads to deeper understanding — and limit opportunities for social interaction central to collaborative learning (Goddard et al., 2012). A constructivist spirit involves designing AI-supported learning that keeps people — not algorithms — at the center and fosters dialogue, collaboration, and shared understanding.

Cognitive Load Theory and Its Applications to AI

Cognitive Load Theory (CLT) provides another valuable lens for understanding how AI can enhance or disrupt learning. CLT posits that learning occurs most effectively when cognitive effort is balanced across three types of load: intrinsic (the task's inherent difficulty), extraneous (distracting or poorly designed elements), and germane (the mental effort devoted to schema formation). AI can help manage these loads by tailoring how information is presented and how tasks are sequenced. Adaptive learning platforms, for instance, can reduce extraneous load by filtering irrelevant information or regulate intrinsic load by adjusting task difficulty in real time (Center for Innovation, Design, and Digital Learning [CIDDL], 2023).

When well-designed, AI also reinforces germane load by freeing cognitive capacity for reflection and synthesis. Automated feedback systems and natural-language interfaces can support deeper learning by guiding learners through iterative improvement — rather than supplying answers outright. In professional development, these tools translate into more efficient upskilling, allowing employees to focus on higher-order reasoning while routine processing is handled by AI systems.

However, the same technologies that manage cognitive load can also undermine it. Overdependence on automation may lead to “cognitive offloading,” where learners bypass the effortful reasoning required to internalize new knowledge. Automation bias — the tendency to uncritically accept AI-generated outputs — can further erode critical thinking and self-regulation (Jose et al., 2025). Thus, applying CLT to AI-based instruction requires deliberate design choices that promote mental engagement, which helps ensure that technology supports, rather than supplants, cognitive effort.

These insights provide a natural bridge to examining how AI usage opportunities are playing out in the workplace.

AI in Professional Development (L&D & HR)

In these environments, AI engines now reside in diverse content-generation platforms. Instructional design (ID) practitioners are already experimenting with AI toolsets to enhance their workflows, while others are just beginning to explore their potential. For creative applications, such as image, text-to-speech, video, or avatar generation, AI is quickly becoming the agent of choice.

Innovative Examples of Using AI in L&D

For more sophisticated L&D endeavors, however, pioneering practitioners are upping the ante. Below are examples drawn from current case studies that showcase relatively advanced and imaginative uses of AI:

- AI-driven testing and upskilling
  As described in “How to Use GenAI to Enhance Upskilling Through Smarter Testing and Training,” AI can analyze learner performance, tailor test items, and recommend adaptive follow-up training to address specific gaps.
- Curriculum co-design with AI
  In “Envisioning an AI-Centric Approach to Design and Delivery,” L&D teams use AI to map competencies to roles, simulate learner journeys, and auto-generate draft content that can be iteratively refined.
- AI-augmented apprenticeships
  As detailed in “Scaling Apprenticeships with AI,” AI acts as a digital coach, offering real-time feedback on soft skills through speech and behavior analytics — especially in frontline or hands-on job roles.

The Allure of Over-Simplifying AI Use

In general, though, marketing narratives around AI in the workplace promise effortless content creation. A variety of tools offer appealing shortcuts to generating job aids, assessments, case studies, lessons, or entire courses with just a prompt, or by uploading articles, transcripts, white papers, or slide decks.

A simplified, “one and done” approach to content creation is tempting to time-pressured practitioners who would greatly prefer a single-pass solution, and to those who are intimidated by the technology. After all, AI’s outputs are grammatically polished, often cogent, and surprisingly complete.

In many cases, the results surpass what a non-expert (or a less-proficient writer) might produce without AI. So, if the content appears credible and is likely to be well-received by the audience — such as clients, colleagues, learners, or stakeholders — why not just run with the first pass?

The notion that content must be further honed by iteratively collaborating with AI may seem highly inefficient or even unnecessary. Yet relying on the initial output without further review or refinement could lead to superficial outcomes at best — and professional liability or legal exposure at worst.

Herein lies the tension: Should professionals be expected to spend more time refining something that already seems “good enough”? Are we setting unrealistic expectations by suggesting that more extensive interactions with AI are always required?

In workplace settings, the answer depends on the stakes. When quality, tone, and legal or instructional integrity matter — such as in regulated industries, compliance training, or performance-critical job roles — AI output should be treated as a draft, not a final deliverable ready for publication or use. While the speed of AI is a boon, the coherence of the result still rests on human judgment. That makes collaborative iteration more essential, not less.

