


**CONFLUENCE**
**Journal of Multidisciplinary Studies**

**e-ISSN: 3085-5411**
**Journal Homepage**: https://journals.imist.ma/index.php/confluence/index

# Learning in the Age of AI: How AI Is Transforming Adult Learning in Corporate Contexts

**Videhi Bhamidi, Divya Joseph, and Maathangi Mohan**
Independent Researchers

https://doi.org/10.34874/PRSM.cjms-vol2iss4.13078

**Videhi Bhamidi** is an edtech product and policy research consultant with vast experience across startups, corporations, think tanks, and nonprofits. She holds a Master's in Education (Learning and Technology) from the University of Oxford and is co-author of *Employee-Generated Learning* (Kogan Page, 2024). Her interests include AI and corporate learning, employee-generated learning, mobile learning, workplace learning, edtech product discovery, and evidence-led edtech design.

videhi.visali@gmail.com https://orcid.org/0009-0007-0152-9861

**Divya Joseph** is an education researcher and independent consultant. She holds an MSc in Education (Learning and Technology) from the University of Oxford and an MA in Education from Azim Premji University. She has led education programs with governments, NGOs, and multilateral bodies. Her research interests include AI and digital education, adult learning, teacher professional development, and participatory approaches to education.

1015.divyajoseph@gmail.com https://orcid.org/0009-0007-8538-5868

**Maathangi Mohan** is an independent researcher and consultant working across education, technology, and international development. She has worked with international organizations, including the British Council, UNESCO, and UNICEF, on initiatives spanning AI in education, open educational resources, and digital learning, as well as with philanthropic organizations on education strategy and program design. She holds a Postgraduate Diploma in Liberal Studies and Leadership from Ashoka University. Her interests include AI and workplace learning, adult learning, digital education, and the social implications of emerging technologies.

maathangi.mohan@gmail.com https://orcid.org/0009-0009-8721-0249

Received: 01-08-2026 Accepted: 27-10-2026 Published: 30-10-2026

# Learning in the Age of AI: How AI Is Transforming Adult Learning in Corporate Contexts

**Videhi Bhamidi, Divya Joseph, and Maathangi Mohan**
Independent Researchers

## ABSTRACT

This conceptual scholar-practitioner paper examines how generative AI reshapes the conditions under which adults learn at work. As AI enters everyday knowledge work, learning with AI increasingly happens in the flow of work, raising the question of what is being learned and what is merely performed. Synthesizing andragogy and self-directed learning, sociocultural learning theory, and experiential learning, the paper develops a provisional model of the depth-speed tension across four dimensions of workplace learning, namely learner agency and self-direction, learning through practice and experimentation, social and peer learning, and knowledge in the flow of work. It proposes that AI accelerates access to information and task completion but, under certain conditions, can compress the productive struggle, reflection, and human relationships through which durable skills develop. The moderating conditions, including learner expertise, AI literacy, task complexity, organizational culture, and performance pressure, shape whether AI strengthens or weakens learning. The paper identifies the cognitive and relational work that remains hard to delegate to AI, offers five propositions to guide future empirical testing in workplace settings, and outlines implications for learners, managers, learning professionals, and organizations. Its guiding principle is to get the human learning conditions right before reaching for the technology.

## KEYWORDS

**Adult Learning**

**Depth-Speed Tension**

**Generative AI**

**Knowledge Work**

**Self-Directed Learning**

**Workplace Learning**

## Introduction

Since the public release of ChatGPT in late 2022, generative AI tools have come into wide use in knowledge work (Lee et al., sec. 1). Because these tools are largely consumer products that individual workers experiment with on their own, Mohammad Hossein Jarrahi et al. argue that organizations need to invest in training to build workers' AI literacy (18). This raises the question of how learning is supported when technology use develops ahead of deliberate learning design. Adult education scholars note that generative AI is already changing self-directed learning, offering possible benefits such as personalized support and prompt feedback in some contexts while also raising new challenges (Morris et al. 121).

In this paper, "AI" refers primarily to generative AI tools, meaning end-user tools built on deep-learning generative models (Lee et al., sec. 1), used as cognitive assistants in workplace tasks. Examples include conversational chatbots, productivity copilots, and coding or content-generation assistants.

Contact ✉ videhi.visali@gmail.com
©2026

Related configurations, including retrieval-augmented generation (RAG) systems, adaptive learning platforms, AI tutors, and agentic systems, are identified in the AI Configurations section and discussed where relevant.

The paper focuses on knowledge workers, whom Thomas H. Davenport describes as people with high levels of expertise, education, or experience whose jobs center on creating, distributing, or applying knowledge (10). Knowledge workers are one group of adult learners. We draw in particular on self-directed learning, which Thomas Howard Morris et al. describe as a core pillar of lifelong learning theory in which learners take responsibility for goals relevant to their own context (121).

In workplace settings, adults tend to use generative AI less as a formal learning intervention than as an everyday assistant. In a digital diary and interview study of professionals in academic, IT, healthcare, education, and consulting roles, Jarrahi et al. found that generative AI took on roles such as retriever, originator of first drafts, brainstormer, and reviewer of written text (table 2). Learning in these settings is therefore likely to happen in the flow of work. It is embedded in tasks, prompted by problems, and supported at the moment of need, rather than confined to scheduled programs. Practitioner scholarship has emphasized that employees develop meaningful knowledge and skills through experimentation, contextual application, and peer validation, alongside formal learning initiatives (Spiro and Bhamidi 46). By making retrieval, synthesis, and task support immediately available, AI may change each of these processes.

If AI changes how employees work through tasks, it also raises the question of whether doing a task well with AI means learning from it. Following Nicholas C. Soderstrom and Robert A. Bjork, we treat learning as the relatively permanent changes in knowledge or behavior that support long-term retention and transfer, and performance as the temporary changes that can be observed during or immediately after practice (176). Their review shows that large gains in performance often fail to produce corresponding gains in learning, and that people often mistake their performance during practice for evidence of long-term learning (176). Although this evidence comes from experimental research on motor and verbal learning, it bears directly on AI-assisted work. Generative AI can accelerate access to information, reduce the effort of routine tasks, and provide immediate support, all of which can improve performance. Whether this also produces durable learning may depend on whether AI replaces opportunities for retrieval, reflection, error diagnosis, and peer exchange, or frees time for further inquiry, iteration, feedback, and application. The central question is therefore not whether AI necessarily reduces learning, but under what conditions its use supports, reorganizes, or constrains the development of professional capability.

