The Risks of Skill Erosion and Judgment Loss Under AI Task Delegation: A Scoping Review on Professional Development

Angrisani Tommaso
Politecnico di Torino
Torino, Italy

Carpenzano Giacomo
Politecnico di Torino
Torino, Italy

Cesaria Francesco Luigi Karol
Politecnico di Torino
Torino, Italy

Del Debbio Luca
Politecnico di Torino
Torino, Italy

Gallea Luca
Politecnico di Torino
Torino, Italy

Mossetto Filippo
Politecnico di Torino
Torino, Italy

Preti Andrea
Politecnico di Torino
Torino, Italy

Protasio Brend Margarette
Politecnico di Torino
Torino, Italy

Saladini Lorenzo
Politecnico di Torino
Torino, Italy

Scimone Tiziano
Politecnico di Torino
Torino, Italy

Sdiri Mohamed
Politecnico di Torino
Torino, Italy

Abstract

The rapid integration of Artificial Intelligence agents into knowledge work is radically transforming the nature of professional tasks, introducing productivity gains that risk being offset by a critical erosion of skills and human judgment. This scoping review aims to map the conditions under which delegating tasks to AI contributes to deskilling, with a focus on the mechanisms that lead to the loss of professional expertise from the worker's perspective. Following the Population, Concept, and Context (PCC) framework, the review examined studies involving professional workers engaged in processes of technological delegation within digital work environments. The methodology involved a systematic search across eight databases, leading to the selection of 36 sources published between 2015 and 2026, including 10 empirical studies and 3 sources from industrial practice. The thematic analysis identified three fundamental pillars of skill erosion: individual cognitive mechanisms, such as cognitive offloading and automation bias; risks for professional development, including the "never-skilling" phenomenon for junior profiles and the loss of tacit knowledge; and structural factors related to "capacity-hostile" environments and the lack of organizational incentives for human oversight. In conclusion, the study suggests that, to prevent an irreversible decline in expertise, it is necessary to transition from purely efficiency-driven automation toward augmentative integration that preserves cognitive effort and critical judgment as central elements of professional training and practice.

CCS Concepts

• **Social and professional topics** → **Professional topics**; • **Human-centered computing** → *Collaborative and social computing*.

Keywords

AI Task Delegation, Skill Erosion, Deskilling, Professional Expertise, Human Judgment, Cognitive Offloading, Never-skilling

1 Introduction

The rapid diffusion of generative artificial intelligence (GAI) and agentic systems is reshaping knowledge-intensive work. Recent industry reports indicate that AI usage is widespread at the individual level, with around 72% of employees [2] using it regularly, alongside an increase in experimentation with autonomous agents, capable of planning and executing multi-step tasks. These technologies offer substantial productivity gains and cost efficiencies, however they also introduce a new critical problem: the gradual erosion of human expertise and professional judgment. With the integration of AI as a primary task executor, human involvement shifts from active creation to passive supervision [10].

This phenomenon, often described as "skill erosion" or "deskilling", is not simply a side effect of automation, but a more complex cognitive and structural process. When analytical and creative tasks are delegated to AI, workers tend to engage less in planning and problem-solving, a dynamic commonly referred to as "cognitive offloading" [9, 11]. This creates a vicious cycle: as workers rely more on AI to handle routine and complex activities, they lose the opportunity for "productive struggle" [9] (the effortful thinking essential for consolidating skills) and increase their dependence on the technology [13]. This dynamic is leading to a growing structural dependency: recent surveys indicate that two in five employees report that they sometimes or often cannot complete their work without the constant help of AI [35]. Moreover, the concept of "cognitive debt" suggests that the immediate efficiency gains brought by AI assistance may eventually cost a long-term decline in the quality of human reasoning.

The repetitive tasks that are now handled by AI were traditionally how junior staff developed pattern recognition and domain intuition. Without these foundational experiences, a generation of workers may fail to acquire essential expertise, leaving them unable to effectively oversee or verify AI outputs when they reach senior roles. This "decoupled learning" creates a dangerous gap: professionals may appear competent thanks to AI assistance, but lack the expertise required to handle new challenges or detect when technology is failing.

Despite the growing amount of research on AI in the workspace, the specific conditions and mechanisms through which task delegation erodes professional judgment remain fragmented. By synthesizing findings across diverse professional domains, this review aims to provide a comprehensive framework for understanding AI-induced deskilling and identifying strategies to preserve the human expertise that remains essential for responsible and effective professional practice.

