Working Smarter or Losing Skills? How Artificial Intelligence Use Affects Skill Levels of Knowledge Workers

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The rapid evolution of Generative Artificial Intelligence (GenAI) has produced a major transformation in organisational contexts and the digital economy. Unlike traditional AI applications, which depended on algorithms designed to mimic human cognitive abilities for tasks such as pattern recognition or classification, GenAI extends far beyond these analytical capabilities. Built on Large Language Models (LLMs) and deep learning architectures, GenAI utilises vast datasets and predictive word sequences to synthesise and generate entirely new content, including text, computer code, and images (Kumar et al., 2025). With 88% of organisations already deploying GenAI and global investments reaching $33.9 billion in 2024 (James, 2026), adoption has become an organisational imperative rather than a strategic choice.

Because these tools can function more like collaborative digital assistants than passive analytical software, they hold transformational potential to automate mundane tasks and revolutionise knowledge work. GenAI is fundamentally reshaping how employees acquire information, acting as a digital "exoskeleton", temporarily augmenting human capabilities and enabling non-technical professionals to perform highly complex tasks that were previously far outside their existing skill sets (Wiles et al., 2024). However, this augmentation is accompanied by a critical caveat: when the GenAI tool is removed, employees demonstrate little or no independent knowledge retention, showing that demonstrated technical capabilities do not equate to genuine skill acquisition (Wiles et al., 2024).

This gap between immediate performance and genuine underlying competence, termed the "Performance-Competence Gap" (Qiao et al., 2025), constitutes the central problem motivating this work. If knowledge workers skip traditional learning processes and rely blindly on automated outputs, organisations face the risk of "knowledge shifting" — the permanent loss of tacit organisational memory gained through hands-on human experience (Retkowsky et al., 2024; Storey, 2025). Against this backdrop, this paper is guided by the following research question: *How does Artificial Intelligence use affect the skill levels of knowledge workers?*

Related Work

Knowledge workers are professionals whose daily tasks centre around handling, processing, and creating information rather than manual labour (Rizun, 2017). Unlike earlier AI applications that were specialised for single tasks, GenAI tools are general-purpose and highly versatile (Alavi et al., 2024). As a result of recent model improvements, GenAI is no longer viewed merely as a passive tool for automating routine tasks. Instead, they are conceptualized as collaborative agents or "AI teammates". This integration fosters a new human-AI division of labour, where the technology performs as an active participant in solving problems, compressing massive amounts of information to generate knowledge and thereby augmenting human cognition rather than merely replacing it (Nguyen et al., 2026).

With this context in mind, this study draws on three interconnected bodies of literature to situate the research question theoretically.

First, Cognitive Offloading Theory (Risko & Gilbert, 2016, as cited in Bilderback, 2025) conceptualises the externalisation of cognitive processes to external tools in order to reduce mental demand. In the context of GenAI, cognitive offloading provides short-term efficiency gains by freeing cognitive resources for higher-value tasks (Grinschgl et al., 2021). However, the theory also addresses a fundamental trade-off: while offloading accelerates immediate task completion, it diminishes long-term memory retention and independent skill development. Gerlich (2025) provides empirical evidence of a negative correlation between high AI tool usage and critical thinking ability. Such developments can further lead to “deskilling”, a phenomenon in which the continuous substitution of cognitive effort prevents the development of independent skills (Shukla et al., 2025).

Second, socio-technical systems and adoption frameworks situate GenAI within the broader debate between augmentation and substitution. Although GenAI raises valid concerns about the potential displacement of knowledge workers, task-level analyses suggest that pure AI substitution is a rare edge case, with over 86% of work operating within a complementary “mixed zone” (Walkowiak, 2025, p. 37), where thanks to a “structured novelty effect” (p. 45), synergies allow GenAI to deliver its highest productivity gains not when it replaces humans entirely, but when its codified efficiency is combined with human-driven innovative thinking – an ideal outcome of a “joint optimization” (Bostrom & Heinen, 1977, p. 27) within the socio-technical system of an AI-enabled organization.

Third, the adoption of GenAI mirrors trends observed in the integration of earlier technologies, making the literature on automation bias directly relevant. Kumar et al. (2025) characterise GenAI adoption as a push-and-pull dynamic: while knowledge workers are motivated by its convenience and generative capacity, they are simultaneously hindered by its tendency to produce inaccurate information (hallucinations). This tension is where automation bias takes hold — the process by which employees blindly trust and favour AI-generated output over their own judgment (Carnat, 2024). Because GenAI produces syntactically fluent responses, workers may treat well-formed output as reliable output, overlooking incomplete or inaccurate content (Cruz et al., 2025).