Existing scholarship addresses parts of this question. In a concept paper, Andreas Rausch examines how AI can support informal workplace learning and describes an "AI ghost learner effect," which can arise when employees adopt AI-generated solutions without the deeper processing and reflection needed to learn from them (sec. 3.3). He also notes that employees may mistake improved performance for improved competence (sec. 3.3), but he does not develop this distinction or specify the conditions under which it arises. In a survey of 319 knowledge workers, Hao-Ping Lee et al. found that higher self-reported confidence in generative AI was associated with less critical thinking (sec. 6.1.1). They also found that generative AI moved workers' effort away from gathering information, solving problems, and executing tasks, and toward verifying information, integrating AI responses, and overseeing the work, a role they call task stewardship (sec. 6.2). Morris et al. describe research on generative AI and self-directed learning as a new field in urgent need of further study (124). Reviewing research on AI and lifelong learning, Ted Palenski et al. find that studies treating AI as part of a wider reconfiguration of people and their contexts are the least represented in the literature

(1216), and they call for deeper engagement with theories of learning and technology (1233). What remains less developed is an integrated account that uses the distinction between performance and learning to specify when everyday generative AI use in knowledge work is likely to strengthen or weaken learning across cognition, tacit knowledge, self-direction, reflection, and social participation.

Responding to that call, this conceptual paper synthesizes andragogy, sociocultural learning theory, and experiential learning, and identifies conditions that moderate the relationship between AI use and workplace learning. The authors' practitioner experience informed the questions guiding the analysis but is not treated as empirical data, and the paper does not claim that the relationships it proposes generalize across organizational settings. Instead, it offers a provisional model and propositions for empirical testing.

## Methodology

This article is a conceptual paper that develops a model for understanding how AI may influence how adults learn in corporate settings. In conceptual papers, arguments are built from previously developed concepts and theories rather than from data in the traditional sense (Jaakkola 19). The paper uses a theory-synthesis design, which integrates several theories to offer a new or enhanced view of a phenomenon (Jaakkola 21). Because it also proposes a model of how AI use, learning mechanisms, and outcomes relate (fig. 1), it combines synthesis with elements of what Elina Jaakkola calls a model design, and she notes that such designs are often combined (21-22). The paper therefore reports no empirical sample and makes no claim of empirical generalization.

The starting point was a problem of practice that the authors encountered in their professional work in adult learning, learning design, and knowledge work. AI-assisted tasks could be completed much faster, yet it was unclear whether durable learning kept pace. The analysis borrows the logic of abduction, in which an unexpected observation is read against several existing theories to produce new explanations (Timmermans and Tavory 167, 169). Stefan Timmermans and Iddo Tavory note that recognizing such a surprise depends on the researcher's position and familiarity with theory (173), which is the role practitioner experience played here, consistent with Donald A. Schön's account of how professionals reflect on puzzling situations in their practice. Practitioner experience shaped the guiding questions but was not treated as empirical data, and no practitioner observations were coded.

Sources were selected for their focus on adults using AI to learn or adults using AI in the workplace, were identified through Google Scholar, and were limited to work published in approximately the last ten years. Foundational works in each theoretical tradition, along with sources that define the AI systems discussed, were added regardless of publication date to anchor the synthesis.

Three theoretical traditions were selected because each foregrounds a different process central to workplace learning. Following Jaakkola's guidance for papers that start from a phenomenon, each tradition was chosen for its fit with that phenomenon and the complementary insight it adds (19). Andragogy explains learner agency and the assumption that adults increasingly take responsibility for directing their own learning (Knowles 43-50). Self-directed learning further explains the processes involved, including the distinction between managing learning activities and monitoring one's understanding (Garrison 21-27). Sociocultural learning theory focuses on participation, relationships, and learning mediated by tools and other people (Vygotsky 25, 30, 54-55, 90-91; Lave and Wenger 29-37). Experiential learning focuses on how experience is transformed through reflection and experimentation (Kolb), a process closely tied to tacit knowledge (Polanyi).

The traditions converge in treating learning as more than acquiring information, but they locate the key mechanism differently. Andragogy and self-directed learning locate it within the individual, in the learner's ability to set goals, manage their learning, and monitor their own understanding. Sociocultural theory locates it between people, in mentoring, feedback, and participation in a community of practice. Experiential learning centers on the individual's reflection, but in this paper's reading it also depends on concrete experiences that are often shared with others. The point of divergence is therefore about whether the individual or the community is the main site of learning. When an employee turns to AI instead of a more experienced colleague, andragogy would see greater independence, since the learner gets answers on demand without relying on others. Sociocultural theory would see a lost opportunity for feedback, mentoring, and participation in the community where professional judgment develops. Experiential learning adds a further concern, since a fast, ready-made answer may shorten the cycle of experience, reflection, and experimentation.

Taken separately, each tradition explains only part of what changes. Andragogy can account for gains in learner control but not for the loss of peer exchange, sociocultural theory can account for changes in participation but less for individual self-monitoring, and experiential learning can account for reduced reflection but not for who provides feedback. Read together, they show that the same gain in speed can affect agency, participation, and reflection at once, sometimes in opposite directions. This combined view underlies what the paper calls the depth-speed tension, developed in the next section. The synthesis organizes the analysis around four theory-derived dimensions. Learner agency and self-direction draw mainly on andragogy, learning through practice and experimentation on experiential learning, and social and peer learning on sociocultural theory. Knowledge in the flow of work draws on situated cognition and tacit knowledge.

Each dimension is examined through a common question, which asks under what conditions AI-assisted work might support, reorganize, or constrain the development of professional capability. The analysis of each dimension draws on those of the eight moderating conditions, set out in the Provisional Model, that bear most directly on it.