2 Methods

This scoping review was conducted following the PRISMA-ScR (Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews) guidelines, with the idea of mapping the complex relationship between AI delegation and professional skill erosion.

2.1 Eligibility Criteria (PCC Framework)

To define the research boundaries, we applied the Population, Concept, and Context (PCC) framework as recommended for scoping reviews. As shown in Table 1, the review includes studies involving professional workers and students across various domains. The core concept is the erosion of skills and judgment resulting from task delegation to AI. The context includes digital work environments and professional training programs where AI is integrated into workflows.

Table 1: PCC Eligibility Criteria

Category	Description
Population	Knowledge workers, medical professionals, programmers, and students in professional training.
Concept	Mechanisms of skill erosion, deskilling, "never-skilling," and the loss of human judgment or tacit knowledge.
Context	Professional and educational settings involving Human-AI interaction and task delegation to GAI or autonomous agents.

2.2 Search Strategy

A systematic search was conducted across eight databases: ACM Digital Library, Scopus, Google Scholar, arXiv, CJAI, Springer Nature, Frontiers and ScienceDirect. In order to ensure relevance to current generative AI capabilities, the search was limited to English-language publications from 2015 to 2026. The search string combined terms such as "AI task delegation", "skill erosion", "deskilling", and "professional expertise". Grey literature, such as high-impact industry reports from organizations like Microsoft, BCG, and McKinsey, was also searched to capture professional practice perspectives.

2.3 Source Selection

The selection process followed a two-stage screening approach. In the first stage two reviewers independently screened titles and abstracts against the eligibility criteria. Disagreements were resolved through discussion or a third reviewer. Second, full-text versions of the remaining papers were assessed. Sources were excluded if they focused exclusively on technical AI performance without addressing the human skill dimension. A total of 36 sources were selected for final analysis, including 10 empirical studies and 3 industry reports.

2.4 Data Charting and Analysis

Data were extracted using a standardized charting form to capture key information: author, year, study type, domain, and specific risk factors for skill erosion. The extracted factors were then synthesized using thematic analysis to identify general mechanisms (e.g., cognitive offloading, structural barriers) that define the current state of AI-driven deskilling. Whereas peer reviewed studies provided empirical data on cognitive and professional risks, industry reports [2, 10, 29] were explicitly coded to identify organizational barriers, management perspectives, and structural dependencies that are typically underrepresented in academic literature.

3 Results

3.1 Characteristics of Sources

The majority of the included studies were published between 2024 and 2026, reflecting the urgent nature of this topic in the era of generative AI. The most represented domains are medicine and healthcare, followed by software engineering and financial services. Approximately 47% of the empirical sources utilize qualitative methods, such as interviews and observations, while 53% adopt quantitative or mixed-methods approaches.

3.2 Thematic Synthesis: The Skill Erosion Framework

Through thematic analysis, the extracted risk factors were grouped into a broader framework describing how AI delegation drives the erosion of professional expertise.

3.2.1 Individual Cognitive Mechanisms. The delegation of reasoning and problem-solving by workers has been shown to affect their cognitive processes in measurable ways, reducing mental engagement and leading to measurable cognitive atrophy [3, 13].

This process facilitates a loss of "Productive Struggle" as AI removes the thinking effort necessary for deep understanding and the formation of robust mental models [5, 8]. **As illustrated in Figure 1, empirical evidence indicates a significant decrease in library-specific skills, such as code reading and debugging, when workers rely on AI assistance without active engagement [21].** Moreover, "Automation Bias and Complacency" leads professionals to accept incorrect AI outputs without critical verification [8].

Quantitative data reinforces these concerns: nearly half of employees (49%) admit to delegating tasks to AI instead of acquiring the necessary skills themselves, while 43% report a perceived inability to complete work without AI assistance. **However, the impact**

on skill formation is highly dependent on usage patterns; as shown in Figure 2, certain high-engagement behaviors allow users to remain cognitively active despite the use of AI assistance [21]. Furthermore, a significant majority (72%) acknowledge reduced effort due to AI reliance, and 66% accept AI-generated outputs without conducting a critical evaluation [35].

