AI Agents as Cognitive Partners in Micro-Project-Based Learning: A Professional Development Workshop

Yuhong Zhao[1*], Qing Zhang[1], Weiwei Li[1]
[1] Xi'an Jiaotong-Liverpool University
[*] yawnzhao@gmail.com

Abstract: *This case study examines how an LLM-based AI agent supported adult learners in professional development during a micro-project-based learning (micro-PBL) workshop. In this activity, learners developed their individually owned "ideas worth spreading" into mini TED-style talks through iterative cycles of reflection, critique, and public presentation. Interviews with 10 participants revealed four generative themes underlying learners' interactions with the AI agent: (1) momentum restoration via cognitive extension under time pressure to overcome a cognitive impasse; (2) role negotiation, in which learners repositioned AI from tool to partner; (3) appropriate reliance, enacted through trust calibration routines; and (4) affect regulation, providing a psychologically safe space for experimentation. Building on these themes, we propose four design principles for AI-supported micro-PBL: ensure learner ownership, design for momentum, orchestrate multi-source feedback, and embed calibration routines. The study offers an explanatory account of how AI becomes a "cognitive partner" in compressed, ill-structured learning tasks.*

Keywords: LLM-based AI agent, micro-project-based learning, adult learning, professional development, design principles

1. Introduction

Large language model (LLM) systems are increasingly used not only for information retrieval but also for ideation, structuring, drafting, and iterative refinement in everyday learning and work (Dwivedi et al., 2023; Mollick, 2024). This shift is particularly consequential in adult professional learning, where participants often work under time pressure, produce public-facing artefacts, and must balance efficiency with authenticity. In such settings, AI may function not simply as a tool, but as an interactive partner that shapes how learners think, decide, and move forward, echoing recent arguments that AI in education is increasingly experienced as a meaning-making subject rather than merely an instructional object (Veletsianos et al., 2024).

This paper focuses on micro-project-based learning (micro-PBL), a compressed workshop-based form of project learning in which learners create an authentic artefact through rapid cycles of reflection, critique, and revision. In our case, participants developed individually owned "ideas worth spreading" into mini TED-style talks. Compared with conventional PBL, this form of learning is marked by temporal scarcity, rapid decision-making, and heightened social accountability. These features can intensify cognitive load, especially when learners must generate structure from ambiguous ideas while maintaining a personal voice. From a learning design perspective, scaffolding can reduce extraneous cognitive load and support higher-order thinking (Belland, 2017; Sweller, 1988; Sweller et al., 2019).

In this context, dialogic AI may serve as a dynamic scaffold. It can externalise structure, propose alternatives, and support rapid iteration. At the same time, AI-supported learning introduces new challenges. Learners must decide what role the AI should play, how much to rely on its outputs, and how to preserve ownership over a personally meaningful public product. These issues are especially salient when the final artefact is not only technically adequate but also rhetorically authentic. Effective human–AI collaboration, therefore, depends not only on assistance but also on appropriate reliance and trust calibration (Lee & See, 2004). In addition, because micro-PBL often involves personal expression and public presentation, psychologically safe conditions remain important for experimentation and reflection (Edmondson, 2018).

Building on cognitive load theory and research on trust in automation, this study examines how adult learners experienced AI support during a sprint-formatted micro-PBL workshop. Rather than treating AI as a generic "benefit," we focus on the mechanisms through which it shapes learners' task progress, role negotiation, reliance decisions, and affective experience. The guiding research question is: How do adult learners experience AI as a cognitive partner in a time-bounded micro-PBL workshop?

We argue that, in compressed project settings, AI becomes a cognitive partner not by replacing learner agency, but by helping learners restore momentum, negotiate functional roles, calibrate trust, and explore ideas with lower social risk.

