AMERICAN PSYCHOLOGICAL ASSOCIATION

Journal of Applied Psychology

ISSN: 0021-9010

2025, Vol. 110, No. 12, 1561–1573
https://doi.org/10.1037/apl0001296

RESEARCH REPORT

How and for Whom Using Generative AI Affects Creativity: A Field Experiment

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We develop a theoretical perspective on how and for whom large language model (LLM) assistance influences creativity in the workplace. We propose that LLM assistance increases employees' creativity by providing cognitive job resources. Furthermore, we hypothesize that employees with high levels of metacognitive strategies—who actively monitor and regulate their thinking to achieve goals and solve problems—are more likely to leverage LLM assistance effectively to acquire cognitive job resources, thereby increasing creativity. Our hypotheses were supported by a field experiment, in which we randomly assigned employees in a technology consulting firm to either receive LLM assistance or not. The results are robust across both supervisor and external evaluator ratings of employee creativity. Our findings indicate that LLM assistance enhances employees' creativity by providing cognitive job resources, especially for employees with high (vs. low) levels of metacognitive strategies. Overall, our field experiment offers novel insights into the mediating and moderating mechanisms linking LLM assistance and employee creativity in the workplace.

Keywords: generative artificial intelligence, large language models, creativity, metacognitive strategies, cognitive job resources

Supplemental materials: https://doi.org/10.1037/apl0001296.supp

In November 2022, OpenAI launched ChatGPT, a large language model (LLM)-based generative artificial intelligence (AI) that marked a new era in AI technology. LLMs are considered general-purpose technologies akin to steam engines because of their potential to transform how work is done (Eloundou et al., 2023). Corporate investment in LLM tools is surging (Tiwari, 2024), with companies aiming to leverage them to boost employee creativity (Ivcevic & Grandinetti, 2024), defined as the generation of novel and useful ideas (Amabile, 1988). However, a large-scale, nationally representative survey conducted by Gallup found that only 26% of employees using LLM tools report improved creativity (Den Houter, 2024). This raises an important question: Do LLMs increase employee creativity in the workplace?

This question demands rigorous research attention for three key reasons. First, employee creativity is crucial for organizational success, as it drives innovation and enables companies to adapt to changing market demands. By generating creative ideas, employees contribute to the development of new products, services, and processes, ultimately strengthening an organization's competitive advantage (N. Anderson et al., 2014). Second, organizations are increasingly deploying LLMs to boost their competitive edge, with the expectation that they will help enhance employee creativity.

This article was published Online First June 16, 2025.
Fred Oswald served as action editor.
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Shuhua Sun and Zhuyi Angelina Li contributed equally. The authors thank Huaizhong Chen, Jane Minyan Chen, Jiaqi Li, Sophia Yat-Mei Suen, and Anna Manyi Zheng for their helpful feedback on earlier versions of the article.

Shuhua Sun played a lead role in conceptualization, formal analysis, methodology, software, supervision, validation, visualization, writing–original draft, and writing–review and editing. Zhuyi Angelina Li played a lead role in data curation, funding acquisition, investigation, methodology, project administration, resources, and a supporting role in formal analysis. Maw-Der Foo played a lead role in methodology and a supporting role in writing–review and editing. Jing Zhou played a lead role in methodology and a supporting role in conceptualization and writing–review and editing. Jackson G. Lu played a lead role in visualization and writing–review and editing, and a supporting role in conceptualization, methodology, resources, software, supervision, and validation.
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It is, therefore, important to understand the actual impact of LLMs on employee creativity (Ivcevic & Grandinetti, 2024). Third, a review of the existing literature reveals little direct evidence about the impact of LLMs on employee creativity in real-world organizational settings. Most studies on LLMs and creativity were conducted in online or lab settings, and almost all of them focused on isolated, single tasks (e.g., B. R. Anderson et al., 2024; Boussioux et al., 2024; Z. Chen & Chan, 2024; Doshi & Hauser, 2024; Hitsuwari et al., 2023). It remains unclear whether LLMs boost employee creativity in actual workplaces where employees juggle multiple tasks and make complex decisions.

Why might LLMs foster employee creativity? To answer this question, we draw on *the cognitive approach to creativity* (Amabile, 1988; de Jonge et al., 2012; Zhou & Shalley, 2011). According to this perspective, creativity is inherently cognitive, requiring individuals to search within and across knowledge domains to gather diverse information, integrate ideas from multiple sources, and experiment with new ways of approaching tasks (Zhou & Shalley, 2011). From this cognitive viewpoint, *cognitive job resources*—defined as resources essential for addressing the cognitive demands of work—play a central role in fostering creativity (de Jonge et al., 2012; Hargadon, 2002; Niks et al., 2016; Zhou & Shalley, 2011). Cognitive job resources include information and knowledge, as well as “the opportunity to determine a variety of task aspects and to use problem-solving skills”—opportunities to adjust work methods and tasks such as switching between complex and simple tasks and taking mental breaks (de Jonge et al., 2012, p. 328). Information and knowledge are essential for creativity because creativity fundamentally involves recombining and synthesizing information in novel and useful ways (Fleming et al., 2007; Hargadon, 2002). Similarly, opportunities to switch between tasks and take mental breaks are vital for creativity because they allow employees to break fixed mindsets and restore cognitive capacity (Elsbach & Hargadon, 2006; Madjar & Shalley, 2008). Overall, cognitive job resources provide employees with “room to think about existing problems and to develop new and innovative ways of how to handle the cognitive job demands” (de Jonge et al., 2012, p. 326). We thus propose that LLMs can enhance employee creativity by increasing cognitive job resources, as LLMs are capable of providing information and knowledge and assisting with various tasks, which would allow employees to switch between complex and simple tasks and take mental breaks as needed (Acemoglu, 2025; Zhao et al., 2023).