## Theoretical Framework

### Self-Directed Learning and Andragogy

Malcolm S. Knowles's andragogy frames adult learning around increasing learner agency, the relevance of learning to practical needs, and readiness to address tasks and responsibilities (43-45). In this view, adults are increasingly inclined to take responsibility for identifying their learning needs, setting goals, and directing their development (Knowles 47-49). Their motivation is often strengthened when learning is relevant to the problems they encounter in practice (Knowles 47-48, 53-54). These are guiding assumptions rather than universal characteristics: self-direction varies across individuals and situations, and also depends on learners' skills and circumstances, including their information literacy (Morris et al. 123). Andragogy therefore explains adults' orientation toward self-direction, but offers less detail on the cognitive and regulatory processes through which it takes place.

D. Randy Garrison extends this picture with a model of self-directed learning built on three overlapping dimensions (21). Self-management concerns task control, meaning the external side of learning, such as carrying out learning goals and managing resources and support (22). Self-monitoring concerns cognitive responsibility. It covers the metacognitive work of tracking one's learning strategies and thinking about one's own thinking, and it is the process through which learners take responsibility for constructing meaning by integrating new ideas with what

they already know (24). Motivation covers both the commitment to a learning goal and the persistence to stay with it (26-27). Garrison treats self-monitoring as central to judging the quality of learning outcomes (24), which makes it the dimension most relevant to the questions this paper asks about AI. Although Garrison developed the model for formal educational settings, this paper applies it to learning at work, where colleagues and managers can play the supporting role he gives to teachers.

AI can considerably extend the self-management dimension. Learners can obtain synthesized, context-specific information on demand, remove practical barriers to inquiry, and pursue their own learning paths without going through formal programs. In a survey of knowledge workers, many participants reported spending less effort finding and organizing information because generative AI gathered it and presented it in a readable form (Lee et al., sec. 5.2.1). Jarrahi et al. likewise found that generative AI helped with breaking down complex concepts and helping professionals see the bigger picture of a topic (table 2; 13).

Self-monitoring poses a different challenge. It concerns the learner's judgment about whether they understand, what remains uncertain, and whether they can apply what they have learned beyond the immediate task. This judgment remains the learner's responsibility, but Garrison notes that self-monitoring depends on both internal and external feedback, and that internal feedback alone may be inaccurate (24-25). Feedback, prompts, assessment, and structured reflection from other people and systems can therefore support it. The concern is not that monitoring cannot be supported from outside, but that fluent, ready-made answers may reduce the learner's own evaluative work. Lee et al. found that knowledge workers who trusted generative AI to handle a task were less likely to reflect critically on its output, and that some accepted that output by default when they doubted their own ability (sec. 4.3.2). When AI is used mainly to produce an acceptable answer, learners may have fewer reasons to retrieve, explain, test, or challenge what they know. When it is used to highlight discrepancies, generate questions, give feedback, or prompt explanation, it can support monitoring instead (Rausch, sec. 3.4).

## Sociocultural Learning Theory: ZPD and Communities of Practice

Where andragogy places the individual at the center of learning, sociocultural theory holds that learning takes place through participation in social relationships and communities of practice. As noted in the Methodology, the two traditions diverge on where learning happens. Self-directed learning describes what the learner does, while sociocultural theory describes the relationships and communities through which that activity becomes meaningful and recognized.

Lev S. Vygotsky's zone of proximal development describes the gap between what a learner can do alone and what they can do with guidance from, or in collaboration with, a more capable person (86). In this paper's reading, the more capable other plays a calibrating role, judging where the learner stands, anticipating what they could do next, and adjusting support as their understanding grows (Vygotsky 86-87). Vygotsky developed the concept in studies of children, so its use here for adult professionals is an extension rather than a direct application. AI systems can provide feedback, scaffolding, and adaptation, but many current systems have less access than a long-standing human mentor to the learner's full cognitive, organizational, and developmental context. Jean Lave and Etienne Wenger extend this relational view from the mentoring pair to the wider communities in which professional learning takes place. Through legitimate peripheral participation, newcomers move from the edges toward the center of a community of practice, gaining not only explicit skills but also the tacit norms, values, and situational judgment that mark competent membership (Lave and Wenger 29). Wenger later

argued that learning in communities of practice is also a process of forming identity, so that learning cannot be separated from belonging.

AI does not remove these relational dimensions of learning. Jarrahi et al. note that knowledge workers largely experiment with generative AI tools on their own, and suggest that communities of practice, where workers share experiences and practical tips, can support collective sensemaking around these tools (18). AI may also augment participation by helping learners find information, prepare for discussions, or rehearse ideas. At the same time, it can replace some interactions. Lee et al. describe workers using generative AI to get feedback on their writing instead of going through rounds of review with colleagues (sec. 5.2.3). Whether this weakens learning depends on whether such interactions still offer feedback, modeling, interpretation, and shared practice. The sociocultural lens therefore points to forms of professional learning that may weaken when AI substitutes for participation, but may strengthen when AI reduces routine effort and frees time for richer human interaction.

### Experiential Learning and the Depth-Speed Tension

The third tradition is David A. Kolb's experiential learning theory, which defines learning as the process through which knowledge is created by transforming experience (38). Kolb describes this as a cycle of four stages, namely concrete experience, reflective observation, abstract conceptualization, and active experimentation. When learners pass through the stages only superficially, especially experience and reflection, they may become familiar with a concept without understanding it well enough to transfer it.

This cycle gives precision to what this paper calls the depth-speed tension. AI helps people complete work faster, but that speed can bypass the slower processes through which skills develop, such as working through a problem from scratch, making and correcting errors, reflecting on the result, and seeking feedback from others. By supplying ready-made conceptualizations in response to a prompt, AI can compress parts of Kolb's cycle, particularly when learners accept an output without working through the underlying problem, reflection, or experimentation themselves. In such cases the learner receives the product of a reasoning process without the experiences through which understanding develops. The same technology can be used differently. Learners may ask AI to explain alternatives, expose assumptions, identify errors, or structure experiments, and use the time saved to deepen their engagement with the cycle rather than replace it.

