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Deskilling in the Era of Automation: The Hidden Cost of Convenience

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Abstract *- Artificial Intelligence and automated tools have become significant in the current workplace, where their integration has delivered exceptional efficiency. Yet they raise serious concerns related to employees losing their foundational judgement. This research paper focuses on whether the increasing reliance on automated tools leads to erosion of professional foundations (deskilling) and has diminished their analytical capacity. It then evaluates the actionable strategies and policies that the organisations can formulate in order to reduce these risks. This study adopts a research design that utilises a mixture of both primary data and secondary data. Secondary data is collected from existing works, case studies, journals, and literature reviews, whereas primary data has been gathered using a structured survey through a questionnaire answered by professionals or employees working in various sectors to synthesise a detailed analysis. The study reveals that though the emergence of automated tools has made tasks easier, leading to maximising productivity, it also led to the deskilling of personnel over time. To foster the analytical skills and cognitive efficiency of employees, organisations must ensure the intervention of human resources through upskilling strategies such as the implementation of "Human-in-the-loop" frameworks.*

Index Terms *- Artificial Intelligence (AI), deskilling, foundational judgement, hyper-automation, training, workflow automation.*

I. Introduction

Automation has evolved from supporting routine manual labour to shaping cognitive and professional work across multiple domains like accounting, engineering, sales, and administration [1]–[3]. This shift has greatly improved efficiency, productivity, speed, and cost reduction, because of which organisations are increasingly relying on AI-enabled tools for decision-making, analysis, reporting, and service delivery [1], [3], [4]. Despite the convenience that improves efficiency in the short term, it can also lead to the gradual erosion of human skills in the long term [1], [5], [6].

Deskilling is not just the replacement of one task by software. It is a deeper process in which employees lose opportunities to practice work, refine skills, and trust their own expertise [3], [7]. When workers rely on automated outputs excessively, it can make it difficult for them to detect errors, render them less willing to question suggestions, and leave them less confident to act independently if the system fails [1], [8], [9]. Therefore, the concern is not only related to technical proficiency, but also the weakening of the ability to make independent decisions and defend judgments without taking the help of automated tools [9], [10].

This issue matters because modern organizations increasingly expect humans to remain accountable even when machines are heavily involved in decisions [1], [7]. If workers are responsible for outcomes but have lost the competence to verify or override automation, convenience turns into hidden vulnerability [1], [5], [11]. This paper addresses two objectives: first, examining whether employees who rely on automated tools lose foundational judgment over time; and second, analyzing how training programs can mitigate that risk by fostering critical thinking, monitoring skills, and independent judgment [3], [4], [11].

II. Literature Review

The literature on automation and deskilling is broad, establishing that skill decay follows reduced use. Skill decay is generally defined as deterioration in knowledge and ability caused by lack of practice [3], [7]. AI systems cause this by reducing the frequency of skill execution and limiting opportunities for future skill acquisition [3]. Workers may continue to produce acceptable outputs, but the underlying competence required to generate, test, and revise those outputs begins to weaken [1], [7], [12].

Secondly, deskilling often emerges gradually and remains unnoticed. In accounting case studies, growing reliance on automated software led to complacency, reduced mindfulness, and eventually eroded competence maintenance [1]. This erosion often remains obscure until an operational disruption exposes the dependence [1], [12].

Furthermore, cognitive offloading—the delegation of mental work to external systems—exhibits distinct dimensions [4]. Recent scholarship distinguishes between assistive offloading (supporting cognition while preserving user control), substitutive offloading (replacing mental effort), and disruptive offloading (impairing reflection, self-monitoring, and autonomy) [4], [10]. Over-reliance creates an "illusion of competence," causing users to overestimate their understanding while lowering introspection accuracy and critical feedback loops [4].

Another major stream focuses on automation bias—the ten-

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dency to over-rely on automated recommendations even when contradictory evidence exists [8], [9], [13]. It leads to omission and commission errors across novices and experts alike [13]. At an institutional level, organizational norms often make contesting automated suggestions costly or risky, which repositions human disagreement as exceptional behavior and erodes confidence [9].

Sector-specific evidence reinforces these patterns. In aviation, sustained reliance on flight-planning automation degraded pilots' manual calculation and estimation capacities [14]. In healthcare, AI-supported diagnostics risk converting clinicians into passive machine validators, creating clinical and moral deskilling risks [7], [11]. In software engineering, code-generation tools raise task completion speed—especially among junior developers—without guaranteeing equivalent conceptual mastery [12]. However, literature notes that deskilling and upskilling can co-occur [3], [12], [15], highlighting the indispensable role of logic-focused continuous training, AI literacy, reflective prompts, and intentional unsupported practice [3], [4], [6], [8], [11], [16]–[18].

III. Research Objectives

The study is guided by two specific research objectives:

1. To understand the long-term effects of using automated tools on the critical judgement and reasoning ability of employees.
2. To examine the role of training programs in mitigating the risk of deskilling.

IV. Methodology

This study adopts a mixed-method research design combining primary empirical survey data with secondary literature synthesis.