However, this proposition hinges on the assumption that employees can effectively leverage LLMs to acquire these cognitive job resources. To deepen our theorizing, we draw on metacognition research to propose that the cognitive job resources mechanism is more likely to hold for employees with high levels of metacognitive strategies. Metacognition research emphasizes that successfully utilizing tools to acquire task-related resources depends on individuals’ *metacognitive strategies*, which involve “actively analyzing tasks and then planning, self-monitoring, and revising strategies” (P. Chen et al., 2020, p. 14066; Flavell, 1979; Veenman et al., 2004). Specifically, by continuously evaluating tasks and tracking the effectiveness of their strategies, individuals can better determine what information and knowledge they need, as well as when to switch tasks or take mental breaks to restore cognitive capacity and break cognitive fixation (Davidson & Sternberg, 1998; Sun, 2024; Winne & Nesbit, 2010). Consequently, employees with higher (vs. lower) levels of metacognitive strategies are more likely to leverage LLMs effectively to acquire cognitive job resources, thereby increasing creativity.

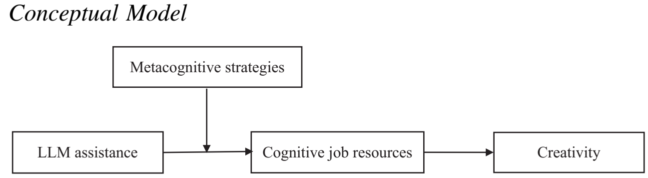
In sum, we hypothesize that for LLMs to enhance employee creativity, employees need high levels of metacognitive strategies to effectively utilize LLMs to acquire the cognitive job resources necessary for generating creative ideas. Figure 1 illustrates our conceptual model. To test our hypotheses, we conducted a field experiment to compare employees’ creativity—assessed with both supervisor and external evaluator ratings—across conditions with and without LLM assistance.

This research offers important empirical, theoretical, and practical contributions. First, by unpacking the mediating and moderating mechanisms that underlie the impact of LLMs on employee creativity in a field experiment, we advance the theoretical and empirical understanding of how and for whom LLMs can enhance creativity in organizational settings. Our findings show that LLMs enhance employees’ creativity by providing cognitive job resources, especially for employees who possess high levels of metacognitive strategies. This suggests that to fully benefit from LLM use, employees must actively adopt metacognitive strategies—analyzing tasks and their own thought processes, planning, self-monitoring, and revising strategies (P. Chen et al., 2020; Flavell, 1979)—rather than being passive consumers of LLMs.

Second, our research contributes to the literature on cognitive job resources by demonstrating how these resources can be enhanced through the effective use of LLMs. While past research has highlighted the positive impact of cognitive job resources on creativity (Amabile & Gryskiewicz, 1987; de Jonge et al., 2012; Elsbach & Hargadon, 2006; Lu et al., 2017; Niks et al., 2016), little attention has been given to the antecedents of cognitive job resources and how these resources can be enhanced through interventions in the workplace.

Third, our study extends the literature on metacognitive strategies by examining how they enable employees to leverage LLMs to enhance cognitive job resources and, in turn, creativity at work. Prior research has mainly examined metacognitive strategies in educational and nonwork contexts (for reviews, see Sun, 2024). By demonstrating their value in organizational settings, our findings suggest that organizations should consider employees’ metacognitive abilities when deploying LLMs. Even the most advanced LLMs may fail to boost creativity if employees lack the metacognitive strategies needed to use them effectively. This insight is practically significant, as metacognitive strategies—though often viewed as an individual difference—can be developed through targeted training (Bell & Kozlowski, 2008; Sun, 2024).

Figure 1
Conceptual Model



Note. LLM = large language model.

Theory and Hypothesis Development

Effect of LLM Assistance on Creativity: The Mediating Role of Cognitive Job Resources

The cognitive approach to creativity underscores the cognitive nature of creativity and the crucial role of cognitive job resources in fostering creativity (Amabile, 1988; de Jonge et al., 2012; Zhou & Shalley, 2011). As Niks et al. (2016, p. 185) summarized: "Only if there are sufficient cognitive resources (such as access to useful information), there is room for thinking about problems and developing new ideas about how to deal with the job demands." Therefore, for LLMs to increase employee creativity, they must be able to provide the cognitive job resources needed to generate creative ideas. Cognitive job resources involve access to information and knowledge (as measured by items such as "I have access to useful information to help solve complex tasks," Van den Tooren & de Jonge, 2010, p. 40) and "the opportunity to determine a variety of task aspects and to use problem-solving skills" (de Jonge et al., 2012, p. 328; as measured by items such as "I have the opportunity to switch between simple and complex tasks"). Below, we review the benefits of these cognitive job resources on employee creativity and theorize how LLMs can increase each of these cognitive job resources.

