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Empowering Learning in the Age of AI: Towards Inclusive and Human-Centered Workplaces

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As artificial intelligence (AI) transforms the workplace, its role in reshaping how professionals learn, grow, and adapt has moved to the forefront of lifelong learning debates. This chapter explores how AI can be harnessed to foster inclusive workplace learning and empower workers. Focusing on cases from the finance, insurance, and hospitality sectors in Singapore, the chapter builds on the concept of socially embedded capability (Boyadjieva & Ilieva-Trichkova, 2021). It proposes that meaningful empowerment emerges when AI is embedded in work that expands both individual agency and workplace affordances.

Using secondary qualitative research method (Cheong et al., 2023), we examine how AI tools (e.g., adaptive learning platforms, analytics dashboards, AI robots, AI mentors) are being deployed to scaffold learning, drive performance, and reconfigure work roles and practices. Through these cases, the chapter reveals both the empowering possibilities of AI and the risks of deepening inequality when AI is deployed without attention to access, equity, and workers' active participation.

Integrating three theoretical perspectives: socially embedded capability (Boyadjieva & Ilieva-Trichkova, 2021), personal and relational agency at the workplace (Littlejohn, 2023; Edwards, 2010), and cognitive-behavioural research on deep learning (Bjork et al., 2013; Ryan & Deci, 2017), the chapter shows that effective AI design must support both individual reflection and collective sense-making. The three organisations examined, namely, Prudential (insurance), OCBC Bank (finance), and Hilton Singapore (hospitality), operate in sectors where trust, judgment, and human interaction are central to professional practice. Insurance relies on careful assessment and ethical decision-making; banking emphasises advisory relationships and long-term customer confidence; and hospitality depends on emotional intelligence and frontline empathy. These sectors, therefore, provide rich contexts for examining how AI interacts with socially embedded capabilities, personal and relational agency, and deep learning processes, illustrating how intelligent systems can both enhance and constrain reflection, collaboration, and human development in high-touch, safety-critical environments.

The chapter concludes that AI should be perceived not merely as an instrument of efficiency but as a medium for expanding human potential. It calls for organisational and policy frameworks that ensure inclusive access, participatory design, and a human-centred approach to AI adoption in the workplace.

Keywords: Workplace learning, Artificial Intelligence (AI), socially embedded capability, personal agency, relational agency, cognitive-behavioural research

Introduction

The interaction between humans and machines is becoming commonplace. It unfolds every morning when office workers boot up their computers, every afternoon when hotel staff coordinate with service robots, and every evening when call centre agents conclude conversations guided by Artificial Intelligence (AI) insights.

Such interactions extend far beyond the straightforward, familiar narrative of efficiency and productivity. It addresses the core of what it means to grow, to develop expertise, and to become more capable human beings in an interconnected world. The question is no longer whether machines can perform our tasks; it is whether they can become thoughtful companions in our journey towards mastery.

Against this backdrop of evolving human-machine collaboration, Singapore offers a uniquely illuminating vantage point. The nation has long positioned lifelong learning as the bedrock of economic competitiveness, investing heavily in initiatives like SkillsFuture that encourage continuous skill development (SkillsFuture, n. d.). This commitment provides a strong foundation for exploring how AI can enhance, rather than replace, human learning.

While the city-state's economy rests on a diversified base, the finance, insurance, and hospitality sectors provide affluent contexts for studying AI adoption. These sectors are not only critical drivers of Singapore's competitiveness but also domains where service quality, trust, and human interaction remain indispensable. They therefore offer valuable settings for examining how learning, judgment, and professional identity are reshaped alongside intelligent systems.

In this chapter, we explore how artificial intelligence is reshaping the conditions under which people learn, act, and develop in their workplaces. Guided by this context, the chapter is organised around three interconnected research questions. First, how does AI shape socially embedded capability in the workplace, particularly workers' opportunities to participate meaningfully in learning, to feel included, and to sustain confidence and professional identity? Second, how does AI influence workplace learning agency, at both personal and relational levels, as employees learn to reflect, collaborate, and exercise judgment alongside intelligent systems? Third, how do AI-enabled tools and environments support or hinder deep learning processes, such as metacognition, retrieval, and the development of adaptive expertise in real-world work settings?

To explore these questions, the chapter uses analytic case narratives drawn from publicly available organisational documents, media reports, and industry publications. The cases are written as composite and fictionalised accounts, not to represent specific individuals, but to synthesise recurring patterns observed across documented practices within each sector. This approach is well established in organisational and social research, where narrative inquiry treats stories as analytic devices for interpreting action, meaning, and sense-making rather than as literal accounts of events (Czarniawska, 2004). Recent methodological work further demonstrates how composite character narratives grounded in empirical data can be used to surface social mechanisms and relational dynamics while maintaining analytic rigour and ethical clarity (Arjomand, 2022). The case narratives, therefore, function as interpretive lenses through which broader processes of capability, agency, and learning with AI can be examined.

Taken together, this chapter frames AI not simply as a technical intervention, but as a social and cognitive phenomenon that interacts with capability, agency, and learning at multiple levels. It is organised in three sections. It begins by introducing the theoretical lenses that guide our discussion: socially embedded capability, workplace learning agency, and perspectives from cognitive and behavioural sciences. It then examines sectoral cases drawn from publicly available sources, each illustrating how AI can act as a learning companion while also exposing risks of exclusion and inequity. The final section compares insights across these cases, draws out implications for organisational and policy design, and concludes with a call for human-centred and inclusive approaches to AI adoption.