A. Research Design and Primary Data

A structured questionnaire was administered to working professionals across corporate, public, academic, and other sectors. Experience levels ranged from entry-level (< 1 year) to senior staff (> 5 years). The questionnaire measured daily AI tool usage, manual difficulty without tools, troubleshooting confidence, double-checking behavior, autonomy to question AI recommendations, and enterprise training orientation (logic vs. operational). A total of 85 responses were gathered, yielding 80–85 usable responses across analytical tests after listwise deletion of incomplete entries.

B. Measurement Items

Table I summarizes the survey variables and corresponding measurement focus.

Table 1: Survey Variables and Operational Definitions

Variable	Measurement Focus	Scale
Experience	Total professional work experience	Categorical
Industry	Employment sector / industry	Categorical
Department	Specialization / functional area	Categorical
Know_AI	General awareness of AI tools	Binary
AI_use	Daily usage of AI / automation	Binary
Double-Check	Verification of automated results	Likert (1–5)
Difficulty-Manual	Hardship working without tools	Likert (1–5)
Confidence-Fix	Confidence troubleshooting errors	Likert (1–5)
Team-Solve	Team problem-solving ability	Likert (1–5)
Encouraged-Question	utonomy to override AI advice	Likert (1–5)
Training_Type	Focus: process logic vs. software	Categorical
Practice-Manual	Frequency of manual skill practice	Likert (1–5)

V. Primary Data Analysis

A. Pearson Correlation Analysis

To assess associations between manual practice, troubleshooting confidence, and task difficulty, Pearson correlation coefficients were computed across respondents ($N = 80$–85), as displayed in Table II.

Table 2: Pearson Correlation Matrix

Variable Pair	r	p-value	Significance
Practice-Manual × Difficulty-Manual	-0.242	0.031	Significant ($p <$
Practice-Manual × Confidence-Fix	0.390	< 0.001	Significant ($p <$
Double-Check × Confidence-Fix	0.222	0.048	Significant ($p <$
Confidence-Fix × Team-Solve	0.608	< 0.001	Significant ($p <$
Encouraged-Question × Confidence-Fix	0.336	0.002	Significant ($p <$
Difficulty-Manual × Confidence-Fix	-0.197	0.079	Non-sig. trend

Key correlation findings indicate:

- Regular manual practice significantly reduces perceived difficulty when tools are unavailable ($r = -0.242$, $p = .031$) and strongly reinforces troubleshooting confidence ($r = 0.390$, $p < .001$).
- Active verification (Double-Check) correlates positively with troubleshooting confidence ($r = 0.222$, $p = .048$), proving human-in-the-loop habits sustain competence.
- Individual confidence strongly predicts collective team problem-solving efficacy ($r = 0.608$, $p < .001$).
- Autonomy to question AI suggestions elevates individual

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confidence ($r = 0.336$, $p = .002$).

B. One-Way ANOVA Evaluations

1) Training Type: Comparing training models against manual coping ability showed a strong trend ($F = 2.53$, $p = .063$). Employees in organizations focusing deeply on underlying process logic reported significantly lower difficulty coping without automation ($M = 1.25$, $n = 4$–5) compared to those receiving tool-only training ($M = 3.21$, $n = 14$) or no formal training ($M = 2.59$, $n = 34$). Confidence-Fix ($F = 0.73$, $p = .536$) and Practice-Manual ($F = 1.08$, $p = .364$) showed no significant variance across training groups.

2) Work Experience: A significant effect emerged across experience bands on Difficulty-Manual ($F = 3.57$, $p = .018$, $\eta^2 = 0.121$). Tukey HSD revealed that early-career staff (1–3 years experience) experienced significantly higher difficulty performing tasks manually ($M = 4.13$) compared to senior professionals with 5+ years experience ($M = 2.49$, $p = .020$). This demonstrates a generational cohort vulnerability where newer entrants enter pre-automated environments without establishing foundational manual routines.

3) Industry Sector: Sectoral analysis revealed significant variance in automation dependency ($F = 3.93$, $p = .012$, $\eta^2 = 0.131$). Corporate sector employees reported significantly greater difficulty operating without automated tools ($M = 3.31$, $n = 29$) than public sector personnel ($M = 2.37$, $n = 41$, $p = .012$), reflecting deeper algorithmic dependency in private enterprises.

VI. Discussion and Interpretation

The empirical and secondary analyses converge on several strategic realities:

- **Hands-on Practice as Counter-Deskilling Buffer:** Deliberate manual execution remains the single most impactful safeguard against analytical deterioration ($r = 0.39$).
- **Cohort Vulnerability:** Early-career employees face heightened deskilling risks because their baseline training occurs alongside automated assistants, skipping foundational manual struggle.
- **Cognitive vs. Operational Training:** Tool-centric operational training accelerates software adoption but leaves employees defenseless during system anomalies. Training emphasizing process logic shields workers from skill degradation.
- **Organizational Autonomy Culture:** Empowering employees to challenge algorithmic outputs actively preserves critical reasoning and team capability ($r = 0.61$).