LLMs can help employees access and process a wide range of *information and knowledge* to generate creative ideas. Information and knowledge are the central ingredients for creativity, as creativity is fundamentally about information and knowledge recombination (Hargadon, 2002). Extensive research highlights the critical role of both a large number of and a diverse body of knowledge bases in fostering creativity (Fleming, 2001; Mumford & Gustafson, 1988). Individuals with access to a large number of knowledge components tend to produce novel ideas because they can experiment with different combinations and recombinations of knowledge (Oldham & Cummings, 1996; Reiter-Palmon & Arreola, 2015). Likewise, individuals with access to diverse knowledge domains tend to produce creative ideas through the uncommon recombination of distinct knowledge bases (Hargadon & Sutton, 1997; Leahey et al., 2017).

Acquiring information and knowledge, however, is a costly process because of what Jones (2009) labeled the "knowledge burden," which refers to the underlying tension between the limited time and cognitive capacity an individual has and the large amount of knowledge the individual needs to acquire for problem-solving (Teodoridis et al., 2019). For instance, searching for information and knowledge requires significant time and effort, as does processing and absorbing them (Leahey et al., 2017). Additionally, to access knowledge outside one's primary domain, an individual needs to invest considerable time and resources in building social networks with people from different areas of expertise who offer diverse perspectives and specialized knowledge that may not be available within the individual's immediate work environment (Perry-Smith, 2006).

LLMs can complement employees by helping them access a diverse array of knowledge bases because LLMs are trained on large corpora of data (e.g., articles, books, and websites) and can summarize and explain information and knowledge in accessible terms (Zhao et al., 2023). Importantly, LLMs can perform these functions—knowledge retrieval, summarization, and elaboration—almost instantaneously. As such, considerable time and resources are conserved, which can be used to experiment with and mull over ideas to solve problems creatively. Moreover, LLMs' efficient processing and elaboration of diverse information reduce the chances of "combinatorial exhaustion"—a situation wherein novel knowledge recombination within a set of knowledge bases is exhausted—that all humans face due to finite knowledge and limited time (Fleming, 2001; Teodoridis et al., 2019).

In addition to information and knowledge, LLM assistance can provide employees with greater *opportunities to adjust work methods and tasks*—such as switching between complex and simple tasks and taking mental breaks, which can foster creativity (de Jonge et al., 2012; Elsbach & Hargadon, 2006). As Elsbach and Hargadon (2006) highlighted in their model of workday design, alternating between complex and simple tasks throughout the workday can facilitate creativity. While complex tasks often stimulate the creative process (Zhou & Shalley, 2003), constantly working on complex tasks can be cognitively straining and ultimately hinder creativity (de Jonge & Dormann, 2006; Sonnentag et al., 2010; Sun et al., 2020). The opportunity to alternate between complex and simple tasks enables employees to focus on complex problem solving while using simpler tasks and mental breaks to restore cognitive capacity and shift away from fixed mindsets (Elsbach & Hargadon, 2006; Lu et al., 2017; Madjar & Shalley, 2008). As a result, creative insights are more likely to "spring to mind" when individuals have the opportunity to switch tasks and take mental breaks after periods of concentration (Beeftink et al., 2008; Smith, 1995).

However, in fast-paced professional environments, employees often have limited opportunities to switch tasks or take breaks (Elsbach & Hargadon, 2006; Pfeffer, 2018). LLMs can expand these opportunities by assisting with a wide range of tasks (Eloundou et al., 2023). For example, employees can delegate routine, repetitive work to LLMs to free up resources for complex problem solving (Davenport & Kirby, 2016). Common tasks such as summarizing text, managing data, and drafting content are well within LLMs' capabilities (Acemoglu, 2025). Moreover, employees can use LLMs for support with complex, cognitively demanding tasks while periodically shifting to simpler ones, allowing them to restore mental capacity and break fixed mindsets. In this way, LLMs' demonstrated capabilities in handling complex, knowledge-intensive tasks (Zhao et al., 2023) make them valuable tools for reducing cognitive overload and optimizing task management in support of creativity.

In sum, we propose that employees can enhance their creativity through LLM assistance by acquiring cognitive job resources. Accordingly, we hypothesize:

> *Hypothesis 1:* Employees with LLM assistance gain more cognitive job resources than employees without LLM assistance.
>
> *Hypothesis 2:* Employees with LLM assistance exhibit higher levels of creativity than employees without LLM assistance.
>
> *Hypothesis 3:* Cognitive job resources mediate the relationship between LLM assistance and employee creativity.