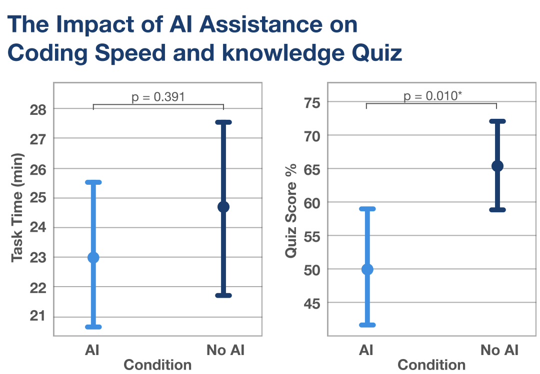

Figure 1: Impact of AI assistance on the retention of library-specific skills, including conceptual understanding, code reading, and debugging.

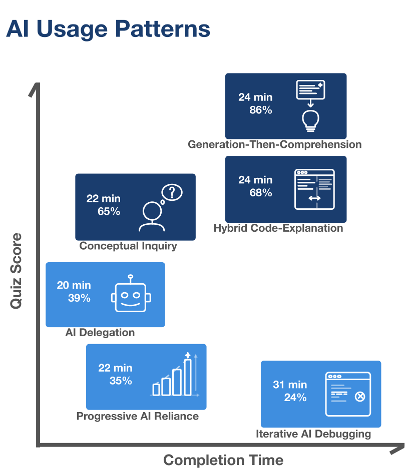

Figure 2: Classification of AI interaction patterns and their relative levels of cognitive engagement and skill development.

3.2.2 Professional Development and Expertise Risks. This theme explores the impact on long-term career trajectories and the intergenerational transmission of knowledge. Junior professionals who are delegating foundational tasks to AI may fail to develop the basic skills [1, 3, 9, 11] needed to effectively oversee these systems in the future. This risk is corroborated by research involving 5,179 customer support agents: while access to AI tools boosted overall productivity by 14%, this increase was exclusively restricted to novice and low-skilled workers, who saw a 34% improvement. This suggests that AI acts as a performance leveler that may, however, hinder the learning curve necessary to acquire deep expertise [4].

However, the impact of delegation varies with experience. In a study of sales professionals, experienced workers reported significant augmentation: productivity and confidence both increased by 34%, perceived work impact by 31%, and stress management by 29%. These gains were most pronounced among those with longer tenure, indicating that senior workers are not necessarily displaced by AI but can be significantly empowered when the technology is introduced with proper institutional support [29]. Interestingly, while studies show a clear risk of deskilling for junior profiles in technical domains such as medicine [6], customer support [4], and finance [16], in more relational or experience-based sectors, such as sales [29], AI tends to act as a performance amplifier for senior workers, boosting both productivity and confidence. This suggests that the impact of AI on expertise is not uniform, but depends heavily on professional domain, level of experience, and the nature of the task. This leads to decoupled learning, where performance remains high only with the support of AI: once technological support is removed or fails, the worker's independent performance drops drastically. Empirical evidence of this phenomenon, though still limited, is consistent across specialties. For instance, in a multicenter randomized trial in colonoscopy, the adenoma detection rate dropped significantly from 28.4% to 22.4% when endoscopists reverted to manual procedures after repeated AI use, whereas it remained stable at 25.3% as long as AI assistance was active [6]. Additionally, delegation can undermine the development of essential practical skills, as it reduces opportunities to learn through direct experience, including repetitive tasks [3, 4, 13].

Among all the competencies, the most at risk are the analytical ones, in particular primary source analysis, adversarial thinking, and source evaluation, all of which require the worker to use independent judgment, creative thinking and skepticism [3].

3.2.3 Structural and Organizational Factors. The work environment acts as either a catalyst or a mitigator of erosion. Many organizations inadvertently foster environments that prioritize immediate AI-driven efficiency over the long-term cultivation of human capabilities [10, 13]. This tendency is reflected in industry data, where only 36% [2] of employees report receiving adequate training to work effectively with AI systems.

The resulting structural dependency is quantified in Figure 3, which shows that roughly 40% of employees feel unable to complete their work without constant AI assistance [35]. This suggests that the problem is not only a lack of skills but also an absence of organizational direction, as only 25% of workers report receiving sufficient guidance from leadership on how and when to use AI at work [2]. This reveals a critical paradox between individual readiness and corporate strategy: despite 94% of workers stating they are ready to learn new skills to work with generative AI, only 5% of organizations are actively reskilling their workforce at scale [29]. Moreover, when organizations integrate AI without redesigning their workflows to accommodate for dedicated critical review time, human oversight becomes structurally hindered [2, 10], thus accelerating the shift from active judgment to passive acceptance of AI outputs across the entire team.