The Paradox of Using AI in Professional Contexts

As noted above, AI promises a painless way to speed up production and reduce complexity. But for many L&D and HR tasks, the content must meet high standards for accuracy, instructional integrity, tone, and compliance. That creates a paradox: the very convenience that makes AI attractive also increases the risk of overlooking serious flaws. Table 3 describes how three key metrics, speed, quality, and value, are likely to factor into the perceptions that professionals have of AI.

Table 3

Risks of Oversimplifying AI Use in Professional Contexts

Metric	Observation	Implication
Speed of the process	Content-creation platforms sell speed and low effort — not co-creation or critical review.	Iteration is often viewed as a time sink, not a value-added activity.
Quality of the outputs	AI’s initial-pass outputs are often quite strong, many times surpassing what a subject matter expert (SME) or novice writer could produce.	If the result looks “good enough,” there’s little incentive to refine it — even when it matters.
Value to the audience	The audience (customers, learners, readers) may not care how the content was produced, as long as it appears polished and credible.	Assessing the value may hinge on audience approval, even if that audience lacks relevant expertise.

Some AI-generated content may truly be “good enough.” But if instructional quality or legal precision matters, it's important to slow the process down. That way, you can review and refine the output to ensure it meets the professional standards your audience or organization depends on.

Guidelines for Going Beyond “One and Done”

AI tools can produce outputs that look polished, sound authoritative, and appear “done.” But without an understanding of learning science, content sequencing, and assessment strategies, the results may be instructionally thin. Worse, they may be dangerously misleading in regulated or technical fields. There are no obvious red flags unless someone with relevant expertise intervenes.

What’s the best way to resolve this dilemma? Table 4 shows recommendations for various AI tasks...

Table 4

Guidelines for Reviewing AI Output Based on Use Case Risk

AI Task	Risk of Misuse	Review of AI Output Needed?
Drafting a trivia quiz	Low	Probably not. One pass may be fine.
Writing compliance training on sensitive workplace issues	Medium-high	Yes. Plan for a SME review and at least one more refinement pass.
Generating learner feedback or personalized guidance	High, if not aligned to the target audience	Yes. Nuance and voice matter, so a SME review is called for.
Drafting the phrasing of performance evaluations	High ethical stakes for sensitive interactions	Yes. HR or legal oversight is critical, so plan for additional refinement.
Creating online courseware by uploading text files and slide decks to an AI content engine	High, if the output does not reflect best practices for instructional design	Yes. Requires ID proficiency (or SME review) to verify instructional integrity and content accuracy.

To summarize, in many instances, the effective use of AI in the workplace involves:

- Framing the problem clearly
- Collaborating with AI iteratively
- Vetting and refining the AI output rigorously, and
- Co-authoring with human SMEs when appropriate

Ultimately, L&D and HR teams must weigh AI’s speed and convenience against instructional soundness and professional accountability. It’s a balancing act that shapes how AI becomes a muse, sparring partner, or ghostwriter.

Building on these insights, we can look more closely at the body of research that illuminates AI's applications in workplace training and development. In these settings, opportunities and risks are shaped less by academic concerns and more by organizational demands.

AI in Workplace Learning: Emerging Practices and Challenges

As we've seen, in professional development settings, AI is emerging as a multifaceted performance-support engine. Rather than emphasizing academic integrity and formative growth, workplaces tend to value efficiency and transfer of skills to the job. In this domain, adult learning theory and transfer-of-training principles take center stage. For instance, as previously noted, Knowles (1984, as summarized in Pappas, 2025) explains that "as people mature, their self-concept evolves from being dependent to becoming more self-directed."

Similarly, Baldwin and Ford (1988) conclude that "the conditions of transfer include both the generalization of learned material to the job and the maintenance of trained skills over a period of time on the job." Both sets of perspectives highlight the need to align learner needs with instructional intent and application to real-world tasks.

Emerging applications for professional use include personalized AI-driven training and coaching systems. For example, Ifenthaler and Yau (2020) found in their review of learning analytics that AI systems can identify at-risk learners, predict performance, and recommend interventions that support just-in-time skill application.

Likewise, Huang and Rust (2021) note that AI-driven systems can provide personalized recommendations, nudges, and feedback to enhance customer and employee engagement. These observations underscore the role of digital coaching as a way to supplement — but not replace — human mentoring. These uses also align with principles of performance improvement. AI technology is most effective when it supports practice, reflection, and skill transfer, rather than simply accelerating content production.

At the same time, obstacles to AI integration in the workplace mirror those seen in educational settings. An over-reliance on automated feedback can degrade employee performance if not paired with opportunities for self-direction and collaboration. Concerns about equal access also arise. While large firms may integrate sophisticated AI systems, smaller organizations risk being left behind due to cost or infrastructure barriers. Li et al. (2023) observed that AI adoption can both promote and inhibit on-the-job learning, depending on whether employees perceive AI as a tool for support or as a threat to autonomy. Ethical issues also exist, such as around data privacy in corporate learning environments that collect sensitive performance metrics.