Boundary Condition: The Moderating Role of Metacognitive Strategies

However, access to LLMs does not guarantee that employees can acquire cognitive job resources from their use. Drawing on metacognition research, we propose that metacognitive strategies moderate the relationship between LLM use and the acquisition of cognitive job resources. Metacognitive strategies involve actively monitoring and regulating one's thinking to complete tasks and achieve goals (P. Chen et al., 2020; Flavell, 1979; Sun, 2024). Examples include "thinking through the steps one needs to take to perform tasks," "keeping track of how effective one's approach is," and "reassessing one's approach when noticing a lack of progress" (P. Chen et al., 2020). Through ongoing evaluation of task demands and strategy effectiveness, individuals become more attuned to task difficulty, knowledge gaps, and mental states (Flavell, 1979; Sun, 2024). This awareness enables them to identify needed information and to know when to switch tasks or take breaks to restore cognitive capacity and break rigid thinking (Davidson & Sternberg, 1998; Winne & Nesbit, 2010). Consequently, employees with higher (vs. lower) levels of metacognitive strategies are better equipped to leverage LLMs to acquire cognitive job resources that enhance creativity. Below, we elaborate on the moderating role of metacognitive strategies.

To begin with, employees with high levels of metacognitive strategies can effectively utilize LLMs to acquire helpful information and knowledge that facilitate creative problem solving. These employees actively monitor and evaluate their tasks and cognitive processes, allowing them to recognize their thinking and knowledge gaps (Davidson & Sternberg, 1998). By recognizing these gaps, they can conduct targeted information searches (McCormick, 2003). For instance, by assessing the effectiveness of their problem solving, they can iteratively refine LLM prompts to retrieve more relevant and precise information. This adaptive approach enhances their ability to generate deeper insights and more creative solutions. By contrast, if employees lack the metacognitive strategies to monitor tasks and thinking processes, they will lack awareness of their knowledge gaps (Flavell, 1979). As a result, they may fail to leverage LLMs to acquire relevant information, limiting their creative problem solving.

Besides acquiring information and knowledge, employees with strong metacognitive strategies can effectively leverage LLMs to adjust work methods and tasks—such as switching between complex and simple tasks and taking mental breaks—which foster creativity (Beeftink et al., 2008; Elsbach & Hargadon, 2006). Metacognitive strategies involve analyzing tasks and reflecting on one's problem-solving strengths and weaknesses (P. Chen et al., 2020; Veenman et al., 2004). Employees with high levels of metacognitive strategies keep track of which tasks are better suited for them so that they can delegate other tasks to LLMs (Davenport & Kirby, 2016), freeing cognitive resources for in-depth problem solving and idea generation. Furthermore, metacognitive strategies help employees monitor their cognitive load during cognitively demanding tasks (Sun, 2024; Winne & Nesbit, 2010). This awareness enables them to strategically offload work to LLMs, creating opportunities for mental breaks or transitions to simpler tasks, which help restore cognitive capacity and prevent mental fixation (Elsbach & Hargadon, 2006; Lu et al., 2017).

In sum, metacognitive strategies equip individuals with continuous monitoring and assessment of task demands and problem-solving approaches, enabling them to engage with LLMs effectively to obtain cognitive job resources that enhance creativity. Hence, we hypothesize:

> *Hypothesis 4:* The acquisition of cognitive job resources through LLM assistance depends on an employee's metacognitive strategies. Specifically, employees with higher (vs. lower) levels of metacognitive strategies are more (vs. less) likely to obtain cognitive job resources from LLM assistance.

> *Hypothesis 5:* The mediated effect of LLM assistance on employee creativity via cognitive job resources is moderated by employees' metacognitive strategies. Specifically, the mediated effect is expected to be stronger (vs. weaker) for employees with higher (vs. lower) levels of metacognitive strategies.

Method

Transparency and Openness

The experiment was approved by Renmin University of China (protocol #2023R19). We describe our sampling plan, data exclusions (if any), manipulations, and measures and adhere to the *Journal of Applied Psychology* methodological checklist. This study is not preregistered. Data were analyzed using Stata 16. While we are unable to publicly share the data because of a confidentiality agreement with the firm, the data and materials are available upon request.

Empirical Setting

We conducted our field experiment in a technology consulting firm in China. The company is attuned to technological innovations and, at the time of this research (August 2023), had already established a research unit experimenting with OpenAI's application programming interface (API). It is worth noting that since its initial release, ChatGPT has not been directly available for use in China. However, AI developers in China could access ChatGPT through OpenAI's API service until the service was suspended in 2024 (Reuters, 2024). At the time of our research, the firm's research team had developed an API-based interface and was preparing for internal deployment. We thus exploited this opportunity to implement our randomized field experiment. This consulting firm was also an ideal context for studying the impact of LLMs on employee creativity: Creativity is highly valued in consulting wherein employees need to generate original ideas and develop customized solutions for diverse clients (Lu, 2024; Unsworth, 2001).

Participants and Procedure

All nonmanagerial employees, except those experimenting with ChatGPT API service, were invited to participate, yielding a pool of 286 eligible employees across three departments: technology, sales/consulting, and administration. The study proceeded in three phases. First, eligible employees were invited to attend information sessions. Participants were informed that the study concerned work and work-related behaviors and that they would receive ¥100 as a token of appreciation for completing two surveys. After completing consent procedures, we distributed the initial survey covering demographics and job-related variables. Due to business travel and illnesses, 36 employees did not participate, resulting in a final sample of 250 employees. Among them, 64.8% were male, with an average age of 29.59 years (SD = 4.37); 66.4% held a bachelor's degree, 32.4% a master's degree, and 1.2% a doctoral degree.