Literature Review: AI, Capabilities, and Agency in Nested Systems of Learning

Artificial intelligence in workplaces is too often described in practical terms: streamlining workflows, improving efficiency, or boosting productivity. While these outcomes matter, such views miss the deeper question: how does AI reshape the conditions under which people learn, exercise judgment, and grow as professionals? Addressing this question requires moving beyond descriptions of tools and applications to frameworks that consider learning as part of a wider organisational and social system.

This section draws on three interconnected strands of thinking to examine both the promise and the risk of AI as a learning companion: socially embedded capability, workplace learning agency, and cognitive and behavioural insights. Together, these perspectives help resist what Selwyn (2011) calls technological determinism, defined as the assumption that technology produces progress. As scholars such as Crawford (2021) and Regmi (2024) remind us, technologies are never neutral; their effects depend on the social, organisational, and policy contexts in which they are created and used, and on the power relations that determine who benefits from them. Thinking about AI in this way situates it within a nested system of learning, where individual actions, workplace practices, and institutional structures continuously shape one another (Engeström, 2001; Bronfenbrenner, 1979). Within such systems, AI can either extend human capability and inclusion or deepen existing divides in workplaces.

Socially Embedded Capability: Learning as a Collective Achievement

The capabilities approach, initially developed by Amartya Sen (1999) and later extended to educational contexts by Martha Nussbaum (2011), underscores that what people can do and become depends not only on their own abilities but also on the social and institutional conditions in which they live. Building on this perspective, Boyadjieva & Ilieva-Trichkova (2021) describe learning as socially constructed rather than personally achieved. This suggests that access to learning technologies is insufficient unless learners are meaningfully empowered to engage with them (Pan, 2023). These enabling conditions include social support, cultural understanding, and institutional recognition. Studies show that the impact of technology depends less on the tools themselves and more on the social and organisational environments in which they are used. Tawfik et al. (2016) highlight how learning technologies often reproduce existing inequalities when organisational structures remain unchanged, while Mishra et al. (2020) demonstrate that social networks and peer support are stronger predictors of learning success than mere access to devices or software.

This socially embedded capability perspective is particularly relevant for understanding how AI could potentially shape opportunities for learning at work. What matters is not how advanced the technology is, but whether it supports or limits people's ability to learn and collaborate. As Flores-Crespo (2007) notes, capability expansion "requires friendly conditions" (p. 60), not simply the presence of resources or tools. Just as schools need supportive pedagogical and institutional arrangements, workplaces must provide enabling cultures, structures, and affordances if AI is to enhance learning and participation genuinely. Afterall, beyond access and structure, participation also depends on how included and valued people feel. Social support does more than enable learning; it sustains motivation and belonging, the psychological conditions that turn opportunity into engagement (Deci & Ryan, 2000). When thoughtfully designed, AI can strengthen these relationships by connecting people with similar goals, surfacing shared challenges, and supporting reflective dialogue.

Recent studies show that AI-enabled tools and analytics can foster collaboration and reflective dialogue among professionals, helping learners situate their work and development within a shared, collective process. For example, Wang et al. (2025) demonstrate how intelligent teaching analytics support collaborative reflection and shared regulation, while Arefian, Esfandiari, and Zarei (2025) show that AI-based reflective tools can function as collaborative partners that deepen joint sense-making. Complementing this, Wei et al. (2025) find that generative AI can enhance collaborative problem-solving and team performance, suggesting that well-designed AI systems can contribute meaningfully to collective learning and professional growth.

While social participation is central to professional learning (Wenger, 1998; Billett, 2004), recent studies of AI-mediated feedback warn that automation can weaken learning relationships by displacing dialogue and shared interpretation (Kukulska-Hulme & Ilic, 2025). Notably, Shibani and Buckingham Shum (2024) highlight ecosystem-level risks in AI-assisted writing, cautioning that design must foreground interpretability, human judgment, and equitable practices rather than merely boosting efficiency.

Additionally, Boyadjieva and Ilieva-Trichkova (2021) emphasise that lifelong learning depends on social structures that either enable or constrain individual action, such as workplace cultures, organisational norms, and institutional recognition. In Singapore, Chen and Tan (2024) found that adult educators' willingness to engage with digital learning tools depends on factors such as organisational support, workplace affordances, and innovative culture.

These insights above shift the conversation from access to capability, underscoring that AI's promise lies not in technological sophistication but in the social and institutional scaffolds that enable people to learn, reflect, and act together. The impact of AI on workplace learning, therefore, hinges less on the power of algorithms and more on whether organisations preserve and strengthen the human conditions, dialogue, trust, and collective sense-making, through which real empowerment and professional growth emerge.

Workplace Learning Agency: Personal and Relational Dimensions of Learning

While the previous section focused on how learning opportunities are socially created and sustained through organisational and institutional conditions, this section turns to how people exercise agency within those environments. In other words, it shifts attention from the availability of learning affordances to the ways workers interpret, take up, or resist learning opportunities in practice.