Instructional design principles provide guidance in this domain as well. The observations of Sweller, van Merriënboer, and Paas (2019, p. 2), which pertain to the negative effects of any unnecessary demands imposed on the cognitive system, apply here. In workplace settings, this translates into the need for careful sequencing. When using AI tools to develop training, designers should systematically assess cognitive load to produce smooth, manageable performance outcomes.

In short, AI in workplace learning reflects the same paradox observed in education: its effectiveness is not inherent in the tool itself, but in how thoughtfully it is integrated. AI must be combined with principles that prioritize adult learners' self-direction, the need to manage cognitive load, and the systematic transfer of skills to the job. When those conditions are satisfied, AI can extend the reach of professional development. Absent such a foundation, however, it risks reducing learning to superficial efficiency gains.

These parallels and divergences point to broader implications that cut across environments. They are raising the question of how education and employment settings might converge — or continue to diverge — in their use of AI.

AI and Workplace Efficiency: Emerging Evidence

Across industries, most applications of AI in Human Resources (HR) and Learning & Development (L&D) are still motivated by efficiency. The evidence shows that companies in medical, hospitality, and tech, for example, utilize AI to automate routine tasks, streamline processes, and reduce costs. While strategic applications are emerging, the immediate and tangible returns on investment (ROI) from efficiency gains make it a major driver for adoption.

For instance, recruiting platforms use AI to screen resumes, draft job descriptions, and schedule interviews. HR departments rely on chatbots to answer routine policy or benefits questions. L&D teams use AI to speed up content development, generate learning modules, and automate administrative tasks such as enrollment and tracking. These uses reduce cost and turnaround time, which explains why early adoption has focused on automation rather than strategy. Studies have found measurable savings in time and budget — sometimes as much as 20–30 percent (Hayes & Downie, n.d.; Korn Ferry Institute, 2024; Maurer, 2024).

Healthcare, technology, and retail firms echo this pattern by applying AI to schedule staff hours, cut error rates, and improve throughput. For example, hospitals are using AI to automate documentation tasks and reduce administrative burden (Cedars-Sinai, 2025), and companies like Microsoft have deployed AI agents within HR to streamline case triage and HR workflow (Microsoft, 2024).

Practitioners and analysts reinforce this emphasis. Bersin (2023) describes AI's main impact in learning as delivering knowledge tools "on demand," a model prized for its immediacy. Deloitte's High-Impact Learning Organization research shows that high-performing L&D groups are more likely to adopt AI to accelerate processes (Deloitte, 2024), while a Workday overview found that many executives view efficiency and automation as the primary gains (Workday, n.d.). Even where personalization or coaching is cited as a benefit, it is often framed as an efficiency of scale — making training more timely, targeted, or convenient without adding staff (Cornerstone, 2025). These perspectives confirm that efficiency remains the central story, even in organizations exploring more advanced uses.

That efficiency-first stance is not without drawbacks. Analysts and vendors caution that an overreliance on automation risks narrowing the human side of HR and L&D (Visier, n.d.). If left unchecked, the quest for speed could undermine instructional quality, ethics, or employee trust. For instructional designers, this creates a challenge: efficiency may be the driver of adoption, but depth is the standard by which learning must ultimately be judged. The task is not to reject AI's productivity benefits, but to balance them with practices that safeguard rigor, accuracy, and professional integrity.

Comparing AI in Education vs. Professional Development

We can sum up the philosophical and functional fork in the road as follows…

- In education, instructors seek to spark rigorous intellectual growth. AI is a tool to sharpen thinking, test assumptions, and help learners refine their ideas through guided interactions.
- In the workplace, practitioners seek to streamline content creation, especially when under pressure from tight budgets and timelines. AI is often positioned as a production multiplier to boost creativity, reduce repetition, and improve consistency.

These differences aren't just stylistic; they reflect fundamentally different goals. Force-fitting a single AI "best practice" across both settings risks two types of failure:

- Under-challenging students, by making learning too superficial (a common concern in education), or
- Overwhelming professionals, by requiring iterative collaboration with AI when their primary goal is to save time — unless the instructional or legal considerations of the subject matter demand more rigor.

Table 5 summarizes how these core goals and expectations often diverge:

Table 5

Comparing AI Use in Education and Professional Development

Context	Goals of Using AI	Engagement Level	Implication
Public education	Enrich thinking, reinforce skill development	Rigorous, high-effort collaboration	AI is a tutor, editorial challenger, mirror
Professional development (HR, L&D)	Minimize time, reduce workload, increase output	Simplified, low-effort automation	AI is a push-button assistant, shortcut, ghostwriter

This broader perspective invites taking a step back. What do these differences reveal about the larger relationship between education and the workplace in the age of AI?

