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Generative AI Use and Employee Creativity in Banking: A Conservation of Resources Perspective on the Moderating Role of AI Literacy

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Abstract
Purpose – Banks are rapidly deploying generative artificial intelligence (GenAI) tools, yet it is unclear whether these tools make bank employees more or less creative. Drawing on conservation of resources (COR) theory, this conceptual paper develops a model explaining how GenAI use can simultaneously enhance and undermine employee creativity in banking. **Design/methodology/approach** – The paper integrates recent (2025) evidence from management, psychology, economics, human–computer interaction and banking research to build a theory-driven model and a set of testable propositions. **Findings** – The model proposes that GenAI use raises creativity through a resource-gain path (perceived upskilling) and lowers it through a resource-loss path (AI dependence). AI literacy is proposed to strengthen the gain path and weaken the loss path, and therefore to determine which effect dominates. Six propositions formalize these relationships. **Research limitations/implications** – The propositions require empirical testing. The paper sets out a three-wave, multi-source research design and recommended measures for doing so. **Practical implications** – For banks, providing GenAI tools is not enough. Creative returns depend on building employees' AI literacy, designing workflows that protect independent judgment and monitoring over-reliance, which matters especially in a regulated industry where unchecked AI output carries compliance risk. **Originality/value** – The paper is one of the few to theorize both the gain and the loss sides of GenAI use for employee creativity in banking, and it positions AI literacy as a trainable boundary condition.

Keywords: generative AI; employee creativity; banking; conservation of resources theory; AI literacy; AI dependence; conceptual paper

1. Introduction

Generative artificial intelligence has moved from novelty to routine workplace tool in a very short time, and early evidence on its performance effects is encouraging. In a large study of customer-support agents, access to a GenAI assistant raised productivity by roughly 14%, with the largest gains among less experienced workers (Brynjolfsson et al., 2025). Evidence on creativity is also promising: in a field experiment in a technology consulting firm, employees randomly assigned to large language model (LLM) assistance produced more creative ideas, as rated by both supervisors and external evaluators, because the tool supplied cognitive job resources (Sun et al., 2025).

Banking is a particularly important setting for these questions. In a 2025 survey of more than 400 banks worldwide, 11% had already implemented GenAI and a further 43% were in the process of doing so (ABA Banking Journal, 2025). Bank managers interviewed by Moharrak and Mogaji (2025) identified five factors (recognition, requirement, reliability, regulation and responsiveness) that shape whether GenAI integration succeeds in this highly regulated industry. For relationship managers, credit analysts and compliance officers, GenAI can support drafting, summarizing and analysis, and it can also be used to generate new product, service and process ideas.

A parallel stream of research, however, points to hidden costs. In a survey of 319 knowledge workers, greater confidence in GenAI was associated with less critical thinking, and GenAI shifted workers' effort from producing solutions toward verifying and integrating machine output (Lee et al., 2025). Across 666 participants, more frequent AI tool use was linked to weaker critical thinking, largely through cognitive offloading (Gerlich, 2025). Experimental work shows that collaborating with GenAI improves immediate task performance but lowers intrinsic motivation and raises boredom when people return to tasks without AI support (Wu et al., 2025), and that ChatGPT-assisted brainstorming produces a narrower set of ideas than unassisted brainstorming (Meincke et al., 2025). Real-world evidence of deskilling has also emerged: after clinicians began routinely using AI for polyp detection, their detection rate in standard, non-AI procedures fell (Budzyń et al., 2025).

These two streams suggest that GenAI is a double-edged resource for creative work, but the management literature has not yet fully explained when each edge dominates. Three gaps motivate this study. First, much organizational research on GenAI has focused on why employees adopt it, rather than on what happens to their capabilities and creativity after adoption. Recent studies have begun to model both sides at once, showing that GenAI usage can build domain-relevant skills while also increasing dependence on intelligent machines (Guo et al., 2025), and that AI usage can simultaneously raise psychological availability and reduce work alienation (X. Liu & Li, 2025). However, such dual-path evidence on creativity remains scarce.