Soderstrom and Bjork's finding that gains in performance often do not translate into lasting learning (176) helps locate where this risk is greatest in Kolb's cycle. AI is most likely to raise performance without a matching gain in learning when it takes the place of reflective observation and active experimentation, since these are the stages in which learners test and revise their own understanding. It is least likely to do so when learners treat AI output as material for those stages, for example by comparing an AI explanation with their own attempt, or by trying an AI-suggested approach and reflecting on the result.

Survey evidence from knowledge workers points in both directions. Lee et al. found that while generative AI can make work more efficient, it can also reduce critical engagement and may lead to long-term overreliance and weaker independent problem-solving (sec. 7). They note that without regular practice in routine and low-stakes tasks, cognitive abilities can weaken over time (sec. 4.3.2). The same study also found that some workers used generative AI deliberately to build their own skills, for example by working through AI-suggested corrections to improve their writing (sec. 4.3.1). The next section brings these elements together in a provisional model (fig. 1).

## AI Configurations

AI is not treated here as a single technological category. As defined in the Introduction, the analysis centers on generative AI tools used as cognitive assistants in workplace tasks, and terms such as "AI-assisted" and "AI-supported" refer to work involving these tools. Throughout the paper, "AI" refers to these tools unless another configuration is named. Related configurations differ in their levels of autonomy, forms of interaction, and roles in supporting learning, and are discussed where relevant rather than treated as equivalent cases. Within the primary category, coding assistants warrant separate mention because they generate or modify executable artifacts. This creates particular opportunities for iterative experimentation but also for the delegation of technical reasoning. Retrieval-augmented generation (RAG) systems combine a generative model with information retrieved from an external knowledge source (Lewis et al. 9459), which may change the reliability and traceability of workplace information. Adaptive learning platforms and AI tutors can organize task selection, practice, feedback, and assessment more explicitly around learning goals. Agentic systems go beyond generating or recommending content to planning and carrying out multistep actions (Wang et al., sec. 2.1), which increases the extent to which task processes themselves may be delegated. The type of system therefore shapes its learning effects, since what a system does determines which cognitive, social, and experiential processes remain with the learner.

## Provisional Model

Across these configurations, the paper treats the following conditions as moderators of the relationship between AI use and workplace learning. These are (1) learner expertise, (2) task complexity and risk, (3) organizational culture, (4) AI literacy, (5) managerial expectations and performance pressure, (6) system reliability and transparency, (7) the availability and quality of feedback, and (8) whether AI is used mainly for immediate production or for longer-term capability development. These conditions shape whether the speed AI offers represents a productive reallocation of effort or the displacement of learning opportunities.

Building on this synthesis, figure 1 presents a provisional model of how AI use may shape workplace learning. It distinguishes the conditions that shape engagement with AI, forms of use, learning mechanisms, and potential outcomes.

The model runs from left to right. Antecedent conditions shape how a worker engages with an AI system. These include characteristics of the learner, such as expertise, AI literacy, self-regulation, and motivation, features of the task, such as its complexity, stakes, and novelty, and features of the organization, such as its learning culture, managerial expectations, and access to experts. Some of these factors also appear among the moderating conditions, because they shape both how a worker first engages with AI and which pathway that engagement then follows. Engagement is best understood as a spectrum rather than a binary. At one end is substitutive use, where a worker accepts a finished output and delegates much of the underlying thinking. At the other is augmentative use, where the worker asks the system to explain, works through the problem in stages, and stays engaged in the reasoning, reflection, and experimentation the task involves.

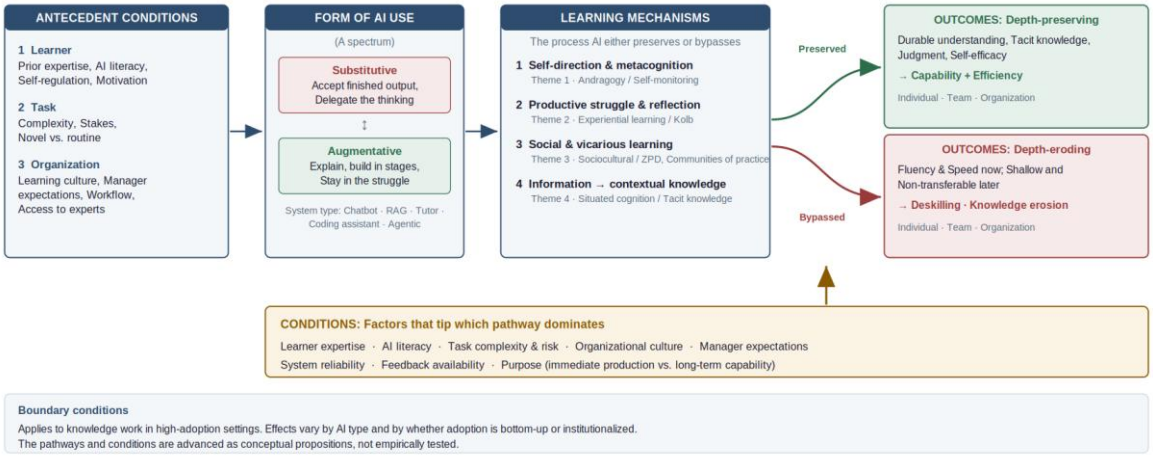



**Fig. 1.** Provisional Model of AI and Workplace Learning: The Depth-Speed Tension

These forms of use may affect four learning mechanisms, which correspond to the paper's four dimensions, namely learner agency and self-direction, learning through practice and experimentation, social and peer learning, and knowledge in the flow of work.

From these mechanisms, the model divides into two potential pathways. On the depth-preserving pathway, the learning mechanisms are maintained or supported, so that AI-assisted work can move faster while also supporting deeper learning. On the depth-eroding pathway, some of these mechanisms are reduced, displaced, or bypassed. This may produce strong immediate performance without equivalent gains in durable or transferable understanding. If sustained, it may contribute to deskilling among individuals and teams and to the erosion of knowledge within organizations.