VII. Methodological Limitations

The total sample size ($N = 85$) is modest, resulting in small cell sizes for certain subgroups (e.g., deep-logic training group $n = 4$–5; academic sector $n = 5$). Outcome measures relied on self-reported Likert items rather than direct psychometric or task performance tests. Additionally, the cross-sectional nature captures correlational associations rather than direct longitudinal causality.

VIII. Recommendations

Table III outlines core organizational strategies for mitigating deskilling risks.

Table 3: Organizational Strategies to Mitigate Deskilling

Strategy	Operational Focus	Basis
AI Literacy Programs	Educate on algorithmic limits, error modes, and bias	**[6], [8]**
AI-Free Practice	Mandatory manual problem-solving sessions	[7], [11]
Frictional Interfaces	Prompts demanding rationale before tool execution	[4], [8]
Continuous Reskilling	Logic-centered developmental curricula	[16], [17]
Human-in-the-Loop	Cultural permission to override automated advice	[1], [9]

IX. Conclusion

Automation delivers unmatched speed and operational efficiency, but excessive cognitive offloading without deliberate skill preservation leads to insidious deskilling. When professionals lose the foundational capability to verify, critique, and troubleshoot systems independently, convenience transforms into operational fragility. Protecting foundational judgment requires an organizational shift toward cognitive sustainability—pairing automation with logic-based training, intentional manual practice, and an institutional culture that empowers human discernment.

References

[1] T. Rinta-Kahila, E. Penttinen, A. Salovaara, W. Soliman, and J. Ruissalo, "The vicious circles of skill erosion: A case study of cognitive automation," *J. Assoc. Inf. Syst.*, vol. 24, no. 2, 2023.

[2] J. Rafner *et al.*, "Deskilling, upskilling, and reskilling: A case for hybrid intelligence," *Morals & Machines*, vol. 1, no. 2, pp. 24–36, 2021.

[3] S. Morandini *et al.*, "The impact of artificial intelligence on workers' skills: Upskilling and reskilling in organisations," *Informing Sci.*, vol. 26, pp. 39–68, 2023.

[4] B. Jose *et al.*, "Outsourcing cognition: The psychological costs of AI-era convenience," *Front. Psychol.*, vol. 16, Art. no. 1645237, 2025.

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International Journal of Engineering Research & Technology (IJERT)
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[5] V. Azarov and V. V. Gorokhov, "Cognitive offloading or atrophy? Risks of skill degradation and new forms of dependence," in *Proc. IEEE QM&TIS&IT*, 2025, pp. 166–168.

[6] A. Apida *et al.*, "Conceptual review of artificial intelligence over reliance: Opportunities and challenges for employee competencies," *Studi Ilmu Manajemen dan Organisasi*, vol. 6, no. 4, 2026.

[7] C. Natali, L. Marconi, L. D. D. Duran, and F. Cabitza, "AI-induced deskilling in medicine: A mixed-method review," *Artif. Intell. Rev.*, vol. 58, 2025.

[8] G. Romeo and D. Conti, "Exploring automation bias in human–AI collaboration: A review and implications for explainable AI," *AI & Soc.*, vol. 41, pp. 259–278, 2025.

[9] P. Jovchevski, S. Buijsman, and M. A. Neerincx, "What is wrong with automation bias?," *Philos. Technol.*, vol. 39, 2026.

[10] D. A. Garcia-Barrios, "Epistemic partner or cognitive crutch: A conceptual model of cognitive offloading in human–AI collaboration," *IEEE Internet Comput.*, vol. 29, pp. 7–16, 2025.

[11] S. E. A. Tarhouny and A. Farghaly, "Deskilling dilemma: Brain over automation," *Front. Med.*, vol. 13, Art. no. 1765692, 2026.

[12] K. Crowston and F. Bolici, "Deskilling and upskilling with AI systems," *Inf. Res.*, vol. 30, pp. 1009–1023, 2025.

[13] R. Parasuraman and D. Manzey, "Complacency and bias in human use of automation: An attentional integration," *Hum. Factors*, vol. 52, no. 3, pp. 381–410, 2010.

[14] K. Volz and M. Dorneich, "Evaluation of cognitive skill degradation in flight planning," *J. Cogn. Eng. Decis. Mak.*, vol. 14, no. 4, pp. 263–287, 2020.

[15] S. McGuinness, K. Pouliakas, and P. Redmond, "Skills-displacing technological change and its impact on jobs: Challenging technological alarmism?," *Econ. Innov. New Technol.*, vol. 32, pp. 370–392, 2021.

[16] L. Li, "Reskilling and upskilling the future-ready workforce for Industry 4.0 and beyond," *Inf. Syst. Front.*, pp. 1–16, 2022.

[17] K. Iyer, "Upskilling and reskilling for workforce of the future," 2020.

[18] S. K. Bharati and Y. M. Gosavi, "The future of work: Up-skilling strategies in the age of automation," *Scriptora Int. J. Res. Innov.*, vol. 1, no. 5, 2025.

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