2. Method

This study adopted an exploratory qualitative case study design centred on one professional development workshop (Yin, 2017). The broader cohort included 15 adult professionals from diverse industries, all with at least five years of work experience, and 10 participants volunteered for semi-structured post-workshop interviews. The workshop was structured as a sprint-formatted micro-PBL activity in which learners developed individually owned mini TED-style talks for public delivery. This bounded case design allowed in-depth examination of how adult learners interacted with AI across a compressed project cycle (Yin, 2017). Participants used DeepSeek-R1 and Doubao via a browser interface, with facilitator-provided examples for ideation, outlining, revision, and rehearsal, while retaining freedom to adapt prompts to their own workflow. All participants provided informed consent, and data were anonymised.

Data came primarily from semi-structured interviews, with interaction logs used as supplementary evidence. The interviews focused on how participants used AI across different stages of the project cycle, including idea selection, drafting, feedback integration, revision, and preparation for public delivery. Thematic analysis was used to identify recurring cross-case patterns (Braun & Clarke, 2006). Transcripts were coded line by line, codes were grouped into categories, and categories were refined into broader themes. To strengthen analytic rigour, we triangulated interviews with interaction logs, maintained an audit trail, and used peer debriefing. Interview prompts elicited both frustrations and successes.

3. Findings and Discussion

3.1 AI restored momentum under time pressure

The first theme concerned momentum restoration. In this sprint-formatted workshop, participants frequently described AI as useful when they were cognitively stuck, short on time, or unsure how to structure an emerging idea. Rather than simply "saving time," AI helped convert vague thoughts into workable outlines, examples, phrasing options, and next steps. In this sense, AI functioned as a dynamic scaffold for overcoming blank-page paralysis.

This theme was strongly reflected in the initial coding, where participants associated AI with workload reduction, cognitive kickstarting, and structured sensemaking. One participant noted that when they could not immediately generate content, AI helped expand aspects of the topic; another described AI as providing systematic structure when framework thinking was lacking. The interaction-log examples similarly showed learners using iterative prompting to generate "golden sentences" or more suitable speech endings under time pressure.

From a theoretical perspective, this finding can be interpreted through cognitive load theory. In compressed project work, learners face substantial extraneous demands: organising ideas, making rapid rhetorical choices, and translating personal experience into a coherent public product. AI appeared valuable when it reduced these burdens and helped learners re-enter productive thought. Importantly, participants did not describe AI as doing the thinking for them. Rather, they used it to regain pace and free cognitive resources for higher-order judgment (Sweller, 1988; Sweller et al., 2019). This suggests that the value of AI lies less in full automation than in providing momentum during cognitive impasses.

3.2 AI's role was negotiated rather than fixed

A second theme was role negotiation. Participants did not treat AI as a stable or singular entity. Instead, they framed it differently depending on task stage and purpose: sometimes as an assistant, sometimes as an amplifier of their own capability, and at other times as a reviewer or sparring partner.

What matters here is not anthropomorphism for its own sake, but functional positioning. Participants actively decided what they wanted AI to do and, just as importantly, what they did not want it to do. This was especially visible when they were writing for public speaking. Several participants were willing to ask AI for options, structures, or stylistic alternatives, but resisted letting it produce the final narrative voice. One representative example from the study showed a learner asking the system for five narrative styles while explicitly instructing it not to write the full script. The learner explained that "the final voice must be mine."

This finding clarifies what "cognitive partner" means in practice. AI was not experienced as inherently partner-like. It became partner-like when learners pragmatically assigned it a role that served their current need while preserving personal ownership of the final product. This interpretation also aligns with recent discussions of AI as a collaborative rather than purely instrumental presence in learning and knowledge work (Mollick, 2024; Veletsianos et al., 2024).

3.3 Trust depended on calibration, not acceptance

The third theme concerned trust calibration. Participants repeatedly noted that AI output could be useful yet limited. They described errors, superficial responses, and misalignment with their actual intentions. However, these limitations did not necessarily lead them to abandon AI. Instead, participants engaged in active calibration behaviours, such as verifying outputs, rephrasing prompts, asking the model to explain its reasoning, and retaining human control over final decisions.

AI support was therefore not effective because learners trusted it blindly. It was effective when learners treated AI suggestions as provisional and compared them against personal intent, audience fit, and, where available, peer or mentor input. One interaction log example showed a participant asking the model to adjust an output "based on your reasoning" to debug why the response had deviated from their original intent. Rather than accepting or rejecting the AI in a binary way, the learner used explanation-seeking to calibrate reliance.