The model brings together dimensions of learning that are often examined separately and organizes them around the depth-speed tension. It proposes that the same AI system may support, constrain, or reorganize learning depending on the form of use and the conditions around it. The model also has boundary conditions. It applies to knowledge work in settings where AI use is widespread, and its effects are expected to vary by type of AI system and by whether adoption is driven by individual workers or by the organization. The pathways shown in figure 1 are conceptual propositions, not tested findings, and the Conclusion identifies relationships that future research could examine.

## Analysis and Discussion

### Learner Agency and Self-Direction

Self-directed learning is understood as a process in which learners take primary responsibility for identifying their learning needs, setting goals, selecting resources, and evaluating outcomes. AI raises the question of whether greater independence in completing tasks also means greater ownership of learning. At first sight, AI strengthens self-direction by giving learners more control over when, how, and what they learn. In Garrison's terms, this is a gain in self-management. This section asks whether it also supports self-monitoring, the dimension the Theoretical Framework identified as relevant to AI.

Greater control over a task does not necessarily mean deeper self-direction. When learners use AI mainly to automate the thinking needed to reach a performance goal, they can control the task while doing less of the work of building knowledge. Knowles's andragogy assumes

that adults become ready to learn when they need to know how to deal with a task or problem (44). When AI makes it possible to reach the desired outcome without confronting the underlying gap in knowledge, that need may never be felt, and the impulse to inquire and build deeper competence may not arise. Adult learners appear aware of this risk. In an interview study of twenty adult learners, Jinhee Kim et al. found that participants valued AI for tracking their progress but wanted to stay in charge of their own reflection and avoid becoming overly dependent on AI's judgments (1920). They also worried that AI could steer their learning paths and decisions in ways that weaken their agency, and wanted systems that explain their limits and encourage learners to think critically about when to rely on an output (1922, 1924). Although these learners were studied in university online learning rather than at work, their concerns bear directly on employees who use AI in their daily tasks.

Agency in AI-assisted learning is also not simply a matter of being more or less independent. In a mixed-methods study of Chinese undergraduate English learners using generative AI informally, Chun Lai et al. distinguish performance proxy agency, in which learners have the tool complete a task for them, from learning proxy agency, in which they use its output as a resource for learning, for example by comparing an AI translation with their own (8). Both involve delegating to the tool, but only the second turns delegation into learning. Although these participants were language learners rather than employees, the distinction closely parallels the substitutive and augmentative forms of use in figure 1. AI supports agency when learners keep control of their goals, question outputs, compare alternatives, and use the system to extend rather than replace their own reasoning. Several of the moderating conditions set out in the Provisional Model shape which pattern emerges. Learner expertise matters because knowledge workers who are more confident in their own skills tend to evaluate AI output more critically (Lee et al., sec. 6.1.1). Performance pressure matters because workers with little time report having little room to reflect on what AI produces (Lee et al., sec. 4.3.2).

Independence in completing a task and ownership of learning can therefore come apart. A learner who produces the desired output without evaluating its basis, or without considering what they have learned, may gain control over the task without becoming more self-directed. For organizations, this suggests building evaluation, explanation, and reflection into AI-assisted workflows, so that greater self-management is matched by opportunities for self-monitoring.

## Learning through Practice and Experimentation

The speed with which AI produces outputs raises a question about the conditions under which learning occurs. A hypothetical vignette makes this concrete. A business analyst is asked to analyze an unfamiliar dataset and prompts AI to write the code and generate the charts. Within minutes a clean set of results appears, and the task can be delivered. If the analyst accepts the generated code without examining the methods, testing the results, or adapting the analysis, the task may be completed with little development of the underlying capability. In terms of Kolb's cycle, the analyst skips the concrete experience of working through the problem and the reflective observation and active experimentation that would follow it. Matthew Christian Agustin argues that AI can solve problems before learners recognize their knowledge gaps, reducing opportunities for monitoring and reflection and potentially creating a false sense of mastery (sec. 3.5). A finished solution may thus arrive before the analyst has engaged with the problem, reducing opportunities to learn through diagnosis, reflection, and experimentation unless these are taken up elsewhere in the workflow.

Now consider the same analyst approaching the same task differently. Rather than accepting a finished analysis, they ask AI to explain its choice of method, build the code in steps they can follow, and suggest options that they then test against the data themselves. When a result looks

implausible or the code returns an error, the analyst faces a real problem and has to diagnose it. In a concept paper on informal workplace learning, Rausch notes that this kind of reactive learning is typically triggered by deviations from routine, errors, and unfamiliar changes in work tasks, which prompt workers to question what they already know (sec. 2.1). Used this way, the time AI saves on routine work goes into concrete experience, reflection, and experimentation rather than replacing them.

Which path an analyst takes is itself shaped by expertise and prior experience. A novice, with less knowledge to draw on when questioning an output, may be more likely to accept a plausible response without noticing its limits. Lee et al. report that knowledge workers who lacked sufficient domain knowledge found it hard to judge whether AI output was correct (sec. 4.3.2). An experienced analyst is better placed to question methodological choices, spot anomalies, and test alternatives. The same tool may therefore widen or narrow the gap in learning between novices and experts, depending on the learner's prior knowledge, the complexity of the task, and the opportunities available for feedback and experimentation, three of the moderating conditions set out in the Provisional Model.

AI therefore does not in itself deepen or shortcut learning. Whether it speeds up task completion at the expense of understanding, or supports understanding while preserving productive difficulty, depends on how it is used and on the conditions organizations design around that use.

## Social and Peer Learning as an Anchor

Adult learning in organizations is not simply the accumulation of information. It is a relational process through which learners gain access to judgment, practice, and professional identity by interacting with others. In corporate settings, the question is whether AI augments or replaces the human expert, who offers guidance rooted in lived experience and contextual judgment. This section examines three aspects of that role, namely community participation, credible modeling, and tacit knowledge.