To examine this, we draw on Littlejohn's (2023) conceptualisation of workplace learning agency, which offers a robust lens for understanding how both personal and relational agency are enacted within organisational settings. Building on Edward's (2010) distinction, Littlejohn posits that agency is not solely an individual attribute but could be perceived as something that is exercised through ongoing interaction between individuals, others, and the conditions of work. From this viewpoint, effective workplace learning depends not only on individual initiative, self-direction, and reflection, but also on collective sense-making, collaboration, and the capacity to work with others.

This framing is particularly relevant for understanding how AI reshapes learning at work. As intelligent systems increasingly mediate access to information, feedback, and opportunities for action, they become part of the environment through which agency is exercised. AI can therefore either strengthen workplace learning agency by supporting reflection, dialogue, and coordination, or constrain it by narrowing discretion and displacing relational interaction. Littlejohn's (2023) account helps make this tension visible, highlighting why the design and embedding of AI systems matter for how workers learn, adapt, and participate meaningfully in organisational life.

Within this framework, workplace learning agency can be understood through two closely related but analytically distinct dimensions: personal agency and relational agency. Distinguishing between these dimensions clarifies how learning is enacted in practice and why AI systems may support or disrupt learning in different ways. Personal agency foregrounds individuals' responsibility for directing and regulating their own learning. In contrast, relational agency draws attention to how learning unfolds through interaction, collaboration, and shared sense-making with others. Together, these dimensions provide a valuable lens for examining how AI-mediated environments shape not only what workers learn but also how and with whom they learn.

Personal agency involves workers' ability to set learning goals, select appropriate resources, monitor their progress, and adapt their approaches in response to feedback and reflection. This metacognitive dimension of learning agency aligns closely with research on self-regulated learning (Zimmerman, 2002) and expert performance (Ericsson & Pool, 2016), which emphasise learners' active role in orchestrating their own development.

Relational agency, as conceptualised by Edwards (2010), extends beyond individual self-direction to encompass collaborative capacity, that is, the ability to work with others to expand possibilities for action and learning. This involves recognising and mobilising the resources that others bring to shared challenges, negotiating different perspectives and expertise, and co-constructing solutions that individual learners could not achieve independently. Such collaboration depends on psychological safety and mutual trust. Workers are more willing to share, question, and co-create when they believe their contributions are recognised and not displaced by algorithmic systems (Mirbabaie et al., 2022).

The distinction between personal and relational agency is crucial for evaluating implementations of AI learning companions. AI systems can enhance personal agency by providing timely feedback, adaptive challenges, and reflective prompts that support self-regulated learning. However, they risk undermining relational agency if they substitute algorithmic interaction for human collaboration or create competitive dynamics that discourage knowledge sharing and shared sense-making.

While social participation has long been recognised as central to professional learning, recent research on AI and digitally mediated learning highlights how design choices critically shape the quality of learning relationships. Knight, Shibani, and Buckingham Shum (2023) demonstrate that ethical and interpretive design in learning analytics can preserve learner agency by supporting dialogue and reflection rather than delivering automated judgments. Complementing this, Holmes et al. (2022) argue that human-centred AI must be grounded in shared values and collective responsibility, cautioning that efficiency-driven automation risks eroding trust and participation when relational dimensions are neglected.

Research on feedback and dialogue further reinforces this concern. Ajjawi et al. (2025) and Dai et al. (2025) emphasise that effective feedback is inherently relational and dialogic, requiring opportunities for interpretation, response, and shared meaning-making. When feedback becomes overly automated or one-directional, learning relationships may be weakened. At the same time, recent empirical studies show that AI can support collective learning when designed to scaffold collaboration rather than replace it. Wang et al. (2025) illustrate how intelligent analytics can foster collaborative reflection and shared regulation, whereas Wei et al. (2025) demonstrate that generative AI can enhance collaborative problem-solving and team performance.

Synthesising across these findings, the impact of AI on workplace learning depends less on the degree of automation or technical sophistication than on whether systems are designed to sustain dialogue, interpretability, and collective sense making within supportive organisational contexts. Rather than optimising efficiency alone, these studies point to a clear design principle: AI systems should not think for people, but think with them. When AI preserves human discretion, invites interpretation, and supports reflective engagement, it can function as a learning companion, extending professional capability while safeguarding agency, accountability, and responsibility.

Cognitive and Behavioural Science: Building Deep Learning

Research in cognitive psychology and the learning sciences offers important insights into how AI can be designed to strengthen, rather than weaken, learning. A key contribution of this body of work is the recognition that effective learning is not simply a matter of exposure or efficiency, but depends on how learners actively engage with information, regulate their thinking, and work through challenge. Three strands of research are especially relevant to understanding AI-enabled workplace learning: retrieval practice, metacognitive awareness, and the productive role of challenge.

The first concerns retrieval practice, often referred to as the testing effect. A substantial body of evidence indicates that active recall leads to stronger retention and transfer than passive review. Carpenter, Pan, and Butler (2022) demonstrate that long-term understanding improves when learners retrieve and apply knowledge. From this perspective, AI systems can support deep learning by prompting learners to explain ideas, generate examples, or apply knowledge across varied contexts, thereby encouraging active engagement rather than passive consumption.