Next, on August 7, 2023, participants were randomly assigned to either the treatment or control group using a random number generator. Employees in the treatment group received ChatGPT accounts with usage examples and were instructed that the accounts were for personal use only and not to be shared or discussed with others. To alleviate potential job security concerns, the company informed employees in the treatment group that ChatGPT was intended to assist—not replace—their roles (Yam, Tang, et al., 2023).

Finally, on August 15, 2023, all participants were invited to answer a second survey that measured the mediating and moderating variables, as well as several attitudinal and motivational control measures. Additionally, we invited the employees' direct supervisors and two external raters to evaluate each employee's creativity. Both the supervisors and external raters were blind to our research hypotheses and experimental design. Because our surveys used well-established measures originally in English, three bilingual researchers performed translation and back-translation procedures, cross-checking for accuracy (Brislin, 1970).

Measures

Experimental Conditions and Manipulation Checks

To verify that employees in the experimental group used ChatGPT and employees in the control group did not, we collected self-reported data on ChatGPT usage (0 = *no*, 1 = *yes*) and usage frequency (1 = *never*, 5 = *very often*). All participants in the experimental group reported usage ($M_{\text{frequency}} = 4.14$, $SD = 0.81$), while none in the control group reported any usage ($M_{\text{frequency}} = 1$, $SD = 0$). We also obtained usage logs, which tracked the number of times participants in the experimental group used their ChatGPT accounts ($M = 33.72$, $SD = 8.17$) and confirmed that all employees in the experimental group used ChatGPT.

Dependent Variable: Creativity

To ensure the robustness of our findings, we measured creativity using two complementary approaches. First, employees' direct supervisors rated their general creative performance over the week using Zhou and George's (2001) creativity scale. A sample item is "This employee came up with creative solutions to problems" (1 = *strongly disagree*, 5 = *strongly agree*; α = .97). Supervisors were only approached at the end of the experiment. They were unaware of the experiment and were blind to the study's hypotheses. Second, to supplement supervisor ratings, two external raters independently evaluated employees' responses to a question on privacy protection in the digital workplace. In the second survey, employees were asked to respond to the following: "In today's era of widespread digitalization, companies use numerous digital devices. What suggestions/opinions/methods do you have for protecting employee privacy (e.g., preventing personal information leakage and the possibility of company leadership monitoring every action) when using these digital devices?" They were instructed to provide detailed responses of at least 70 Chinese characters. Following the consensual assessment technique (Amabile, 1982), the raters independently evaluated the novelty and usefulness of each response (1 = *least*, 5 = *most*; Lu et al., 2017). Interrater reliability was good ($ICC_{\text{novelty}} = .78$; $ICC_{\text{usefulness}} = .69$).[1] Importantly, supervisor ratings and external rater ratings were significantly correlated (novelty: $r = .35$, $p < .001$; usefulness: $r = .37$, $p < .001$), reinforcing the validity of our creativity measures.

Mediator and Moderator

Cognitive job resources. We measured cognitive job resources using the scale from de Jonge et al. (2012). Starting with the item stem "Over the last week," a sample item is: "I had access to useful information to help solve complex tasks" (1 = *strongly disagree,* 5 = *strongly agree*; α = .91).

Metacognitive strategies. We measured metacognitive strategies using the scale from P. Chen et al. (2020). A sample item is: "While working towards my goal, I kept track of how effective my approach was" (1 = *never*, 5 = *most of the time*; α = .85).

Controls

Although control variables are not required to test the treatment effects in a randomized experiment, we explored several motivational and attitudinal variables as potential alternative mediators (Liu et al., 2016; Yam, Tang, et al., 2023): creative self-efficacy (Tierney & Farmer, 2011; α = .86), intrinsic motivation (Grant, 2008; α = .82), and job insecurity (Feather & Rauter, 2004; α = .90). To account for job differences, we also controlled for task characteristics, specifically heuristic tasks, which are known to require creative problem solving (Zhou, 2022). We used established measures of heuristic tasks from George and Zhou (2001), including unclear ends (α = .88) and unclear means (α = .84). Additionally, we included employee past job performance from company records given that high and low performers may respond to AI differently (Z. Chen & Chan, 2024). We presented results with controls in the main text and results without controls in the Supplemental Materials to illustrate the robustness of our findings.

Results

Table 1 presents the descriptive statistics. Table 2 summarizes cognitive job resources and creativity measures—supervisor-rated creativity (hereafter, *creativity*) and external-rater-rated novelty (*novelty*) and usefulness (*usefulness*)—across experimental conditions (see Figure 2 for visual illustrations). We formally tested our hypothesis using multilevel analyses given the hierarchical structure of our data: 250 employee participants are nested within 30 supervisors, who are nested within three departments (Bliese & Hanges, 2004).

In support of H1, LLM assistance increased cognitive job resources (Table 3 Model 1: $\gamma = 0.66$, $SE = 0.10$, $p < .001$).