AI can take on part of the expert's role. In a single-case study of ten employees at a European infrastructure company, Pedro Oliveira et al. found that AI increasingly handled repetitive and analytical tasks, freeing workers for more strategic and creative work, although participants also reported a perceived loss of human interaction. AI can likewise answer questions, surface resources, and structure information. Its outputs, however, can be wrong or poorly suited to the situation. Knowledge workers in Lee et al.'s survey reported spending effort verifying AI responses that turned out to be inaccurate (sec. 5.2.1), and Morris et al. point to the risk of bias in the information AI systems generate (122). Applying an answer to a specific situation therefore still depends on someone with relevant experience. The question is not whether AI can replace expertise wholesale, but which parts of expert practice AI can support and which still depend on participation in human contexts.

The first aspect is participation in a community of practice. As outlined in the Theoretical Framework, newcomers become competent practitioners by moving gradually toward full participation in a community's practice (Lave and Wenger 29), observing peers, trying things out, and checking their understanding with others. AI-assisted interactions can provide information and even simulated dialogue, but they do not necessarily provide shared participation, mutual accountability, or the situated experience of belonging to a workplace community. Knowledge held in such a community is continually tested against lived practice. This supports not only the task but also the learner's self-monitoring, by prompting reflection, exposing what is not yet understood, and keeping the learner engaged in the effortful work through which understanding becomes durable.

The second aspect is credible modeling. When learners watch an experienced colleague succeed at a task they have been struggling with, they gain confidence that the task is achievable, a model to follow, and someone to identify with professionally. Albert Bandura identifies this kind of vicarious experience, seeing others succeed, as one source of self-efficacy, the belief in one's own ability to perform (197). AI can also influence self-efficacy, since completing a task with AI support or receiving constructive feedback can give learners evidence that a task is manageable. This differs, however, from observing a credible human model, which offers a socially situated example of success and a basis for professional identification.

The third aspect is the nature of expert knowledge. Much of what experts know is tacit, embedded in experience and personal judgment and resistant to being fully put into words (Polanyi 4), though Stephen Gourlay argues that it is better understood as a process of knowing than as a body of knowledge (1). Ikujiro Nonaka and Hirotaka Takeuchi describe knowledge creation as a continuing conversion between tacit and explicit knowledge, through sharing experience directly (socialization), articulating it in explicit form (externalization), combining explicit knowledge (combination), and absorbing it back into practice by doing (internalization) (62-70). Because tacit knowledge passes largely through observation, shared experience, and practice, it may be hard to capture or transfer through AI alone. AI can nevertheless help articulate, organize, and circulate expertise once it has been made explicit, making some knowledge more available to learners, provided they can connect it to their own situated practice. Jarrahi similarly argues that humans retain an advantage over AI in decisions that are uncertain, ambiguous, or dependent on intuition, while AI is stronger in analyzing information and generating options.

Community participation, credible modeling, and tacit knowledge all point to the continuing importance of lived experience and situated judgment in workplace learning, even as AI helps articulate and circulate parts of professional knowledge. Whether AI weakens or strengthens social learning depends partly on organizational culture and the availability of feedback, two of the moderating conditions in the Provisional Model. Learning needs should therefore guide where AI is introduced, including which activities suit AI support and where human participation, feedback, or supervision remains important.

## Knowledge in the Flow of Work

AI-assisted work can provide information, synthesis, explanations, recommendations, and in some applications direct task execution. These outputs do not automatically translate into knowledge or understanding. Their learning value depends on how learners interpret, contextualize, evaluate, and apply them in practice. Russell L. Ackoff's hierarchy of data, information, knowledge, understanding, and wisdom offers a useful conceptual framing for this distinction. Applied to AI-assisted workplace learning, it draws attention to the processes through which information is transformed into usable knowledge, understanding, and ultimately informed judgment (Ackoff 3-4). Alfred North Whitehead similarly warned that ideas which are received but never used or tested remain inert (1). When AI outputs are accepted without examination or application, information may accumulate without becoming durable knowledge. When learners test, contextualize, and apply them in practice, the same capability can support learning in the flow of work. Lee et al. observe this shift among knowledge workers, whose effort moved from gathering information toward verifying and integrating what AI provides (sec. 6.2).

Situated learning theory holds that knowledge acquires meaning through participation in social and practical contexts (Lave and Wenger 29-35). AI can surface information, generate possibilities, and help learners interpret unfamiliar material, but its learning value depends on

whether these outputs are connected to meaningful activity, where learners encounter problems, judge relevance, apply ideas, and learn from consequences. Conrad Gottfredson and Bob Mosher's practitioner framework of five moments of learning helps identify where this connection matters most. The first two moments, learning something new and learning more about it, may suit AI systems that retrieve, synthesize, and explain codified knowledge. The other three, applying knowledge on the job, solving problems when things go wrong, and adapting when conditions change, place greater demands on contextual judgment (Gottfredson and Mosher). AI can still support these moments when it draws on relevant workplace information, gives context-sensitive feedback, or helps learners explore possible responses, provided learners remain responsible for interpreting and applying them.

The need for contextualization also extends to how organizations manage knowledge. Organizational knowledge is often scattered across systems and applications, and it can be siloed, duplicated, or left out of date. In a systematic review, Jitao Yan et al. find that AI can connect fragmented information, integrate knowledge from internal and external sources, and make explicit knowledge more accessible across an organization (528-29). Keeping that knowledge accurate and current, however, still depends on people, and even well-synthesized information becomes knowledge only when learners connect it to their own context.

The same logic applies to individual cognitive engagement. For routine, well-defined, and low-stakes tasks, AI can lower the barrier to starting work and may free attention for more complex thinking, reflecting the role of task complexity and risk among the moderating conditions in the Provisional Model. Where learners delegate reasoning, retrieval, or evaluation without opportunities to practice them elsewhere, however, sustained use may constrain the development of those capabilities. Lee et al. accordingly recommend that training help workers keep foundational skills in information gathering and problem-solving so that they do not become overreliant on AI (sec. 6.2). Organizations can support this by making explicit which tasks are handled by AI, by people, or jointly, while preserving suitable opportunities for human evaluation and learning.

## Implications

For adult learners, AI can help them access, organize, explain, and test information, but a correct output or success on an immediate task does not necessarily show durable understanding. Learners can stay actively involved by explaining their reasoning, retrieving relevant knowledge before turning to AI, applying outputs in context, and reflecting on what they have learned. In Lai et al.'s terms, this means treating AI as a resource for learning rather than only as a way to complete the task (8).