Second, the boundary conditions of these dual effects are only partly understood. Prior work has examined creative adaptability (Guo et al., 2025) and metacognitive strategies (Sun et al., 2025) as moderators, but AI literacy, a specific and trainable capability for using GenAI well, has not been tested as a factor that both amplifies the benefits and buffers the risks of GenAI for employee creativity. Evidence from a student sample suggests it may play exactly this dual role: AI

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literacy strengthened the positive effect of GenAI adoption on entrepreneurial self-efficacy and weakened its negative effect on fear of failure (Kong et al., 2025). Whether this pattern holds for employees and their creative performance is unknown.

Third, most current evidence comes from Chinese and Western samples drawn from general or mixed industries (e.g., Guo et al., 2025; Y. Liu et al., 2025; X. Liu & Li, 2025), and banking has received little attention despite its distinctive features. Banking combines information-rich knowledge work with strict regulation, so errors in AI output can create compliance and reputational risks (Moharrak & Mogaji, 2025; Saha et al., 2025). These features are likely to intensify both the gains and the losses of GenAI use, which makes banking a revealing context for theory building.

Accordingly, this paper addresses three research questions:

- **RQ1:** Does GenAI use simultaneously increase employees' perceived upskilling and their dependence on AI?
- **RQ2:** Do perceived upskilling and AI dependence carry opposite indirect effects of GenAI use on employee creativity?
- **RQ3:** Does AI literacy strengthen the upskilling path and weaken the dependence path?

This conceptual paper addresses these questions by integrating recent evidence into a COR-based model and deriving six propositions. It makes three contributions. First, it explains why the same GenAI use can both enable and erode creativity by specifying a resource-gain path and a resource-loss path. Second, it identifies AI literacy as a trainable boundary condition that shifts the balance between the two paths. Third, it grounds the model in banking work and offers a research agenda, including a recommended design and measures, to guide empirical testing.

The paper proceeds as follows. Section 2 reviews the theoretical background and the relevant literature, Section 3 develops the propositions, Section 4 illustrates the model with three banking roles, Section 5 sets out a research agenda for testing it, and Sections 6 to 8 discuss contributions, limitations and conclusions.

2. Literature Review and Theoretical Background

2.1 Conservation of resources theory

Conservation of resources (COR) theory holds that people strive to obtain, retain and protect the resources they value, such as skills, energy, knowledge and a sense of control. Two principles are central to this study. First, people invest resources to gain further resources, so that initial gains can build into gain spirals. Second, resource loss is psychologically more salient than equivalent gain, and people who lose resources become less able to invest in demanding activities such as creative work.

COR theory has quickly become a leading lens for studying AI at work. Guo et al. (2025) used it to show that GenAI usage both builds domain-relevant skills, which support creativity, and increases dependence on intelligent machines, which undermines it. Y. Liu et al. (2025) found, in 291 employee pairs, that GenAI adoption encouraged job crafting in the form of seeking resources, seeking challenges and optimizing demands, which in turn raised career commitment. X. Liu and Li (2025) showed in a two-wave study of 279 employees that AI usage raised psychological availability and suppressed work alienation, although high substitution of core tasks by AI could reverse the alienation effect. Sha and Chai (2025) similarly found that digital-AI transformation shaped job crafting through job insecurity, with employees'

AI knowledge acting as a boundary condition. Together, these studies suggest that GenAI can function as a resource that people invest and build on, and as a source of resource threat.

2.2 Generative AI use at work

In this study, GenAI use refers to the frequency and breadth with which employees use GenAI tools to perform their work tasks, such as drafting, analyzing, summarizing, coding and generating ideas. GenAI differs from earlier workplace technologies because it produces content and reasoning, not only information retrieval, so it can take over parts of the cognitive work itself. Sun et al. (2025) argue that LLM assistance provides cognitive job resources that support creative problem-solving. At the same time, how employees make sense of GenAI shapes whether they respond by expanding their work or by withdrawing from it: GenAI awareness can trigger approach-oriented job crafting under some conditions and avoidance-oriented crafting under others (Yan et al., 2025).