H2 posits that LLM use increases employee creativity. In support of H2, LLM assistance increased creativity (Table 3 Model 2: $\gamma = 0.84$, $SE = 0.10$, $p < .001$) and novelty (Table 3 Model 3: $\gamma = 0.25$, $SE = 0.13$, $p = .049$). Although the effect on usefulness was not significant with controls (Table 3 Model 4: $\gamma = 0.17$, $SE = 0.11$, $p = .136$), it was significant without controls (Supplemental Table S5 Model 4: $\gamma = 0.28$, $SE = 0.11$, $p = .009$).[2]

[1] Cicchetti (1994, p. 286) and Hallgren (2012, p. 32) provided the commonly cited ICC cutoffs, with agreement rated poor (<.40), fair (.40–.59), good (.60–.74), and excellent (0.75–1.0).

[2] Both the independent-samples *t* tests (Table 2; *p* values ranging from .010 to <.001) and the multilevel analyses without control variables (Supplemental Materials S4; *p* values ranging from .006 to <.001) find a consistent treatment effect across all three creativity measures (i.e., supervisor-rated creativity, external-rater-rated novelty, and external-rater-rated usefulness). In the main text, we include models with control variables and additional mediators, which lead to attenuated direct effects of LLM assistance on creativity outcomes.

Table 1
Descriptive Statistics and Correlations of Main Study Variables

Variable	*M*	*SD*	1	2	3	4	5	6
1. LLM assistance condition	0.50	0.50	—					
2. Cognitive job resources	3.76	0.92	.42***	*.91*				
3. Metacognitive strategies	4.07	0.60	.08	.32***	*.85*			
4. Creativity (supervisor rating)	3.60	1.03	.53***	.42***	.07	*.97*		
5. Novelty (external raters' ratings)	2.94	0.97	.17**	.22***	−.01	.35***	—	
6. Usefulness (external raters' ratings)	3.01	0.86	.16*	.27***	−.03	.37***	.64***	—

Note. $N = 250$. Reliability coefficients (Cronbach's α) are presented in italics along the diagonal. LLM assistance condition: 0 = control (no LLM assistance), 1 = experimental (with LLM assistance). LLM = large language model.
* $p < .05$. ** $p < .01$. *** $p < .001$.

H3 posits that cognitive job resources mediate the relationship between LLM use and creativity. As depicted in Table 3, LLM assistance increased cognitive job resources (Model 1: $\gamma = 0.66$, $SE = 0.10$, $p < .001$), which were positively related to creativity (Model 5: $\gamma = 0.21$, $SE = 0.06$, $p = .001$), novelty (Model 6: $\gamma = 0.17$, $SE = 0.08$, $p = .021$), and usefulness (Model 7: $\gamma = 0.22$, $SE = 0.07$, $p = .001$). We tested the indirect effects using parametric bootstrapping with 10,000 repetitions (Preacher et al., 2010). Results supported significant mediation effects: for creativity (indirect effect = 0.14, 95% CI [0.052, 0.236]), novelty (indirect effect = 0.12, 95% CI [0.018, 0.228]), and usefulness (indirect effect = 0.15, 95% CI [0.060, 0.252]). Thus, H3 was supported.

H4 states that acquiring cognitive job resources through LLM use depends on employees' metacognitive strategies. Supporting this, we found a significant interaction between LLM assistance and metacognitive strategies on cognitive job resources (Table 3 Model 8: $\gamma = 0.62$, $SE = 0.16$, $p < .001$). To interpret it, we used two methods. First, we follow Aiken and West's (1991) method to plot simple slopes at 1 *SD* below and above the mean of metacognitive strategies. As shown in Figure 3, when metacognitive strategies were low, LLM use did not significantly increase cognitive job resources ($\gamma = 0.26$, $SE = 0.14$, $p = .067$); however, when metacognitive strategies were high, this relationship became significant ($\gamma = 1.01$, $SE = 0.14$, $p < .001$). Second, we used the Johnson–Neyman technique to pinpoint the levels of metacognitive strategies at which the simple slopes become significant (Preacher et al., 2006). As shown in Figure 4, the simple slopes became significant when mean-centered metacognitive strategies were ≥ -0.58, indicating that employees at or above this threshold benefited from LLM use. Thus, H4 was supported.

H5 posits that the indirect effect of LLM use on creativity via cognitive job resources is moderated by metacognitive strategies. As hypothesized, metacognitive strategies moderated the relationship between LLM assistance and cognitive job resources (Model 8: $\gamma = 0.62$, $SE = 0.16$, $p < .001$), which were in turn related to creativity (Model 9: $\gamma = 0.23$, $SE = 0.06$, $p < .001$), novelty (Model 10: $\gamma = 0.16$, $SE = 0.08$, $p = .041$), and usefulness (Model 11: $\gamma = 0.22$, $SE = 0.07$, $p = .001$). We used parametric bootstrapping to estimate conditional indirect effects at 1 *SD* above and below the mean of metacognitive strategies. When metacognitive strategies were high, the indirect effects were significant for creativity (0.23, 95% CI [0.099, 0.375]), novelty (0.16, 95% CI [0.008, 0.328]), and usefulness (0.22, 95% CI [0.083, 0.376]). When metacognitive strategies were low, the effects were nonsignificant: creativity (0.06, 95% CI [−0.005, 0.142]), novelty (0.04, 95% CI [−0.006, 0.118]), and usefulness (0.06, 95% CI [−0.005, 0.142]). In all cases, the difference between the conditional indirect effects at high versus low levels of metacognitive strategies was statistically significant: creativity ($\Delta = 0.17$, 95% CI [0.057, 0.315]), novelty ($\Delta = 0.12$, 95% CI [0.005, 0.267]), and usefulness ($\Delta = 0.16$, 95% CI [0.050, 0.314]). Thus, H5 was supported.