For managers, the main lever is how performance is defined and paced. Where employees are judged only on speed and output, the time AI saves is likely to go into more output rather than into learning, and as the analysis of learner agency showed, time pressure can crowd out reflection. Managers can create space for employees to interpret, challenge, and apply AI outputs, treat errors found in AI-assisted work as opportunities to learn, and keep employees in contact with experienced colleagues who can offer feedback and modeling.

For learning and development professionals, the implication is to design learning into the flow of work rather than only around it. This can include prompts that ask employees to explain or check AI outputs, structured reflection after AI-assisted tasks, and peer review of AI-assisted work. Training in AI literacy should cover not only how to use AI tools but also how to verify, integrate, and question their outputs, while keeping foundational skills in practice (Lee et al., sec. 6.2). Where AI tools are selected or configured, learning professionals can favor systems

that explain their reasoning, signal their limits, and prompt reflection (Kim et al. 1924; Rausch, sec. 3.4).

For organizations, AI deployment should begin with an understanding of the learning processes involved in the work being redesigned. Organizations can identify where reflection, peer exchange, feedback, and experimentation contribute to capability development, and then consider how AI might support these processes or change the opportunities available for them. Decisions about which tasks are suitable for AI-only, human-only, or collaborative execution should reflect longer-term learning objectives as well as operational requirements. Where AI curates and surfaces organizational information at the point of need, it also requires clear ownership of information quality, currency, and relevance, and clear responsibility for evaluating outputs. Because organizational culture is one of the moderating conditions in the Provisional Model, these choices help determine whether AI use tends toward the substitutive or the augmentative end of the spectrum shown in figure 1.

## Limitations

This paper has several limitations. First, it is a conceptual theory synthesis rather than an empirical study. Its four dimensions were derived from the theoretical literature rather than coded from workplace observations, and the framework and propositions have not been tested, so the relationships proposed should be read as provisional. Second, the authors' practitioner backgrounds shaped the questions the paper asks, and different starting points might have brought other theories or concerns into view. Third, the evidence base has limits. Sources were identified through Google Scholar and were mostly published in English in the last ten years, in a field that is changing quickly. Several of the studies cited involve university students, language learners, or small samples in a single organization, and some rely on self-reported data, so their transfer to corporate settings has been argued rather than demonstrated. Fourth, the paper focuses primarily on generative AI used as a cognitive assistant in knowledge work. Other AI configurations, types of work, and organizational and cultural contexts may shape learning differently, and the framework may need refinement when examined across them.

## Conclusion

This paper develops a provisional model of how AI reshapes the conditions under which adults learn at work. Its central contribution is to explain, through the depth-speed tension, how the same gain in speed can either support or constrain durable understanding and professional capability, depending on how AI is used and the conditions around that use. The model shifts attention from AI's capacity to improve immediate performance to the conditions under which AI-assisted work supports or displaces learning.

The analysis suggests that AI-assisted work may weaken learning when it substitutes for opportunities to retrieve knowledge, evaluate outputs, engage in productive struggle, reflect on experience, or participate in shared practice. These risks may be greater where learners have limited expertise or AI literacy, tasks are complex or high-risk, performance pressure rewards speed, feedback is scarce, or AI outputs are unreliable or hard to evaluate. Conversely, AI may strengthen learning when it supports inquiry, explanation, comparison, experimentation, and reflection, when learners keep an active role in evaluating and applying outputs, and when time saved on routine tasks goes into feedback, peer exchange, and capability development. Organizational culture, and whether AI is introduced mainly to raise immediate productivity or to support longer-term learning, also shape which of these outcomes prevails.

As noted in the Limitations, the model is provisional and untested. Its relationships are a basis for investigation rather than established effects, and future research could examine the following propositions.

1. **Substitutive and augmentative use.** AI use that replaces learners' engagement with reasoning, retrieval, and evaluation may be associated with stronger immediate task performance but weaker durable understanding than AI use that scaffolds these processes.
2. **Expertise and AI literacy.** Learners' prior expertise and AI literacy may shape whether AI-assisted work encourages critical evaluation and experimentation or leads to uncritical acceptance of outputs.
3. **Organizational conditions.** Managerial expectations that prioritize rapid task completion, particularly where opportunities for feedback and reflection are limited, may strengthen the association between substitutive AI use and reduced engagement in learning processes.
4. **Social participation.** Where organizational cultures support peer exchange, mentoring, and shared practice, AI may complement workplace learning by freeing time for human interaction. Where it substitutes for these interactions, opportunities for situated and relational learning may be constrained.
5. **Knowledge development.** The effects of AI on organizational knowledge may depend on whether AI-generated information is contextualized, evaluated, shared, and incorporated into collective practice, rather than simply accessed or synthesized for individual task completion.

The Implications section sets out what these propositions mean for learners, managers, learning and development professionals, and organizations. Across all four, the common thread is to treat the time AI saves as a resource that can be invested in learning rather than absorbed entirely by output. The paper's guiding principle follows from this, which is to get the human learning conditions right before reaching for the technology.

Testing these propositions will require longitudinal, workplace-based research, including ethnographic studies of the kind Palenski et al. call for (1233) and assessments of learning over time, across different AI configurations and organizational contexts. Such research can refine the model, clarify the relationship between immediate performance and durable learning, and identify when AI-enabled efficiencies contribute to rather than displace the development of professional capability.

## Works Cited

Ackoff, Russell L. "From Data to Wisdom." *Journal of Applied Systems Analysis*, vol. 16, 1989, pp. 3-9.

Agustin, Matthew Christian. "AI as a Co-Regulator: Relational Design for Strengthening Self-Regulated Learning." *Frontiers in Education*, vol. 11, 2026, article 1761602, https://doi.org/10.3389/feduc.2026.1761602.

Bandura, Albert. "Self-Efficacy: Toward a Unifying Theory of Behavioral Change." *Psychological Review*, vol. 84, no. 2, 1977, pp. 191-215, https://doi.org/10.1037/0033-295X.84.2.191.