2.3 Employee creativity and generative AI

Employee creativity refers to the generation of novel and useful ideas about products, services, processes and procedures at work. Evidence on GenAI's effect on creativity is mixed. On the positive side, LLM assistance increased supervisor- and evaluator-rated creativity in a randomized field experiment, especially for employees with strong metacognitive strategies (Sun et al., 2025). On the negative side, ChatGPT-assisted brainstorming reduced the diversity of ideas generated across participants, even when individual ideas looked original (Meincke et al., 2025). Human–GenAI collaboration has also been shown to lower intrinsic motivation for subsequent unassisted tasks (Wu et al., 2025), and intrinsic motivation is a key driver of creative effort. These mixed results indicate that GenAI's creative value depends on how employees engage with it.

2.4 Perceived upskilling

Perceived upskilling is defined here as an employee's perception that using GenAI has expanded their job-relevant knowledge, skills and problem-solving ability. This construct captures the resource-gain side of GenAI use. It builds on evidence that GenAI usage strengthens domain-relevant skills (Guo et al., 2025) and that GenAI can transfer know-how to less experienced workers, helping them perform closer to their more experienced peers (Brynjolfsson et al., 2025).

2.5 AI dependence

AI dependence refers to excessive reliance on GenAI, such that employees routinely defer to it for thinking tasks they could perform themselves and feel less capable without it. This construct captures the resource-loss side of GenAI use. Goh et al. (2025) developed a Generative AI Dependency Scale with three dimensions (cognitive preoccupation, negative consequences and withdrawal) and found that dependency was associated with lower task performance and critical thinking, and with more procrastination and cognitive failures. Related evidence shows that reliance on AI can reduce critical-thinking effort (Lee et al., 2025), encourage cognitive offloading (Gerlich, 2025) and erode professional skills that are not regularly practiced (Budzyń et al., 2025).

2.6 AI literacy

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AI literacy refers to an employee's ability to understand, use, critically evaluate and responsibly apply GenAI. X. Liu et al. (2025) developed a workplace GenAI literacy scale with five dimensions: basic technical competence, prompt optimization, content evaluation, innovative application, and ethical and compliance awareness. In their study, GenAI literacy had a strong positive effect on job performance, partly through creative self-efficacy. AI literacy is especially relevant as a moderator because, unlike personality traits, it can be developed through training, and it has already been shown to amplify the benefits and buffer the costs of GenAI adoption in a student sample (Kong et al., 2025).

2.7 Generative AI in banking

Banks have long used AI for tasks such as fraud detection and credit scoring, but GenAI extends AI into the language-heavy work that many bank employees perform every day. Adoption is spreading quickly: in a 2025 survey of more than 400 banks, 54% had implemented or were implementing GenAI, and six in ten respondents expected employees to work alongside AI agents as such tools expand (ABA Banking Journal, 2025). A global survey of GenAI in financial institutions maps both its opportunities and its threats and describes a regulatory landscape that is still taking shape (Saha et al., 2025).

Qualitative evidence from bank managers identifies managerial preparedness, regulatory compliance and data privacy as central challenges of GenAI integration, and it points to recognition, requirement, reliability, regulation and responsiveness as the factors that shape its success (Moharrak & Mogaji, 2025). For bank employees, this context carries two implications for the model developed here. Because banking work is information-rich, GenAI can supply substantial cognitive resources. Because banking is heavily regulated, employees who accept AI output without scrutiny expose themselves and their bank to risk, which makes the ability to evaluate AI output, a core part of AI literacy, especially valuable.

3. Propositions Development

Figure 1 summarizes the proposed model. GenAI use is expected to raise creativity through a resource-gain path (perceived upskilling) and to lower it through a resource-loss path (AI dependence), with AI literacy shaping the strength of both paths. Each proposition is followed by an illustration from banking work.