Exploratory Analyses and Robustness Tests

Our findings show that metacognitive strategies moderated the effect of LLM assistance on cognitive job resources, which in turn affected employee creativity. Because the cognitive job resources scale contains multiple items capturing different aspects of job resources, we conducted exploratory analyses at the item level (Supplemental Tables S1–S4). These analyses yielded results similar to those observed for the overall scale, suggesting that the effects are robust across different aspects of the construct. We also ran a set of robustness tests on the moderating role of metacognitive strategies and assessed the practical significance of the moderated mediation effects, which were reported in Supplemental Sections S6–S8.

Discussion

Theoretical Contributions

First, our research contributes to the emerging literature on LLMs and creativity by investigating the impact of LLMs on employee creativity in the workplace. Unlike existing research that relied on the single-task paradigm in online and lab settings (e.g., B. R. Anderson et al., 2024; Boussioux et al., 2024; Z. Chen & Chan, 2024; Doshi & Hauser, 2024), our field experiment captures the complex, multitask nature of organizational work. Importantly, we advance a theory that explains *how* and *for whom* LLM use enhances creativity in the workplace. Regarding the *how* question, our study highlights that LLM use enhances employee creativity by providing cognitive job resources. This mediating role of cognitive job resources—such as opportunities to switch between simple and complex tasks and to take mental breaks—cannot be detected in the single-task paradigm used in prior research. Regarding the *for whom* question, we identify the moderating role of metacognitive strategies, which enable employees to leverage LLMs to acquire cognitive job resources that boost creativity. Because prior experiments often constrained how participants interacted with LLMs, such as through predefined prompt engineering techniques, their research designs prevented participants from using metacognitive strategies to leverage LLMs for creative problem solving. Overall, our field experiment advances a new understanding of the mediating and moderating mechanisms that underlie the impact of LLMs on employee creativity.

Second, an instructive finding of our study is the significant moderating role of metacognitive strategies, indicating that LLM use does not automatically enhance creativity; rather, it depends on how employees engage with LLMs. Specifically, employees with high levels of metacognitive strategies—those who actively analyze tasks, monitor their thought processes, and adjust their approaches (P. Chen et al., 2020; Flavell, 1979)—are better positioned to harness LLMs in ways that foster creativity. By continuously evaluating tasks and assessing the effectiveness of their approaches, these employees can more effectively identify what information they need and when to switch tasks or take mental breaks to restore cognitive capacity (Davidson & Sternberg, 1998; Sun, 2024). Our findings thus highlight the importance of actively monitoring and regulating one's thinking when using LLMs for creative work, offering a valuable theoretical lens for future studies at the intersection of LLMs and creativity.

Third, our research contributes to the theory and research on cognitive job resources. While prior research has highlighted the importance of cognitive job resources in fostering creativity, little attention has been given to their antecedents. Our research identifies LLMs as a *technological source* of cognitive job resources, thus extending this concept beyond conventional job design factors (de Jonge & Dormann, 2006; Oldham & Fried, 2016). Further, although traditional AI tools and human mentors or experts can also provide cognitive job resources, LLMs are fundamentally distinct. Traditional AI tools—such as decision support systems or customer service chatbots—are typically narrow in scope and designed for codifiable, repetitive tasks (Acemoglu, 2025; Autor, 2014). By contrast, LLMs constitute a different class of technology, offering broad, *general-purpose* capabilities (Eloundou et al., 2023).[3] Additionally, unlike human mentors, LLMs offer immediate access to an extensive body of information and knowledge—far exceeding what any single expert, or even a group of experts, can realistically provide (Luo et al., 2025). LLMs also provide flexible, on-demand support for diverse tasks, enabling efficient task switching and mental breaks—support that would be difficult to request repeatedly from human mentors. These distinctions highlight LLMs as a unique and scalable source of cognitive job resources. We further contribute by demonstrating that metacognitive strategies interact with LLM use to shape the acquisition of cognitive job resources, providing a more nuanced understanding of how cognitive job resources emerge through human–AI collaboration.

Practical Implications

Our findings offer practical guidance for organizations considering LLM deployment to boost employee creativity. We show that LLMs enhance employee creativity by providing cognitive job resources, suggesting that organizations should leverage LLMs to boost these cognitive job resources and encourage employees to actively use LLMs to acquire these resources for creativity. Critically, our findings