This theme aligns with trust-in-automation research, which emphasises appropriate reliance rather than uncritical acceptance (Lee & See, 2004). It also extends that literature into a pedagogical context where the final product is public-facing and personally meaningful. When learners are preparing a talk that reflects their own experience, trust becomes both epistemic and identity-related: they are not only checking whether something is correct, but also whether it sounds like them. This suggests that effective design should make verification and comparison routines an explicit part of the learning process.

3.4 AI provided a low-risk space for rehearsal and exploration

The fourth theme was affect regulation. Beyond cognition and task progress, participants described AI as a psychologically easier space in which to test unfinished ideas, rehearse expression, or think aloud without immediate human judgment.

This mattered because the workshop task involved personal storytelling and public speaking. In such conditions, learners are not only producing content; they are exposing identity, uncertainty, and rhetorical vulnerability. AI appeared helpful because it allowed early experimentation without the interpersonal pressure that often comes with peer or mentor critique. Participants could try out half-formed ideas, ask awkward questions, or rehearse phrasing with lower embarrassment. One participant even described playful banter with the AI during preparation, suggesting that the interaction provided emotional support as well as practical support.

At the same time, this did not mean emotional dependence without boundaries. Participants valued convenience and low judgment, but they still distinguished AI from human relationships and retained awareness that it was a one-way support system rather than a reciprocal social bond. This theme is important because it shows that AI as a cognitive partner is not only about reasoning assistance. In compressed learning environments, affect and cognition are intertwined, and psychologically safer conditions can help learners sustain experimentation and revision (Edmondson, 2018).

4. Conclusion and Implications

This study suggests that AI becomes a cognitive partner in micro-PBL not because it autonomously produces strong outputs, but because learners use it to regain momentum, assign functional roles, calibrate reliance, and explore ideas with lower social risk. In this workshop setting, AI support was most valuable when it protected learner ownership while reducing the friction of compressed project work.

Four concise design principles follow. First, AI-supported micro-PBL should preserve learner ownership, especially when the output is public-facing and identity-relevant. Second, learning design should support momentum restoration during cognitive impasses through structured yet flexible scaffolding (Belland, 2017; Sweller et al., 2019). Third, pedagogy should orchestrate multi-source feedback, enabling learners to compare AI, peer, and mentor input without losing narrative control. Fourth, teachers should embed trust-calibration routines, including verification, comparison across feedback sources, and explicit human accountability for public-facing outputs (Lee & See, 2004).

This paper is exploratory and context-specific. The study involved a small, self-selected interview sample and focused on an individually owned workshop task rather than collaborative team PBL, both of which limit transferability. Future work could compare AI support with human coaching or static scaffolds and examine whether these cognitive-partnership patterns persist beyond a single workshop cycle.

References

Belland, B. R. (2017). *Instructional scaffolding in STEM education: Strategies and efficacy evidence*. Springer Nature. https://doi.org/10.1007/978-3-319-02565-0

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., ... & Wright, R. (2023). Opinion paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Edmondson, A. C. (2018). *The fearless organization: Creating psychological safety in the workplace for learning, innovation, and growth*. Wiley.

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors, 46*(1), 50–80. https://doi.org/10.1518/hfes.46.1.50_30392

Mollick, E. (2024). *Co-intelligence: Living and working with AI*. Portfolio.

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12*(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4

Sweller, J., van Merriënboer, J. J. G., & Paas, F. (2019). Cognitive architecture and instructional design: 20 years later. *Educational Psychology Review, 31*(2), 261–292. https://doi.org/10.1007/s10648-019-09465-5

Veletsianos, G., Houlden, S., & Johnson, N. (2024). Is artificial intelligence in education an object or a subject? Evidence from a story completion exercise on learner-AI interactions. *TechTrends*, *68*(3), 411–422. https://doi.org/10.1007/s11528-024-00942-5

Yin, R. K. (2017). *Case study research and applications: Design and methods* (6th ed.). SAGE.