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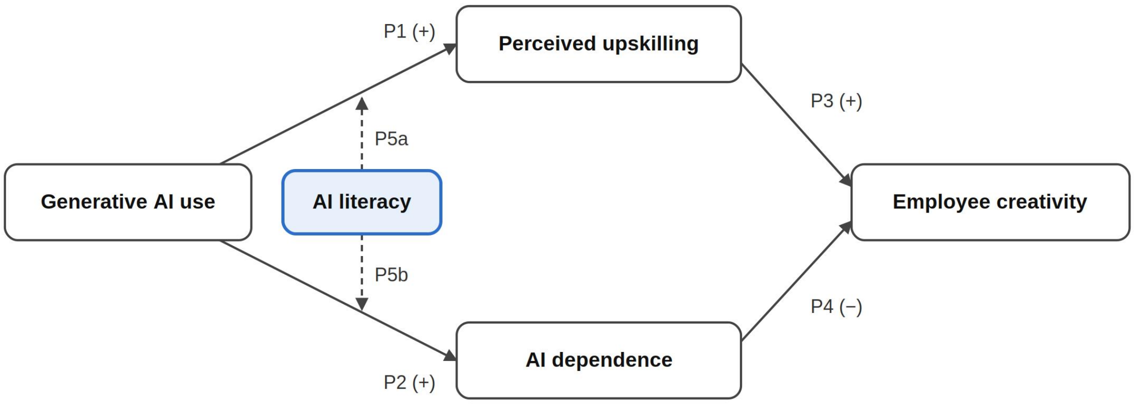
Figure 1
Proposed Research Model



Note. P = proposition. Solid arrows show proposed direct relationships; dashed arrows show moderation by AI literacy (P5a, P5b). P6a and P6b propose that AI literacy also moderates each indirect effect of GenAI use on creativity.

The gain path runs along the top of the model and the loss path along the bottom; AI literacy sits between them because it is expected to strengthen the first and weaken the second.

3.1 GenAI use and perceived upskilling

From a COR perspective, GenAI use gives employees access to a new pool of resources: on-demand explanations, worked examples, alternative perspectives and feedback. Employees who use GenAI to explore unfamiliar problems can convert these inputs into personal resources such as knowledge and skill. Empirically, LLM assistance increased the cognitive job resources available to employees (Sun et al., 2025), GenAI usage enhanced domain-relevant skills (Guo et al., 2025), and GenAI adoption prompted employees to seek new resources and challenges through job crafting (Y. Liu et al., 2025). GenAI also appears to transfer the know-how of experienced workers to less experienced colleagues (Brynjolfsson et al., 2025).

In banking, a junior credit analyst who asks GenAI to explain an unfamiliar financial ratio or an industry-specific risk, and then checks that explanation against the source documents, can build sector knowledge faster than through trial and error alone.

Proposition 1 (P1): GenAI use is positively related to bank employees' perceived upskilling.

3.2 GenAI use and AI dependence

COR theory also implies that people conserve effort when an easier option is available. Because GenAI can produce complete answers at almost no cost, frequent users may increasingly hand over thinking tasks instead of using the tool to support their own thinking. Frequent AI use is associated with more cognitive offloading (Gerlich, 2025), confidence in GenAI is linked to less critical-thinking effort (Lee et al., 2025), and GenAI usage increases dependence on intelligent machines (Guo et al., 2025). Guo et al. (2025) further found that the skill gains from GenAI can themselves deepen dependence, which suggests that the gain and loss paths operate at the same time rather than as alternatives.

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In banking, the same analyst may gradually let GenAI draft entire credit memos, reviewing the wording but no longer working through the numbers, and so lose the habit of independent analysis.

Proposition 2 (P2): GenAI use is positively related to bank employees' AI dependence.

3.3 Perceived upskilling and employee creativity

Creativity requires domain knowledge and the confidence to apply it in new ways. According to COR theory, employees with a richer pool of resources are more able and more willing to invest them in risky, effortful activities such as proposing new ideas. Upskilled employees therefore have more raw material to recombine and more confidence to experiment. Consistent with this view, domain-relevant skills built through GenAI usage supported employee creativity (Guo et al., 2025), and cognitive job resources explained why LLM assistance raised creativity (Sun et al., 2025).

In banking, a relationship manager who has used GenAI to understand a new client segment is better placed to propose an original product bundle or service approach for that segment.

Proposition 3a (P3a): Perceived upskilling is positively related to bank employees' creativity.

Proposition 3b (P3b): Perceived upskilling mediates a positive indirect effect of GenAI use on bank employees' creativity.