The second strand focuses on metacognition, understood as the ability to monitor, regulate, and reflect on one's own learning and thinking processes. Research by Fleming and Dolan (2012) and Dunlosky et al. (2013) shows that skilled learners continually assess their understanding, adapt strategies in response to feedback, and reflect on progress over time. Emerging research suggests that AI can support these metacognitive processes when it is designed to scaffold reflection rather than replace it. For example, Tomisu, Ueda, and Yamanaka (2025) describe a Cognitive Mirror framework in which AI externalises aspects of learners' thinking, enabling them to reflect on their reasoning and identify misconceptions. Similarly, Li et al. (2025) provide empirical evidence on how analytics can capture self-regulated learning strategies and how scaffolding relates to learning performance. What emerges from these studies is that AI systems can make thinking processes more visible and foster reflective habits, provided they enhance rather than automate human judgment.

The third insight concerns the concept of desirable difficulty, which challenges the assumption that learning should always feel smooth or effortless. Research in learning science shows that effortful engagement plays a critical role in durable learning. Bjork, Dunlosky, and Kornell (2013) argue that learning is strengthened when tasks are challenging yet achievable, as such conditions prompt deeper cognitive processing and support long-term retention. Forms of productive struggle, such as varied practice, spaced review, or the need to generate responses rather than recognise them, encourage learners to integrate knowledge more robustly when paired with timely feedback and support. Difficulty, when carefully calibrated, is therefore not an obstacle to learning but a key mechanism through which learning becomes durable and transferable (Kapur, 2024).

These cognitive and behavioural insights align closely with Vygotsky's (1978) notion of the Zone of Proximal Development, defined as the space between what learners can accomplish independently and what they can achieve with guidance. In workplace settings, AI companions can function as responsive supports within this zone by adjusting the level of challenge, prompting reflection, and offering real-time feedback. Importantly, such systems do not replace human mentors or social learning. Instead, they extend moments of coaching and feedback that may otherwise be scarce. However, the potential of AI to act as a developmental scaffold depends critically on the quality of learner engagement and the surrounding motivational conditions. Deep learning requires sustained effort, reflection, and appropriately calibrated challenge. For designers of AI-enabled learning systems, the goal is therefore not to eliminate effort but to make it meaningful. This involves supporting learners in thinking more deeply, acting with greater awareness, and developing capabilities that endure. Challenge becomes productive only when learners feel competent and supported, echoing Self Determination Theory's emphasis on autonomy, competence, and relatedness as foundations for sustained motivation and learning (Ryan & Deci, 2017).

Case Analyses Based on Composite Narratives

To examine how AI reshapes workplace learning, this chapter uses secondary qualitative analysis of publicly available organisational documents, press releases, industry reports, and media coverage of company initiatives in Singapore between 2024 and 2025. These sources form the empirical basis for understanding how AI systems are framed, coordinated, and experienced across organisational contexts. Rather than presenting descriptive summaries alone, the chapter employs analytic case narratives constructed from composite and fictionalised characters. These characters are not intended to depict specific individuals but to synthesise recurring patterns, learning situations, and relational dynamics observed across the documentary data.

Using composite narratives as analytic devices is well established in qualitative research. In his foundational work on narrative methods, Czarniawska (2004) argues that organisational storytelling offers insight into interpretive processes and meaning-making. Similarly, composite narratives are used to present complex situated accounts in ways that maintain contextual richness while protecting anonymity (Willis, 2018). Thompson et al. (2025) demonstrate how composite stories derived from synthesised research findings can humanise data and make findings accessible to broad audiences, illustrating thoughtful procedures for constructing such narratives. Johnston, Wildy, and Shand (2023) illustrate how composite narratives can faithfully reflect multiple participants' experiences in qualitative research by drawing on thematically coded data to represent shared phenomena. Together, these sources show that the composite narrative is not an ad hoc device but a recognised qualitative strategy for making sense of multiple data sources and for emphasising patterns, processes, and typicality.

The specific character construction process in this chapter followed three key analytic steps. First, documentary sources were collected and coded thematically to identify recurrent roles, practices, tensions, and learning dynamics associated with AI adoption. Second, these themes were clustered into typical configurations of work and learning (e.g., career reflection, judgment calibration, empathy training) that cut across multiple sources. Third, composite characters were developed to embody these configurations and to illustrate how individuals might experience and respond to AI in everyday work. To maintain traceability, we preserved an explicit mapping between coded data clusters and narrative elements, consistent with best practice in composite narrative construction (Willis, 2018; Johnston et al., 2023; Thompson et al., 2025). This approach allows the cases to function as interpretive lenses through which broader processes of capability, agency, and learning with AI can be examined across different workplace contexts.

Case Study 1: OCBC Bank – When the Career Conversation Turns Inward

Sarah sits in a quiet OCBC branch during the mid-afternoon lull, the kind of interlude that rarely exists in the constant rhythm of client meetings and portfolio reviews. As a relationship manager in Global Consumer Financial Services, her role requires not only financial expertise but also the ability to anticipate clients' needs and build trust over the long term. These moments of pause, though brief, are precious. She opens MOBI, OCBC's artificial intelligence-powered career growth companion, unveiled in 2024, as part of her personal commitment to staying ahead in a shifting financial landscape.