Davenport, Thomas H. *Thinking for a Living: How to Get Better Performance and Results from Knowledge Workers*. Harvard Business School Press, 2005.

Garrison, D. Randy. "Self-Directed Learning: Toward a Comprehensive Model." *Adult Education Quarterly*, vol. 48, no. 1, 1997, pp. 18-33, https://doi.org/10.1177/074171369704800103.

Gottfredson, Conrad, and Bob Mosher. "Are You Meeting All Five Moments of Learning Need?" *Learning Guild*, 18 June 2012, www.learningguild.com/articles/are-you-meeting-all-five-moments-of-learning-need. Accessed 4 Oct. 2026.

Gourlay, Stephen. "Tacit Knowledge, Tacit Knowing or Behaving?" 3rd European Conference on Organizational Knowledge, Learning and Capabilities, 5-6 Apr. 2002, Athens, Greece, warwick.ac.uk/fac/soc/wbs/conf/olkc/archive/oklc3/id269.pdf. Accessed 4 Oct. 2026.

Jaakkola, Elina. "Designing Conceptual Articles: Four Approaches." *AMS Review*, vol. 10, no. 1-2, 2020, pp. 18-26, https://doi.org/10.1007/s13162-020-00161-0.

Jarrahi, Mohammad Hossein. "Artificial Intelligence and the Future of Work: Human-AI Symbiosis in Organizational Decision Making." *Business Horizons*, vol. 61, no. 4, 2018, pp. 577-86, https://doi.org/10.1016/j.bushor.2018.03.007.

Jarrahi, Mohammad Hossein, et al. "Generative AI and the Augmentation of Information Practices in Knowledge Work." *Behaviour & Information Technology*, 2025, pp. 1-22, https://doi.org/10.1080/0144929X.2025.2551570.

Kim, Jinhee, et al. "Adult Learners' Perspectives of AI Applications in Supporting Andragogy." *Educational Technology Research and Development*, vol. 74, no. 4, 2026, pp. 1911-38, https://doi.org/10.1007/s11423-026-10621-2.

Knowles, Malcolm S. *The Modern Practice of Adult Education: From Pedagogy to Andragogy*. Revised and updated ed., Cambridge Adult Education, 1980.

Kolb, David A. *Experiential Learning: Experience as the Source of Learning and Development*. Prentice-Hall, 1984.

Lai, Chun, et al. "Learner Agency in Self-Directed Use of GenAI for Informal Language Learning." *Innovation in Language Learning and Teaching*, 31 Mar. 2026, pp. 1-23, https://doi.org/10.1080/17501229.2026.2648781.

Lave, Jean, and Etienne Wenger. *Situated Learning: Legitimate Peripheral Participation*. Cambridge UP, 1991.

Lee, Hao-Ping (Hank), et al. "The Impact of Generative AI on Critical Thinking: Self-Reported Reductions in Cognitive Effort and Confidence Effects from a Survey of Knowledge Workers." *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*, Association for Computing Machinery, 2025, pp. 1-22, https://doi.org/10.1145/3706598.3713778.

Lewis, Patrick, et al. "Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks." *Advances in Neural Information Processing Systems*, vol. 33, 2020, pp. 9459-74.

Morris, Thomas Howard, et al. "Self-Directed Lifelong Education and Learning in Times of Generative AI." *International Journal of Lifelong Education*, vol. 45, no. 2, 2026, pp. 121-26, https://doi.org/10.1080/02601370.2026.2633668.

Nonaka, Ikujiro, and Hirotaka Takeuchi. *The Knowledge-Creating Company: How Japanese Companies Create the Dynamics of Innovation*. Oxford UP, 1995.

Oliveira, Pedro, et al. "AI Integration in Organisational Workflows: A Case Study on Job Reconfiguration, Efficiency, and Workforce Adaptation." *Information*, vol. 16, no. 9, 2025, article 764, https://doi.org/10.3390/info16090764.

Palenski, Ted, et al. "How AI Works: Reconfiguring Lifelong Learning." *Postdigital Science and Education*, vol. 6, no. 4, 2024, pp. 1216-39, https://doi.org/10.1007/s42438-024-00496-y.

Polanyi, Michael. *The Tacit Dimension*. Doubleday, 1966.

Rausch, Andreas. "Artificial Intelligence for Informal Workplace Learning: A Problem-Solving Perspective." *Frontiers in Organizational Psychology*, vol. 3, 2025, article 1555429, https://doi.org/10.3389/forgp.2025.1555429.

Schön, Donald A. *The Reflective Practitioner: How Professionals Think in Action*. Basic Books, 1983.

Soderstrom, Nicholas C., and Robert A. Bjork. "Learning versus Performance: An Integrative Review." *Perspectives on Psychological Science*, vol. 10, no. 2, 2015, pp. 176-99, https://doi.org/10.1177/1745691615569000.

Spiro, Kasper, and Videhi Bhamidi. *Employee-Generated Learning: How to Develop Training That Drives Performance*. Kogan Page, 2024.

Timmermans, Stefan, and Iddo Tavory. "Theory Construction in Qualitative Research: From Grounded Theory to Abductive Analysis." *Sociological Theory*, vol. 30, no. 3, 2012, pp. 167-86, https://doi.org/10.1177/0735275112457914.

Vygotsky, Lev S. *Mind in Society: The Development of Higher Psychological Processes*. Edited by Michael Cole et al., Harvard UP, 1978.

Wang, Lei, et al. "A Survey on Large Language Model Based Autonomous Agents." *Frontiers of Computer Science*, vol. 18, no. 6, 2024, article 186345, https://doi.org/10.1007/s11704-024-40231-1.

Wenger, Etienne. *Communities of Practice: Learning, Meaning, and Identity*. Cambridge UP, 1998.

Whitehead, Alfred North. *The Aims of Education and Other Essays*. Macmillan, 1929.

Yan, Jitao, et al. "Transforming Organizational Knowledge Creation through Artificial Intelligence: A Systematic Review of the Emergent Literature." *VINE Journal of Information and Knowledge Management Systems*, vol. 56, no. 2, 2026, pp. 522-40, https://doi.org/10.1108/VJIKMS-08-2024-0296.