3.4 AI dependence and employee creativity

AI dependence represents a resource-loss process. When employees rely on GenAI for thinking they could do themselves, they practice their own problem-solving less, and unpracticed skills can decay, as observed among clinicians who routinely relied on AI (Budzyń et al., 2025). Dependence also weakens the motivational fuel for creativity, since GenAI collaboration reduced intrinsic motivation for subsequent unassisted work (Wu et al., 2025). In addition, dependent users are likely to accept the tool's typical output, which narrows the range of ideas produced (Meincke et al., 2025). Dependency has been directly linked to lower task performance and critical thinking (Goh et al., 2025) and to lower employee creativity (Guo et al., 2025).

In banking, if many staff ask GenAI for ideas to improve a service process and accept its first suggestions, their proposals are likely to converge on the same generic solutions, reducing the variety of ideas the bank can choose from.

Proposition 4a (P4a): AI dependence is negatively related to bank employees' creativity.

Proposition 4b (P4b): AI dependence mediates a negative indirect effect of GenAI use on bank employees' creativity.

3.5 The moderating role of AI literacy

COR theory proposes that people with stronger personal resources are better able to invest resources for gain and are less vulnerable to loss. AI literacy is such a personal resource for GenAI users. Employees with high AI literacy can write better prompts, evaluate output critically and apply GenAI to new problems (X. Liu et al., 2025), so they are more likely to use GenAI as a learning partner. This mirrors the finding that employees with strong metacognitive strategies gained more cognitive job resources from LLM assistance (Sun et al., 2025).

High-literacy employees also understand GenAI's limits and are more likely to verify and adapt its output than to accept it wholesale, which should slow the drift into dependence. Knowledge workers with greater confidence in their own abilities engaged in more critical thinking when using GenAI (Lee et al., 2025). In a related context, AI literacy amplified the positive pathway and weakened the negative pathway of GenAI adoption (Kong et al., 2025).

In banking, two dimensions of AI literacy are especially important: content evaluation and ethical and compliance awareness (X. Liu et al., 2025). A compliance officer who knows that GenAI can misstate or outdate regulatory requirements will check its interpretations against the original circular, learning from the tool without depending on it.

Proposition 5a (P5a): AI literacy moderates the relationship between GenAI use and perceived upskilling, such that the relationship is stronger when AI literacy is high.

Proposition 5b (P5b): AI literacy moderates the relationship between GenAI use and AI dependence, such that the relationship is weaker when AI literacy is high.

3.6 Moderated mediation

Combining the arguments above, AI literacy should shape the indirect effects of GenAI use on creativity through both mediators. Among highly literate bank employees, GenAI use should translate mainly into skill gains and creativity; among less literate employees, it is more likely to translate into dependence and weaker creative contribution.

Proposition 6a (P6a): The positive indirect effect of GenAI use on bank employees' creativity through perceived upskilling is stronger when AI literacy is high.

Proposition 6b (P6b): The negative indirect effect of GenAI use on bank employees' creativity through AI dependence is weaker when AI literacy is high.

4. Illustrating the Model in Banking Work

The same GenAI use can lead a bank employee toward skill gains or toward dependence, depending on how the tool is used. Table 1 maps the two paths onto three common banking roles. The entries are illustrative scenarios derived from the model, not empirical findings.

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Table 1
The Gain and Loss Paths Across Three Banking Roles

Role	Typical GenAI use	Gain path (upskilling)	Loss path (dependence)	How AI literacy helps
Relationship manager	Drafting client proposals and summarizing client needs	Learns faster how to match products to client profiles	Sends generic AI-drafted proposals that converge on the same ideas	Prompts for alternatives and adapts output to each client
Credit analyst	Summarizing financial statements and industry reports	Builds sector knowledge and spots risk factors earlier	Accepts AI summaries without checking the underlying figures	Verifies figures against source documents before concluding
Compliance officer	Interpreting regulatory circulars and drafting policies	Grasps new rules faster and proposes better controls	Relies on AI interpretations that may be inaccurate or outdated	Checks interpretations against the original regulation and escalates doubts

Across the three roles, the pattern is consistent: GenAI creates creative value when employees use it to extend their own thinking, and it creates risk when it replaces that thinking. The regulated nature of banking raises the cost of the loss path, because unverified AI output can lead to compliance breaches (Moharrak & Mogaji, 2025). This is why the content evaluation and ethical and compliance awareness dimensions of AI literacy (X. Liu et al., 2025) are expected to matter more in banking than in less regulated settings.