The application, introduced during OCBC's "Grow Your Way with MOBI" festival and prominently profiled in the bank's 2024 Sustainability Report, is described not as a traditional learning management tool but as a 24/7 career companion. Its design is simple but ambitious: to help every employee, from frontline branch staff to senior executives, understand their current strengths, identify emerging skills, and chart pathways across the organization. Unlike static course catalogues, MOBI maps employees' competencies against OCBC's evolving opportunity landscape, nudging them toward roles, projects, and learning resources aligned with their aspirations.

Sarah scrolls through her dashboard. It includes a short online course on Environmental, Social, and Governance (ESG) communication and a reminder about a mentoring session with a senior specialist in sustainable finance. They are activities that may be of interest to the employee, assembled into the application that allows her to see options she might not otherwise have considered.

She logs in to the ESG course, which provides structured resources and reflective exercises on integrating sustainability into wealth management conversations. Reading the material, Sarah is struck by a realisation: in her own practice, she often frames ESG around compliance and returns, a perfectly rational approach, but one that misses the deeper client motivations about legacy and values. MOBI has not told her this outright; the reflection arises from engaging with the resources it recommended. The system provides the mirror; the insight is her own.

<u>Building an AI-enabled ecosystem</u>

OCBC's evolving learning architecture shows how artificial intelligence (AI) can be integrated into a broader system of human capability rather than serve as a substitute for it. Beginning in 2023, the bank introduced OCBC GPT, a generative AI tool made available to all 30,000 employees worldwide to support writing, research, and idea generation. Pilot tests involving about 1,000 staff found that tasks were completed around 50 percent faster, including time spent reviewing the AI's output (OCBC Bank, 2023). However, the intent was not simply to improve efficiency but to create space for deeper thinking, reflection, and learning.

In 2024, OCBC extended this philosophy through a S$30 million workforce development initiative focused on building resilience and future skills (People Matters Global, 2025). The initiative included an internal career marketplace supported by AI analytics and a large-scale coaching transformation, with more than 100 senior leaders working toward professional coaching certification (OCBC Bank, 2024a). This combination of technology and coaching reflects the bank's belief that human development must remain at the centre of technological adoption. While AI provides data-driven insights and scalability, human mentoring and reflection sustain meaning and motivation.

At the heart of this learning system is MOBI, an AI-powered career growth companion launched in 2024 to help employees map their learning and career pathways. Employees can upload their résumés, identify skills, and receive personalised recommendations for learning, coaching, and internal assignments (OCBC Bank, 2024b). These short-term internal gigs, typically lasting between three and eighteen weeks, enable employees to work across functions, build new capabilities, and contribute to cross-departmental projects. Such practices strengthen networks of shared understanding and nurture what learning researchers describe as communities of practice – spaces where knowledge is developed and shared collectively (Wenger, 1998).

MOBI operates alongside MentorMe, a mentoring initiative that pairs employees with experienced leaders to guide professional growth. Together, these programs demonstrate OCBC's effort to build a learning culture that values both technological and human connections. Although OCBC has not disclosed details of MOBI's analytics, aggregated data from such systems likely support leadership in identifying emerging skills, workforce trends, and priority areas for development. In this way, MOBI functions not only as a personal learning companion but also as a strategic tool that links individual learning journeys with organisational foresight.

As illustrated above, OCBC's various initiatives illustrate a layered model of capability development. At one level, AI tools enhance efficiency and insight; at another, analytics support opportunity mapping and mobility; and at a deeper level, human coaching and mentoring anchor reflection, ethical judgment, and belonging. This approach reflects what capability theorists describe as the social embeddedness of learning: progress depends not on technology alone but on the quality of relationships, culture, and institutional support that enable it. In doing so, OCBC offers a compelling example of how AI can serve as a learning companion that enhances, rather than diminishes, human potential within complex organisational systems.

Case Study 2: Prudential – Trusting the Algorithm, Questioning the Claim

Marcus sits in his office at Prudential, a leading insurance company, reviewing a medical claim for a construction worker who injured his knee on-site. The documentation appears complete, the medical reports are consistent, and the claim amount falls within the usual range.

Before he begins, the company's AI tool, powered by Google's MedLM model and developed through Prudential Singapore's AI Lab, has already processed the case. It summarises the documents, extracts key information, and recommends approval with an 87 percent confidence score. On paper, the reasoning looks sound.

Still, Marcus reviews the documents carefully. After thirty years of assessing claims, he has learned to recognise details that automated systems may overlook, such as the timing of medical visits, the sequence of treatments, or subtle inconsistencies in a doctor's notes. The AI's recommendation prompts him to pause and consider which aspects may require closer examination.

This moment reflects a broader shift in professional work. AI is not only accelerating routine tasks but also changing how people reason and learn. The system provides structure and speed while the human contributes judgment and context. Together, they create a more reflective and deliberate decision-making process.

For Marcus, the AI's high confidence score becomes a cue to examine his own assumptions. For the organisation, this shows how human experience and machine intelligence can complement each other when they are designed and used with care. The interaction is not about deferring to technology but about developing professional awareness, the capacity to sense when to trust, when to question, and how to explain one's reasoning clearly.