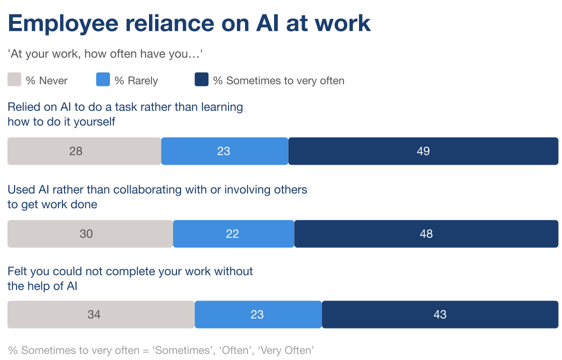

Figure 3: Reported worker dependency on AI tools, highlighting the percentage of employees unable to complete tasks without technological assistance.

4 Case Study: Data Analysis and Statistics

To illustrate how the framework applies in practice, this section examines the impact of AI task delegation in data science, focusing on how the three pillars of skill erosion manifest across a junior analyst's workflow.

At the individual level, tools that automate data cleaning, model selection and trend identification trigger direct cognitive offloading [9, 13]. Tasks like handling missing values or selecting statistical models were traditionally how a junior analyst developed pattern recognition and domain intuition. When delegated to AI, the analyst produces faster outputs but bypasses the productive struggle necessary for forming robust mental models [9]. The same dynamic intensifies at the exploratory analysis stage: using AI to detect trends or discover patterns eliminates the phase of hypothesis formation and verification through data. Experimental evidence shows that when workers receive direct AI recommendation and explanation they gain immediate benefit and their performance improves, but actual learning only takes place when workers receive contextual information and arrive at conclusions themselves [31].

From a professional development perspective, this creates a severe never-skilling risk [11]. A junior analyst operating with AI assistance can appear highly productive while lacking the independent competence to verify their work. The analyst can fail to detect when a model is hallucinating or producing unreliable results, because this requires knowledge that was never formed [1]. This decoupled learning only becomes visible during system failures or novel analytical challenges where AI support is unavailable.

These risks are exacerbated by structural factors that accelerate this dependency. Organisations prioritise reporting speed over analytical depth: BCG reports that 47% of respondents save more than an hour a day by using GenAI [2], and rarely is this time reinvested in data verification. This capacity-hostile environment discourages junior analysts from engaging in slow, critical verification of outputs, gradually eroding the team's collective expertise.

Overall, this use case demonstrates how the three pillars interact: individual cognitive mechanisms are triggered at the task level, professional development risks accumulate silently across junior cohorts, and organisational pressures prevent timely recognition of the erosion.

5 Discussion and Conclusions

The evidence synthesized in this scoping review demonstrates that professional skill erosion is not an inevitable product of AI technology itself, but rather a symptom of poorly designed human interaction with AI. When organizations prioritize immediate efficiency through the unchecked delegation of tasks, they inadvertently dismantle the "judgmental cycle". As professionals transition from active creators to passive supervisors, they lose the productive struggle required to build and maintain robust mental models, leading to the phenomena of cognitive offloading and "never-skilling".

To prevent this deferred "cognitive debt", the fundamental paradigm of AI integration must shift from Automation (delegating tasks to replace human effort) to AI Augmentation (integrating AI to amplify and challenge human cognition). True augmentation occurs when technology acts as a collaborative scaffold that keeps the human firmly in the loop of strategic planning and critical evaluation. However, AI Augmentation is highly context-dependent. Its success or failure relies on specific cognitive, structural, and systemic conditions.

For AI to act as a catalyst for expertise rather than a substitute, specific guardrails must be in place. Augmentation succeeds when workflows intentionally introduce moments of cognitive friction. Instead of one-click acceptance of AI outputs, systems should require users to formulate specific prompts, evaluate multiple AI-generated alternatives, or explicitly justify their selection. This preserves the effortful thinking necessary for skill retention. Augmentation also thrives in "capacity-friendly" environments where leadership actively incentivizes accuracy, ethical review, and deep learning over sheer output volume. This includes providing dedicated time for output verification and formal training on algorithmic literacy.