Method: Scoping Literature Review

To investigate the research question, this study employed a scoping review methodology following the five-stage framework established by Arksey & O’Malley (2007). The scoping review was selected because it is best suited to map key concepts and identify available sources in rapidly evolving and terminologically inconsistent research areas — conditions that precisely characterise the study of GenAI workplace integration, which only entered professional settings in late 2022 (Bick et al., 2025). Reporting adheres to the PRISMA guidelines for Scoping Reviews (PRISMA-ScR; (Tricco et al., 2018)).

The literature search was conducted across three databases — Scopus, ScienceDirect, and EBSCOhost — selected to capture peer-reviewed studies across computer science, management, and the social sciences. Search strings combined the technology term (GenAI, LLM, ChatGPT) with the workplace setting (knowledge work, professionals, white-collar) and behavioural outcome terms (skill decay, deskilling, upskilling, augmentation, cognitive offloading). Studies were included if they were published after 2022, written in English, peer-reviewed, addressed knowledge workers in professional settings, examined Generative AI specifically, and reported on impacts related to skill level, professional competence, or role transformation. Studies concerning traditional AI, work encompassing manual labour, or purely technical or economic outcomes were excluded.

The initial database search yielded 221 results. Following deduplication, title and abstract screening, and full-text review against the inclusion and exclusion criteria, 23 peer-reviewed articles constituted the final scoping set. An inductive coding process was applied to the data to cluster them based on the domain they are situated in, and in which area their dominant finding contributes to.

Results & Implications

The 23 selected studies, all peer-reviewed and published between 2023 and 2026, are concentrated in 2025 (n = 15) and draw predominantly from the Professional and Business Services sector (n = 15). The methodological landscape is overwhelmingly qualitative and conceptual (91%), indicating that the current research priority lies in understanding the human experience of GenAI integration rather than measuring tangible performance outcomes.

A ubiquitous finding across sectors is that the literature reports increases in operational efficiency upon GenAI adoption, with Anto (2025) reporting that 61% of surveyed professionals claim improved decision-making after working with AI chatbots. However, this short-term performance gain does not translate into durable competence. The same tools that accelerate output trigger cognitive atrophy when employees habitually offload problem-solving to the system and bypass the reflective thinking required for independent skill development (Bilderback, 2025; Gerlich, 2025). Lee et al. (2025) provide empirical support, documenting self-reported reductions in cognitive effort as workers shift from active problem-solving to the passive verification of AI-generated outputs. This is, in turn, leading to workers' increased vulnerability to automation bias (Carnat, 2024). Organisations must therefore treat Human-in-the-Loop validation as a core professional competency rather than an assumed safeguard, and introduce targeted reskilling programs to ensure employees remain analytically capable alongside the tools they use (Seufert & Spirgi, 2024).

A related and structurally important finding is the role transformation that GenAI imposes on all knowledge workers. Employees shift from being "Creators" to "Orchestrators" who critique, contextualise, and validate AI-generated content rather than producing it independently (Jarrahi et al., 2025; Retkowsky et al., 2024). For experienced workers, this shift can be enabling. For junior employees, however, it poses a developmental threat. As GenAI removes the routine "scut work" (Retkowsky et al., 2024, p. 518) that traditionally builds foundational competence, novices are elevated to the output level of senior staff without acquiring the underlying skills, producing a "false confidence trap" (Cruz et al., 2025, p. 3575) that blinds managers to where foundational training is needed (Alhusban et al., 2024; Dong et al., 2024; Retkowsky et al., 2024). Organisations must therefore resist treating junior productivity gains upon AI adoption as evidence of genuine skill development, and instead preserve structured pathways for experiential learning that GenAI would otherwise shortcut.

Finally, the literature identifies a social paradox. GenAI augments individual communication, producing written outputs that are perceived as more prosocial and analytical than those drafted independently (Wu et al., 2025). In team settings, it can reduce social friction and counteract groupthink (Johnson et al., 2025). Yet as employees increasingly consult AI agents rather than colleagues, informal knowledge exchange decays, producing "broken knowledge ties" and professional isolation (Retkowsky et al., 2024). This is especially damaging for novices, who bypass senior mentorship and thereby accelerate the loss of tacit organisational knowledge. Managers must actively counteract this by designing intentional live collaboration spaces — including, where necessary, AI-free zones — in which spontaneous peer interaction and the transfer of experiential knowledge are structurally protected (Callari & Puppione, 2025; Retkowsky et al., 2024).

Ultimately, the successful integration of GenAI is not only a technological upgrade but also a social and people-centred transformation. Managers must balance operational efficiency with a commitment to structured training, ethical oversight, and the maintenance of human connections that drive long-term organisational success.

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