Prudential's Responsible AI Journey

Prudential's adoption of artificial intelligence in Singapore exemplifies how efficiency and reflection can coexist within responsible innovation. In 2024, the insurer launched its AI Lab, a regional hub supported by Google Cloud, to develop AI applications that enhance decision quality while maintaining human oversight (Prudential plc, 2024a, 2024b). The Lab operates as a controlled environment where new tools are tested through a secure stage-gate process before being scaled into business operations.

This measured approach reflects Prudential's commitment to governance and trust rather than automation for its own sake. Furthermore, this commitment aligns closely with Singapore's emphasis on ethical and transparent AI use, as articulated in the Monetary Authority of Singapore's FEAT principles, namely, Fairness, Ethics, Accountability, and Transparency (Monetary Authority of Singapore, 2018). In its 2024 Sustainability and Governance Report, Prudential Singapore outlined its internal framework, PruSafeAI, which ensures that all AI and machine learning projects are reviewed for responsible use and subject to multi-level oversight (Prudential Singapore, 2024). Among the first innovations approved through this framework was MedLM, a generative AI model developed in collaboration with Google Cloud to support claims officers in analysing complex medical documentation with greater accuracy and efficiency (Prudential plc, 2024c).

The introduction of MedLM marked a turning point in how AI was framed within the organisation. Instead of positioning the system as a replacement for human expertise, Prudential described it as a cognitive scaffold – an aid that helps professionals think, verify, and learn more effectively. Officers are encouraged to review and question the AI's recommendations, transforming routine claims work into a process of reflection and retrieval. Research in the learning sciences shows that such active engagement strengthens long-term understanding and metacognitive awareness (Carpenter, Pan, & Butler, 2022).

These practices have also reshaped team learning. As officers compared their interpretations and decisions during regular discussions, the system became a shared reference point for professional dialogue and calibration. The AI not only facilitated individual decision-making but also fostered collective learning and shared standards of judgment. As Prudential's Head of Innovation, Magdalene Loh, explained in an interview with the DesignSingapore Council, the company's innovation ethos is rooted in design thinking and structured experimentation, which focuses on helping people "think differently about problems" rather than automate them (DesignSingapore Council, 2023).

Prudential's broader strategy demonstrates that meaningful AI adoption depends as much on organisational learning as on technical sophistication. By embedding governance, cultivating reflective practice, and encouraging collaboration, the company positions AI as a learning companion that augments rather than displaces human judgment. Its recognition in 2025, through global innovation awards and the Million Dollar Round Table (MDRT) Culture of Excellence distinction, further reflects how a culture of trust, experimentation, and ethical leadership can turn technological adoption into a catalyst for deeper learning and capability development (European Business Magazine, 2025).

Ultimately, Prudential's experience suggests that the actual value of AI in the workplace lies not in the speed of automation but in the quality of thought it enables. By making reasoning more transparent and reflective, Prudential's AI journey illustrates how technology can strengthen, rather than erode, the human capacities of discernment, accountability, and learning.

Case Study 3: Hilton Singapore – AI as Soft Skills Coach in Hospitality

In a quiet training room at Hilton Singapore, front desk associate Mei Lin puts on a virtual reality headset for her weekly practice session. Within seconds, the space transforms into a digital replica of a hotel lobby. A guest approaches the reception counter, visibly tired and frustrated after a sleepless night due to a malfunctioning air-conditioning unit.

Drawing on Hilton's HEART (Hear, Empathize, Acknowledge, Respond, Thank) service model, Mei Lin begins: "I can hear how frustrating this has been for you." Her words are correct, but as she speaks, the system is already listening back. Using voice-analysis technology developed through Hilton's collaboration with SweetRush and Google Cloud (Hilton, 2024; SweetRush, 2022), the system detects formality in her tone, rapid pacing, and the absence of emotional resonance. A coaching prompt appears on screen:

> *"Notice how the guest's posture changes when you acknowledge her frustration. Try slowing your pace slightly, match her concern with warmth, and sustain eye contact."*

Mei Lin pauses, adjusts, and tries again. This time her tone softens, her posture conveys attentiveness, and the virtual guest's expression relaxes. Her competency dashboard updates in real time, reflecting improvements in empathy, pacing, and service recovery response time. More than a performance scorecard, the dashboard functions as a learning platform, helping trainers and staff identify areas for growth, tailor development plans, and accelerate mastery across teams.

Hilton's Learning Imperative: Training Emotion at Scale

For Hilton, the challenge is one of scale. With more than 400,000 team members worldwide, how can a service brand consistently nurture emotional intelligence, the skill that defines hospitality? A clean room or prompt check-in may please guests, but it is empathy in moments of stress that earns loyalty. Traditional methods, such as classroom sessions or on-the-job shadowing, are limited in developing the subtle emotional awareness that genuine service requires. They also cannot scale easily or deliver consistent quality across properties.

To address this gap, Hilton began experimenting with immersive learning nearly a decade ago. Partnering with SweetRush, a learning design firm based in San Francisco, the company piloted early virtual reality modules in 2015. What began with small-scale trials in safety and diversity training has evolved into an integrated AI-VR learning ecosystem by 2024 (Hilton, 2023; SweetRush, 2022). Singapore now serves as a strategic hub for these initiatives, reflecting the nation's focus on human-centred technology and service excellence.