Conversely, augmentation strategies frequently fail and collapse back into harmful automation under several conditions. When organizations demand higher output volumes without adjusting deadlines, workers are structurally forced to accept AI outputs without critical review. Under extreme time pressure, augmentation inevitably devolves into blind delegation, triggering severe automation bias. Augmentation tools are often designed assuming the user possesses a baseline of expertise necessary to evaluate the AI's output. When junior professionals use these tools to bypass foundational tasks, they suffer from "decoupled learning". Without a pre-existing mental model, the AI acts as a crutch rather than a scaffold, masking their lack of independent competence until a system failure occurs.

5.1 Limitations and Future Research

The long term impact of AI delegation on skill formation over the years or across generations is still largely unexplored, and there are no standardized metrics to measure silent forms of deskilling such as the fading of tacit knowledge. Future research should track whether augmentation strategies genuinely help junior professionals retain skills over time, and must also examine whether such augmentation is universally viable or if alternative paradigms are required. Specifically, in domains with ultra-high stakes, strict limits on AI delegation may be necessary to protect professional integrity.

In conclusion, the current trajectory of AI adoption in knowledge work risks trading long-term human expertise for short-term productivity gains. While the productivity boosts are undeniable, the silent accumulation of deskilling, particularly among junior cohorts, poses a systemic risk to professional integrity and innovation. Addressing this challenge requires moving beyond the binary debate of human against machine. Organizations and educational institutions must deliberately engineer digital work environments that demand human skepticism, enforce cognitive engagement, and treat critical judgment not as a redundant inefficiency, but as the core asset of professional practice.

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A Appendix

Databases Searched

ACM Digital Library, Scopus, Google Scholar, arXiv, CJAI, Springer Nature, Frontiers, ScienceDirect. Grey literature was identified through targeted manual searches using the Google web search engine and the organizations' official publication portals.

Dates Searched

April 2026.

Search Strings Used

- "AI task delegation" AND "skill erosion"
- "deskilling" AND "professional expertise"
- "cognitive offloading" AND "knowledge work"
- "automation bias" AND "worker judgment"
- "never-skilling" AND "AI"
- "AI delegation" AND "professional development"

Inclusion Criteria

- Studies involving professional workers or students in training
- Focus on AI or algorithmic systems in work or occupational contexts
- Published 2015–2026 (English language)
- Peer-reviewed articles or credible practice sources (industry reports, policy bodies)

Exclusion Criteria

- Purely technical focus on AI performance without addressing the human skill dimension
- No connection to occupational tasks or worker perspective

Screening Process

The systematic screening process followed a multi-stage approach, as illustrated in **Figure 4**.

- 104 non-duplicated records identified across all databases.
- 49 excluded based on title and abstract screening.
- 55 full-text articles assessed for eligibility.
- 36 sources included in the scoping review.

AI Tools Used

ChatGPT (OpenAI), Gemini Pro (Google), Claude (Anthropic), DeepSeek (DeepSeek). AI tools were used to support brainstorming of search terms, to assist with initial organization of extracted factors, to help paraphrase and edit sections of the paper for clarity, and to skim and summarize candidate sources during the screening phase. All AI-generated suggestions were reviewed and validated by team members. No AI-generated content was included without human review and revision. All 36 sources included in this review were individually located, accessed, and read in full by at least one team member. LLMs were later used also to help the team with LaTex format.

Me, Myself, AI

- **Angrisani Tommaso**: s340221@studenti.polito.it
- **Carpenzano Giacomo**: s342042@studenti.polito.it
- **Cesaria Francesco Luigi Karol**: s341586@studenti.polito.it
- **Del Debbio Luca**: s342568@studenti.polito.it
- **Gallea Luca**: s341964@studenti.polito.it
- **Mossetto Filippo**: s342419@studenti.polito.it
- **Preti Andrea**: s297321@studenti.polito.it
- **Protasio Brend Margarette**: s339680@studenti.polito.it
- **Saladini Lorenzo**: s322340@studenti.polito.it
- **Scimone Tiziano**: s337525@studenti.polito.it
- **Sdiri Mohamed**: s341348@studenti.polito.it

Supporting Material

The complete set of supplementary materials is available in the following archive:

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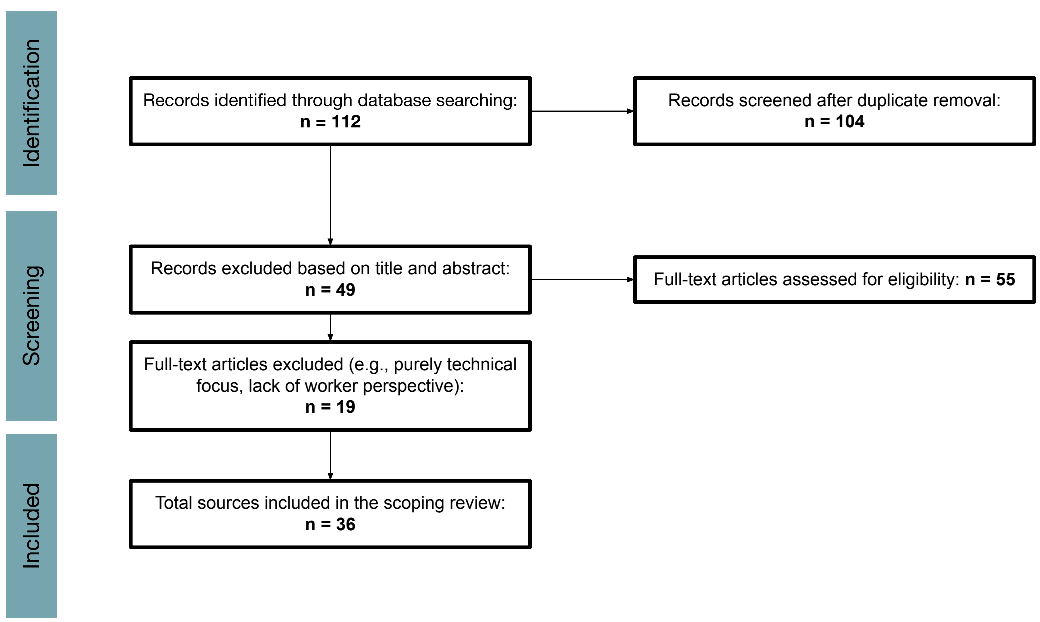

Figure 4: PRISMA-style screening and selection process for the scoping review.