Bridging the Paradox Between Education and Employment

A striking contradiction emerges when comparing AI in educational and workplace settings. In schools, the conversation often centers around academic integrity and whether AI undermines critical thinking. In professional development, the same AI technologies can shorten learning curves, optimize workflows, and foster a culture of personalized growth. This tension highlights the key differences between the two settings, exposing an underlying rift in the purposes that learning serves in each case.

Recent studies illustrate this divergence. In higher education, Zawacki-Richter et al. (2019, p. 1) observed the “weak connection to theoretical pedagogical perspectives” in AI research, and cautioned that much of the work has not yet embraced rigorous instructional design. For example, learners may bypass meaningful intellectual engagement if they perceive AI merely as a shortcut. Conversely, in workplace learning, Li et al. (2023) observed that employees often view AI as a resource to improve efficiency and enhance learning at work. However, they also warn of risks if AI replaces, rather than complements, human judgment.

However, while the uses of AI in education and professional development often appear divergent, they primarily reflect differences in purpose rather than contradictions. Educational settings emphasize formative learning and ethical literacy, whereas workplace contexts prioritize productivity and performance.

The paradox, then, is not about AI's inherent qualities but about the expectations placed upon learning in different settings. In education, the goal is formative development: cultivating critical analysis, reflection, and mental agility. In workplace learning, the emphasis tilts toward transfer and application: ensuring that knowledge translates quickly into measurable performance. Both settings require theoretical discipline to avoid the pitfalls of over-reliance. Cognitive load theory (Sweller et al., 2019, p. 2) reminds us that unmanaged complexity can impede learning regardless of setting. Adult learning theory (Knowles, 1984, as cited in Pappas, 2025) reinforces the importance of self-direction and content relevance for learners of any age.

Rather than treating education and workplace learning as wholly separate spheres, the paradox invites us to ask: what can each adopt from the other? For instance, professional settings could benefit from the emphasis on reflection and ethical questioning in education. Education might borrow from the focus on practical application and efficiency in the workplace. Both settings share a responsibility to ensure fair access and diligent human oversight when implementing AI. This concern was echoed by Luckin (2018), who warns that AI technologies risk widening existing equity gaps if access barriers aren't carefully addressed.

In short, the paradox is less a contradiction than an opportunity for cross-fertilization. By recognizing the varied stakes and purposes of learning, educators and employers can frame AI in similar ways. When guided by theory and robust instructional practices, AI can extend human capacity without diminishing it.

Conclusions

In the final analysis, it helps to summarize how these dynamics play out across contexts. In educational settings, AI can serve as a catalyst for robust scholarship by challenging students to articulate, refine, and defend their ideas. This kind of rigorous interaction helps students develop transferable skills they can carry beyond the classroom.

In workplace settings, professional teams often need AI to support operational efficiency — particularly when speed and flexibility are paramount. In those cases, AI may be best used to streamline content creation, summarize materials, or prototype training content for later review. But as we've seen, AI can produce outputs that appear highly polished and authoritative to the untrained eye. Without expert review, a one-and-done conversion can result in content that is shallow — or even seriously flawed — especially in regulated or technical domains.

Implications for Instructional Designers

Across educational and professional contexts, instructional designers can use AI more purposefully by aligning tool use with clearly defined learning or performance goals. Context-specific checklists can help guide these choices, ensuring that technology serves instructional intent rather than novelty or convenience. The following examples illustrate how these checklists might be applied in different settings:

- If the goal is knowledge exploration (common in K–12 or higher education), emphasize reflective AI use, such as challenging learners to critique and improve upon AI-generated responses or explain the reasoning behind them.
- If the goal is skill acceleration (typical of corporate or healthcare training), focus on adaptive feedback, simulation, or performance analytics that balance efficiency with comprehension.
- If the goal is creative problem-solving or innovation, blend generative AI with collaborative peer review, encouraging learners to evaluate, refine, and augment machine-generated work.

Future research could test the impact of such checklists across contexts through longitudinal or quasi-experimental designs that track measurable improvements in learning transfer, efficiency, and ethical AI literacy. For practitioners, the immediate opportunity is to adopt a goal-first mindset: start with the learning or performance outcome, then decide how AI can best support that aim.

Understanding these differences isn't about drawing strict lines — it's about matching the use of AI to the purpose of the work. When viewed through that lens, AI becomes a strategic partner in each of these domains.

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