The system integrates multiple technologies into a single framework. Built on WebXR, it is accessible via headsets, laptops, or mobile devices, ensuring inclusivity across locations. Generative AI models analyse speech, tone, and pacing to provide real-time coaching and dynamically adapt to guest reactions. The content is organised around three key modules: Delivering on Our Customer Promise, which focuses on service recovery through Hilton's HEART model; Hotel Immersion, which allows corporate staff to experience frontline work; and Exceed with Empathy, which encourages perspective-taking through simulated guest experiences. Together, these modules train both precision and perception, helping staff understand not only what to do but also how to do it with care.

From a learning science perspective, Hilton's approach reflects established research on experiential learning (Kolb, 1984). Each scenario guides employees through a cycle of experience, reflection, and adjustment, creating what psychologists call desirable difficulties, which can be viewed as a challenging practice that strengthens retention and adaptability (Bjork, Dunlosky, & Kornell, 2013). Immediate feedback fosters metacognitive awareness, encouraging staff to observe their own actions and refine them, consistent with principles of deliberate practice (Ericsson & Pool, 2016). The virtual environment provides a safe space for experimentation, reframing mistakes as opportunities for learning rather than as performance failures.

While training begins with individuals, its benefits extend across teams. Staff routinely debrief after sessions, comparing which phrasing, tone, or gestures were most effective in resolving guest tensions. These reflections turn AI feedback into social learning, forming what Wenger (1998) calls "communities of practice." Internal surveys conducted in 2024 found that 87 percent of participants in the "Hotel Immersion" module reported greater empathy for frontline roles, thereby strengthening cohesion and respect across hierarchies (Hilton, 2024).

The results are tangible. Immersive training reduced classroom time from four hours to twenty minutes while maintaining or improving learning outcomes (SweetRush, 2022). Employees trained under the AI-VR system learned up to four times faster and demonstrated greater confidence in managing challenging interactions. Properties adopting the program reported improvements in guest satisfaction and employee engagement. Hilton's initiatives also earned multiple Brandon Hall Awards in 2022 and were cited in Skift's (2024) Future of Hospitality Education report for advancing "technology-enabled empathy."

Hilton's experience illustrates that AI's real value lies not in automation but in amplification. By framing AI as a coach rather than a controller, the company enables employees to practise empathy, reflect on feedback, and strengthen emotional awareness. The system preserves autonomy and judgment, positioning technology as an enabler of deeper learning rather than a replacement for human skill. In doing so, Hilton redefines efficiency, not as doing more in less time, but as learning faster and caring better.

Discussion: AI, Learning, and Agency in Practice

This discussion interprets findings from the three sectoral cases of OCBC, Prudential, and Hilton through the lenses of socially embedded capability, workplace learning agency, and cognitive and behavioural learning sciences. Rather than treating artificial intelligence as a uniform or purely technical intervention, the cross-case analysis shows how AI reshapes workplace learning by mediating participation, judgment, and learning practices in context. Collectively, the cases reveal that AI's educational effects depend on how learning, agency, and care are organised within workplaces, rather than on the technology's sophistication alone.

Socially embedded capability and inclusive participation

The first research question examined how AI shapes socially embedded capability, particularly workers' opportunities to participate meaningfully in learning while sustaining confidence and professional identity. Across the three cases, AI expanded capability most effectively when it lowered barriers to participation and made learning opportunities visible, without positioning workers as passive recipients of algorithmic guidance.

At OCBC, the MOBI platform broadened access to career development by making learning pathways, internal opportunities, and mentoring relationships transparent to a wide range of employees, rather than relying on informal networks or managerial discretion alone. At Prudential, MedLM supported claims officers by externalising complex reasoning processes, enabling both experienced and less experienced staff to engage more confidently with judgment-intensive work. At Hilton, AI-supported simulations created psychologically safe environments in which frontline staff could practise emotional and relational skills without fear of reputational or performance consequences. In each case, AI-supported inclusion did not replace human learning but reshaped the conditions under which participation became possible.

Interpreted through the capability literature, these findings reinforce the argument that empowerment depends on institutional support, recognition, and enabling environments rather than access to tools alone. AI-enhanced socially embedded capability was achieved only when embedded within organisational cultures that valued learning, care, and participation. Where such conditions were present, AI widened participation and supported professional identity. Where they were fragile or absent, AI risked reinforcing existing inequalities. This highlights the importance of organisational and policy contexts in shaping inclusive learning outcomes.

Learning Agency in AI-Mediated Work: Personal and Relational Dimensions

The second research question focused on how AI influences workplace learning agency at both personal and relational levels, as employees learn to reflect, collaborate, and exercise judgment alongside intelligent systems. The cases show that AI strengthened agency when it supported interpretation, reflection, and dialogue, but constrained agency when its outputs were treated as authoritative rather than provisional.

At the level of personal agency, AI functioned as a learning companion by prompting individuals to question, compare, and reflect on their own thinking. At Prudential, MedLM transformed routine claims processing into opportunities for metacognitive engagement, as officers weighed algorithmic recommendations against professional intuition. At OCBC, personalised analytics enabled employees to reexamine possibilities and reflect on their aspirations.