5. Research Agenda for Testing the Model

The propositions are designed to be testable with a three-wave, multi-source survey of bank employees and their supervisors. This section sets out a recommended design, measures and analytical approach.

5.1 Recommended design

A time-lagged design with employee–supervisor dyads would separate the measurement of predictor, mediators and outcome, and obtain creativity ratings from a different source, which reduces common method bias. Recent COR-based studies of AI at work have used comparable multi-wave designs (X. Liu & Li, 2025; Y. Liu et al., 2025; Sha & Chai, 2025). A suitable sample would include bank employees in knowledge-intensive roles, such as relationship management, credit, risk, compliance, operations and customer service, who use GenAI at least weekly. At least 300 matched dyads would exceed the samples of comparable studies, such as 279 employees (X. Liu & Li, 2025) and 291 employee pairs (Y. Liu et al., 2025).

- **Time 1:** employees report GenAI use, AI literacy and control variables.

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- **Time 2 (about four weeks later):** employees report perceived upskilling and AI dependence.
- **Time 3 (about four weeks later):** supervisors rate each employee's creativity.

5.2 Recommended measures

Table 2

Recommended Measures for Testing the Model

Construct	Wave	Rater	Suggested source
GenAI use	T1	Employee	Adapted from Guo et al. (2025) and Y. Liu et al. (2025)
AI literacy	T1	Employee	GenAI literacy scale with five dimensions (X. Liu et al., 2025)
Perceived upskilling	T2	Employee	Adapted from the domain-relevant skills measure in Guo et al. (2025)
AI dependence	T2	Employee	Generative AI Dependency Scale with three dimensions (Goh et al., 2025)
Employee creativity	T3	Supervisor	Supervisor-rated creativity, following Sun et al. (2025)

Control variables should include gender, age, education, tenure, role, months of prior GenAI experience and whether the bank provides approved GenAI tools, since bank policies on permitted tools vary.

5.3 Analytical approach

Partial least squares structural equation modeling (PLS-SEM) suits this model because it includes two mediators, interaction terms and higher-order constructs (Sarstedt et al., 2025). Researchers should assess the measurement model (reliability, convergent validity and discriminant validity), then estimate path coefficients with bootstrapping, test specific indirect effects for P3b and P4b, and test P5 and P6 with interaction terms, simple slopes and the index of moderated mediation. The PROCESS macro, used in similar AI-at-work research (X. Liu & Li, 2025), offers a useful robustness check.

6. Discussion

This paper argues that GenAI is neither simply good nor simply bad for creativity in banking: its effect depends on whether it builds or replaces employees' own capabilities, and AI literacy decides which of these happens.

6.1 Theoretical contributions

First, the paper extends COR theory to GenAI by specifying how a single technology can trigger resource gain and resource loss at the same time. Rather than treating GenAI as uniformly empowering or harmful, the model explains mixed findings in the literature, such as creativity gains in a field experiment (Sun et al., 2025) alongside narrower idea sets (Meincke et al., 2025) and reduced critical thinking (Lee et al., 2025).

Second, the paper positions AI literacy as a personal resource that shapes how employees invest in and protect their resources when using GenAI. This complements recent work on creative adaptability (Guo et al., 2025) and metacognitive strategies

(Sun et al., 2025) by identifying a boundary condition that organizations can train directly.

Third, the paper shifts attention from why employees adopt GenAI to what sustained use does to their capabilities. It does so in banking, a context that combines information-rich work with strict regulation (Moharrak & Mogaji, 2025), and it argues that this combination raises both the potential gains and the potential costs of GenAI use.