Table 2: Coding Scheme

Ref	Authors (Year)	Domain	AI Technology	Skill(s) Eroded	Individual Mechanisms	Professional Risks	Structural Factors
1	Ahmadov (2026)	Banking/Finance	AI-augmented supervision systems	Tacit knowledge, supervisory judgment	CO, AB	TK, NS, IJ	AG, LT
2	BCG (2025)	General	Generative AI	General professional skills	–	NS (implicit)	CH, LT
3	Coney (2025)	General	Generative AI / Automation	Cognitive engagement, problem-solving	PS, CA	DL, UP, NS	CH
4	Crowston & Bolici (2025)	General	Various AI systems	Foundational skills	CO, PS	UP, DL, NS	AS
5	Ferdman (2025a)	General (Public Reason)	AI decision-support	Critical thinking, reasoning	PS, AB	IJ	AS, EI
6	Heudel et al. (2026)	Medicine	AI diagnostic tools	Diagnostic accuracy, clinical reasoning	AB, CO	NS, DL, TK	LT, AG
7	Krishnan (2025)	General (Workforce)	Automation systems	Professional skills, resilience	CA, CO	DL, NS	AS, LT
8	Lee & Tok (2025)	General (Decision-making)	Uncertainty-aware AI	Collaborative decision-making	AB, MR	IJ, DL	EI, AG
9	Macnamara (2024)	Cognitive Psychology	AI assistance tools	Skill development, awareness	PS, CO	NS, DL	–
10	Microsoft Research (2025)	General	Generative AI, Copilot	Independent judgment, creativity	CO, AB	NS, IJ, UP	CH, LT, AG
11	Natali et al. (2025)	Medicine	AI clinical systems	Clinical skills, diagnostic reasoning	CO, AB, PS	NS, TK, DL	AG, AS
12	Charitha (2025)	Knowledge Work	Generative AI	Cognitive skills, decision-making	CO, PS	DL, IJ	AS, LT
13	Rinta-Kahila et al. (2023)	Accounting/Automation	Cognitive automation	Routine analytical skills	CA, CO, PS	UP, TK, DL	CH, AS
14	Sajland & Collins (2025)	Education (Programming)	Generative AI (coding)	Debugging, problem-solving	PS, MR	NS, DL	LT
15	Shukla et al. (2025)	Design	AI-assisted design tools	Design reasoning, creativity	CO, PS	TK, IJ	EI, AG
16	Siderius et al. (2026)	Finance	Automated trading/pricing systems	Price-discovery judgment, pattern recognition	CA, AB	TK, DL, IJ	AS, CH
17	Kim, J. (2025)	General (Ethics)	AI decision systems	Human judgment, moral reasoning	CO, AB	IJ	EI, AG
18	El Tarhouny & Farghaly (2026)	Medicine	Automation in healthcare	Clinical brain work, decision-making	CO, AB	TK, IJ, NS	AS, LT
19	Savardi et al. (2025)	Medicine (Radiology)	AI-supported training	Diagnostic skills (measurable)	PS, AB	UP, NS	LT (implicit), CH
20	Yang et al. (2026)	Education	Generative AI	Cognitive skills, learning strategies	CO, PS, AB	NS, DL, UP	AS
21	Shen & Tamkin (2026)	Software Engineering	Generative AI (coding)	Conceptual understanding, debugging, code reading	PS, CO	NS, DL, TK	AS, LT
22	Ehsan et al. (2026)	Healthcare (RadOnc)	AI decision aid (RadPlan)	Intuition, manual planning skills, agency	CO, AB, PS	IJ, UP, NS	AG, CH
23	Ferdman (2025b)	General (Structural)	AI deployment across sectors	Professional judgment, agency	PS, AB	IJ, TK	AS, CH, EI
24	Buijsman et al. (2025)	General (Ethics/Tech)	AI decision-support systems	Human autonomy, decision-making, value formation	AB, MR, PS	IJ, DL, UP	AS, AG
25	Ersanli et al. (2025)	General (Policy)	AI systems	Reskilling/upskilling barriers	–	DL, NS	LT, CH, AS
26	Kowalik et al. (2025)	Shared Services	Automation/RPA, AI	Autonomy, cognitive skills	(CA, CO risk)	(UP, TK risk)	AS, LT (as mitigating factors)
27	Woodruff et al. (2024)	Knowledge Work	Generative AI	Perceived industry skills	CO (discussed)	IJ (implied)	CH, LT
28	Cardwell (2024)	Social AI	AI companions	Moral judgment, relational skills	AB, CO, PS	TK, NS, IJ, DL	AG, EI, AS
29	Accenture (2024)	General (Consulting)	Generative AI	Workforce skills, expertise	CO, PS	NS, DL	LT, AS
30	Sambasivan & Veeraraghavan (2022)	AI Development	ML systems (data work)	Domain expertise	CO, CA	TK, UP, NS	AS, AG, EI
31	Gajos & Mamykina (2022)	Education/Health	AI assistance	Incidental learning, cognitive engagement	PS, CO	NS, DL	–
32	Grinschgl & Neubauer (2022)	Cognitive Science	Distributed cognition, AI tools	Cognitive processes, memory	CO, CA	DL	–
33	Anthropic (2026)	General (Economics)	Generative AI	Labour skills, economic tasks	CO, PS	DL, NS, UP, TK	AS, CH, LT
34	Autor & Thompson (2025)	General (Economics)	AI systems	Expertise formation	PS (implicit)	TK, NS, DL	CH, AS
35	Gillespie et al. (2025)	General (Trust survey)	Generative AI tools	Trust/Critical evaluation	CO, PS, AB	DL, UP	LT, EI, CH
36	WEF (2025)	General (Policy)	AI and automation	Future job skills, reskilling gaps	–	NS, DL	CH, LT, AS

Individual Cognitive Mechanisms
CO: Cognitive Offloading
AB: Automation Bias / Complacency
PS: Loss of Productive Struggle
CA: Cognitive Atrophy
MR: Miscalibrated Reliance
OR: Over-Reliance on AI Outputs

Professional Development Risks
NS: Never-skilling
DL: Decoupled Learning
TK: Loss of Tacit Knowledge
IJ: Interrupted Judgmental Cycle
UP: Undermining of Practical Skills

Structural / Org. Factors
CH: Capacity-Hostile Env. (Efficiency > Learning)
LT: Lack of Training / Organisational Support
AG: Accountability / Oversight Gaps
EI: Evaluative Inequality (Bias toward AI)
AS: Automation Strategy (Replacement vs. Augmentation)
AI: Absence of Incentives for Human Oversight