At the level of relational agency, learning emerged through dialogue, coordination, and shared sense making. Hilton's immersive simulations foregrounded empathy, collaboration, and emotional attunement, reinforcing learning as a relational process rather than an individual transaction. Across the cases, the agency depended not only on what AI enabled individuals to do, but on how it shaped conversations, relationships, and shared interpretations at work.

Analytically, these patterns align with theoretical accounts of workplace learning agency, which emphasise that agency is exercised through interaction with others and with tools. AI preserved agency when it remained interpretive and dialogic, but risked undermining it when organisational practices encouraged deference to algorithmic outputs.

Deep Learning with AI: Reflection, Effort, and Adaptive Expertise

The third research question examined how AI-enabled tools and environments support or constrain deep learning processes, including metacognition, retrieval, and the development of adaptive expertise. Across the cases, AI contributed most meaningfully to deep learning when it structured experience to include effort, reflection, and appropriately calibrated challenge.

At Prudential, repeated decision-making supported effortful retrieval and reflective comparison, strengthening professional reasoning over time. At Hilton, immersive simulations operationalised experiential learning and deliberate practice, allowing employees to rehearse complex emotional responses under supportive conditions. At

OCBC, reflective prompts and coaching connections helped employees integrate learning with evolving professional identities.

These findings align closely with learning science research showing that deep, sustained learning depends on challenge, feedback, and reflection rather than frictionless efficiency. AI-supported learning not by removing effort, but by making effort visible and meaningful. Where effort was bypassed, or judgment was automated, learning risked becoming shallow or performative.

Synthesis: From Learning Practices to Organisational Meaning

Viewed across the three research questions, the discussion suggests that AI's influence on workplace learning cannot be reduced to individual features, tools, or outcomes. Instead, its effects emerge through how learning opportunities are organised, how agency is exercised in everyday practice, and how organisational values shape what counts as learning and development. Learning with AI, in this sense, is not only about acquiring new skills. It reflects how workplaces configure participation, responsibility, and growth over time.

At the same time, the cases show that AI can support reflection and participation in ways that make organisational priorities more visible. Where learning was framed as developmental and inclusive, AI tended to reinforce opportunities for reflection, dialogue, and professional growth. It did so by making reasoning, pathways, and expectations more explicit. Where efficiency and standardisation were prioritised, however, AI was more likely to narrow learning into compliance-oriented routines. In these settings, opportunities for discretion and sense-making were more limited, particularly when algorithmic outputs were treated as authoritative rather than interpretive. Following this line of thought, AI did not determine organisational culture. Instead, it brought into view how learning was valued, whose judgment was recognised, and how responsibility was shared between humans and systems.

Conclusion: Learning in the Age of Intelligent Companions

This chapter has examined how artificial intelligence can be harnessed to foster inclusive workplace learning and learner empowerment, rather than merely to automate tasks or optimise performance. Drawing on sectoral cases from OCBC, Prudential, and Hilton, and informed by the literature on socially embedded capability, workplace learning agency, and learning sciences, the chapter shows that AI's educational value lies in how it expands participation, supports agency, and enables deeper forms of learning when thoughtfully designed and embedded.

A central finding is that AI supports inclusion by lowering barriers to learning participation and making opportunities for development visible to a broader range of workers. Across the cases, AI enabled more employees to access learning pathways, practise complex skills, and engage in reflective work that might otherwise remain concentrated among those with privileged access to informal networks or mentoring. In this way, AI contributed to learner empowerment not by replacing human learning, but by reshaping organisational conditions so that more people could participate with confidence and sustain a sense of professional identity.

The chapter also demonstrates that learner empowerment depends critically on how AI shapes learning agency. AI empowered learners when it supported reflection, interpretation, and collaboration, allowing workers to exercise judgment alongside intelligent systems. Where AI systems invited dialogue and sense making, both personal and relational agency were strengthened. Where AI risked narrowing discretion or encouraging compliance, empowerment was more fragile. This highlights that AI does not empower learners by default; empowerment emerges when organisations design AI systems and practices that preserve learner voice, discretion, and shared responsibility.

From a learning perspective, the findings further suggest that AI can support deep learning by scaffolding effort, reflection, and care. For example, learning became more meaningful when AI helped learners make their thinking visible, engage in productive challenge, and practise skills in psychologically safe environments. Empowerment, in this sense, involved not the removal of difficulty, but the creation of conditions under which learners could engage with challenge and grow through it.

In summary, the chapter advances the argument that AI can function as a learning companion that supports inclusion and empowerment when it is aligned with organisational cultures that value learning as developmental, relational, and ongoing. At the same time, AI acts as a cultural mirror, revealing whether organisations are prepared to support these values or whether learning is treated instrumentally. These dual roles help explain why similar AI technologies can produce very different learning outcomes across workplaces.

The implication is clear. The future of workplace learning will not be determined by how much AI can automate, but by how intentionally organisations harness AI to expand participation, preserve agency, and support meaningful learning for all workers. For leaders, this requires investing not only in technology, but also in inclusive cultures, reflective practices, and governance arrangements that place learner empowerment at the centre of AI adoption. In the age of intelligent companions, AI's promise lies in its capacity to support people as active participants in their own learning, rather than as passive subjects of technological change.

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