6.2 Practical implications for banks

Build AI literacy, not just access. Banks should pair GenAI roll-outs with training in prompt optimization, critical evaluation of output and responsible, compliant use, which are core dimensions of workplace GenAI literacy (X. Liu et al., 2025). Training that teaches employees to plan, monitor and adjust their use of GenAI is likely to yield larger creative gains (Sun et al., 2025).

Set clear verification rules. Because unverified AI output can create compliance risk, banks should specify which tasks, such as credit decisions, regulatory interpretation and client advice, always require human verification against source documents. This supports the reliability and regulatory factors that bank managers identify as critical to GenAI integration (Moharrak & Mogaji, 2025).

Protect independent thinking. Managers can ask staff to generate their own ideas before consulting GenAI in brainstorming sessions on products or processes, because AI-assisted brainstorming tends to narrow the range of ideas (Meincke et al., 2025). Rotating between AI-assisted and unassisted work can help employees retain core analytical skills (Budzyń et al., 2025).

Monitor over-reliance and motivation. HR teams can include validated items, such as those in the Generative AI Dependency Scale (Goh et al., 2025), in employee surveys to detect early signs of dependence. Because GenAI collaboration can lower intrinsic motivation for later solo tasks (Wu et al., 2025), managers should keep meaningful, challenging parts of work in employees' hands and recognize the human contribution to AI-assisted outputs.

7. Limitations and Future Research

First, as a conceptual paper, this study does not test its propositions. The research agenda in Section 5 offers a starting point, and field experiments that randomly assign GenAI access or AI literacy training, following the approach of Sun et al. (2025), would provide stronger causal evidence.

Second, the model draws on recent evidence that comes mostly from general or mixed-industry samples in China and Western countries. Banking-specific evidence on GenAI and employee creativity is still scarce, so studies in banks, including banks in emerging economies, are needed to confirm whether the proposed relationships hold in this context.

Third, the model focuses on two mediators. Other mechanisms may also link GenAI use to creativity, such as job insecurity (Sha & Chai, 2025), intrinsic motivation (Wu et al., 2025) and job crafting (Y. Liu et al., 2025). Future work could test these alongside the present model.

Fourth, the model is specified at the individual level and over a short period. Gain and loss spirals may unfold over longer periods, so research with more waves and latent growth modeling would clarify how the two paths evolve. Team-level

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studies could examine whether widespread GenAI use narrows the diversity of ideas across a bank's workforce (Meincke et al., 2025).

Finally, GenAI is moving toward autonomous agents that complete multi-step tasks, and many bank employees expect to work alongside such agents (ABA Banking Journal, 2025). Future research should examine whether agentic AI intensifies the dependence path, and whether AI literacy remains protective as tools become more capable. Comparisons with other regulated industries, such as insurance and healthcare, would also test the model's boundaries.

8. Conclusion

Generative AI is neither a creativity machine nor a creativity killer for bank employees; its effect depends on how they use it. Drawing on COR theory, this paper proposes that GenAI use raises creativity by building employees' skills and lowers it by fostering dependence, and that AI literacy determines which path dominates. For banks, the message is that the creative return on GenAI investment depends less on the tools themselves than on the capabilities, workflows and safeguards built around them. The six propositions and the research agenda offered here provide a foundation for testing these ideas empirically.

References

ABA Banking Journal. (2025, May 22). *Survey: Majority of financial institutions deploying generative AI.* https://bankingjournal.aba.com/2025/05/survey-majority-of-financial-institutions-deploying-generative-ai/

Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at work. *The Quarterly Journal of Economics, 140*(2), 889–942. https://doi.org/10.1093/qje/qjae044

Budzyń, K., Romańczyk, M., Kitala, D., Kołodziej, P., Bugajski, M., Adami, H. O., Blom, J., Buszkiewicz, M., Halvorsen, N., Hassan, C., Romańczyk, T., Holme, Ø., Jarus, K., Fielding, S., Kunar, M., Pellise, M., Pilonis, N., Kamiński, M. F., Kalager, M., . . . Mori, Y. (2025). Endoscopist deskilling risk after exposure to artificial intelligence in colonoscopy: A multicentre, observational study. *The Lancet Gastroenterology & Hepatology, 10*(10), 896–903. https://doi.org/10.1016/S2468-1253(25)00133-5

Gerlich, M. (2025). AI tools in society: Impacts on cognitive offloading and the future of critical thinking. *Societies, 15*(1), Article 6. https://doi.org/10.3390/soc15010006

Goh, A. Y. H., Hartanto, A., & Majeed, N. M. (2025). Generative artificial intelligence dependency: Scale development, validation, and its motivational, behavioral, and psychological correlates. *Computers in Human Behavior Reports, 20*, Article 100845. https://doi.org/10.1016/j.chbr.2025.100845

Guo, M., Ma, J., & Tian, H. (2025). The double-edged sword effect of generative artificial intelligence usage on employee creativity: A perspective of conservation of resources theory. *Current Psychology, 44*, 8485–8497. https://doi.org/10.1007/s12144-025-07806-y

Kong, W., Hu, H., Wang, Z., Qiao, J., & Liu, J. (2025). The double-edged sword effect of generative AI adoption on students' sustainable entrepreneurship intentions. *Behavioral Sciences, 15*(12), Article 1705. https://doi.org/10.3390/bs15121705

Lee, H.-P., Sarkar, A., Tankelevitch, L., Drosos, I., Rintel, S., Banks, R., & Wilson, N. (2025). The impact of generative AI on critical thinking: Self-reported reductions in cognitive effort and confidence effects from a survey of knowledge workers. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems* (Article 1121, pp. 1–22). Association for Computing Machinery. https://doi.org/10.1145/3706598.3713778

Liu, X., & Li, Y. (2025). Examining the double-edged sword effect of AI usage on work engagement: The moderating role of core task characteristics substitution. *Behavioral Sciences, 15*(2), Article 206. https://doi.org/10.3390/bs15020206

Liu, X., Zhang, L., & Wei, X. (2025). Generative artificial intelligence literacy: Scale development and its effect on job performance. *Behavioral Sciences, 15*(6), Article 811. https://doi.org/10.3390/bs15060811

Liu, Y., Sheng, F., & Liu, R. (2025). Generative AI adoption and employee outcomes: A conservation of resources perspective on job crafting, career commitment, and the moderating role of liking of AI. *Humanities and Social Sciences Communications, 12*. https://doi.org/10.1057/s41599-025-05656-4

Meincke, L., Nave, G., & Terwiesch, C. (2025). ChatGPT decreases idea diversity in brainstorming. *Nature Human Behaviour, 9*(6), 1107–1109.

Moharrak, M., & Mogaji, E. (2025). Generative AI in banking: Empirical insights on integration, challenges and opportunities in a regulated industry. *International Journal of Bank Marketing, 43*(4), 871–896. https://doi.org/10.1108/IJBM-08-2024-0490

Saha, B., Rani, N., & Shukla, S. K. (2025). *Generative AI in financial institution: A global survey of opportunities, threats, and regulation* [Preprint]. arXiv. https://arxiv.org/abs/2504.21574

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2025). Partial least squares structural equation modeling. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of market research* (pp. 1–56). Springer.

Sha, C., & Chai, T. (2025). When digital-AI transformation sparks adaptation: Job crafting and AI knowledge in job insecurity contexts. *Frontiers in Psychology, 16*, Article 1612245. https://doi.org/10.3389/fpsyg.2025.1612245

Sun, S., Li, Z. A., Foo, M.-D., Zhou, J., & Lu, J. G. (2025). How and for whom using generative AI affects creativity: A field experiment. *Journal of Applied Psychology, 110*(12), 1561–1573. https://doi.org/10.1037/apl0001296

Wu, S., Liu, Y., Ruan, M., Chen, S., & Xie, X.-Y. (2025). Human-generative AI collaboration enhances task performance but undermines human's intrinsic motivation. *Scientific Reports, 15*, Article 15105. https://doi.org/10.1038/s41598-025-98385-2

Yan, Y., Qu, X., Lei, H., & Geng, Y. (2025). Approach or avoidance: How does employees' generative AI awareness shape their job crafting behavior? A sensemaking perspective. *Behavioral Sciences, 15*(6), Article 789. https://doi.org/10.3390/bs15060789