Table 2
Summary Statistics by Conditions

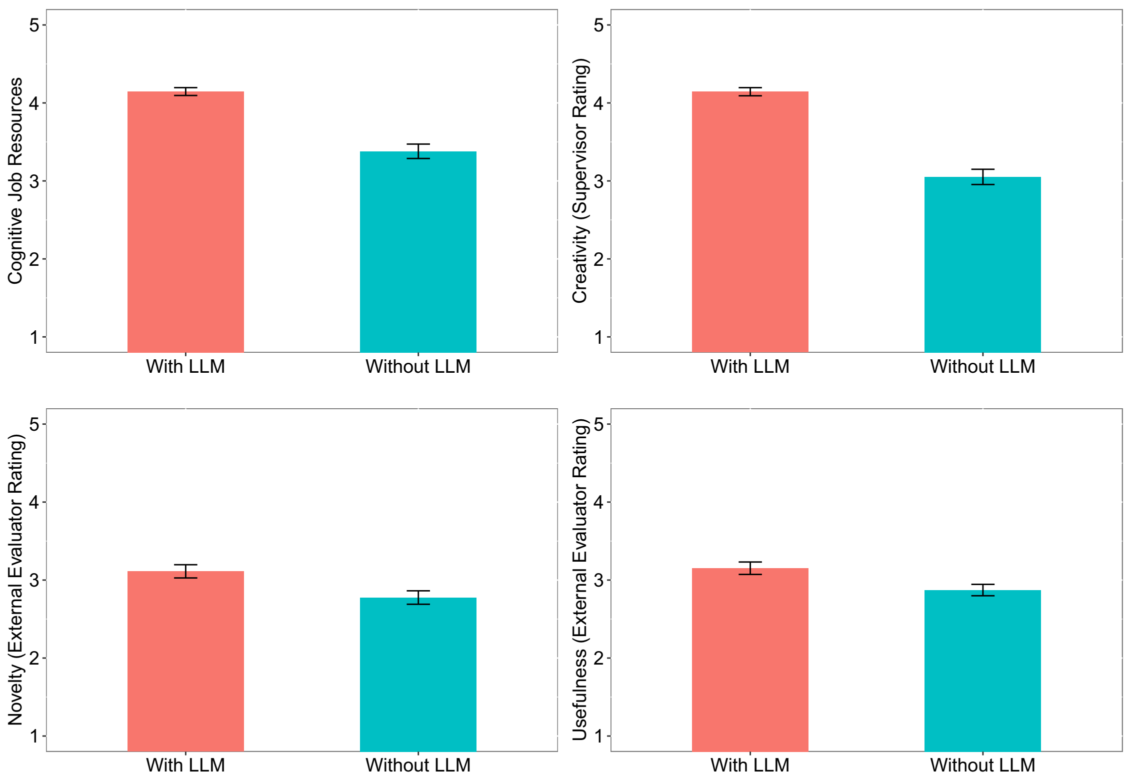
Statistic	Cognitive job resources		Creativity (supervisor rating)		Novelty (external raters' rating)		Usefulness (external raters' rating)	
	Control condition	LLM assistance condition	Control condition	LLM assistance condition	Control condition	LLM assistance condition	Control condition	LLM assistance condition
M	3.38	4.15	3.05	4.14	2.78	3.11	2.87	3.15
SD	1.03	0.56	1.09	0.58	0.96	0.95	0.82	0.89
p value of *t*-test		.000		.000		.006		.010
Cohen's *d*		0.92		1.25		0.35		0.33

Note. LLM = large language model.

[3] Unlike traditional web search engines such as Google, LLMs generate responses based on context, enabling them to synthesize and integrate disparate pieces of knowledge into coherent, accessible outputs rather than merely presenting a list of web pages (Lee & Chung, 2024; Zhao et al., 2023). Traditional search engines also lack the capacity to support the wide range of cognitive tasks that LLMs, as general-purpose technologies, can facilitate (Eloundou et al., 2023; Zhao et al., 2023).

Figure 2

Mean Levels of Cognitive Job Resources and Creativity (Rated by Supervisor and External Raters) Across Experimental Conditions



Note. Error bars indicate standard errors. LLM = large language model. See the online article for the color version of this figure.

highlight the enabling role of employees' metacognitive strategies in leveraging LLMs to acquire these resources. Organizations should therefore consider employees' metacognitive abilities when implementing LLMs and invest in developing these abilities through training. Notably, metacognitive strategies, while often viewed as individual differences, are teachable through interventions (for reviews, see Sun, 2024). Such interventions range from brief social–psychological exercises (e.g., P. Chen et al., 2017, 2020) and training sessions (e.g., Bell & Kozlowski, 2008; Keith & Frese, 2005) to longer programs spanning several days or weeks (e.g., Carpenter et al., 2019; Dierdorff & Ellington, 2012). For instance, P. Chen et al. (2020) developed a brief online exercise using anecdotes and research findings to enhance metacognitive strategies, while Keith and Frese (2005) showed that a 2.5-hr training combining metacognitive instruction and error management significantly improved these abilities. Depending on budget and priorities, organizations may adopt brief interventions or more extensive programs. Organizations may also combine training with selective hiring, though the latter's cost-effectiveness may vary with labor market conditions (Weinstein, 2018).

Limitations and Future Directions

First, our reliance on self-reported metacognitive strategies is a limitation. However, given that the metacognitive strategies involve personal awareness and regulation, self-reporting remains the most direct and practical method for assessment in large participant groups (Craig et al., 2020). Despite this limitation, several features of our design mitigate biases associated with self-reported data (e.g., common method variance). One mitigating factor is that the independent variable was experimentally manipulated, while the dependent variables were assessed by supervisors and external raters, reducing the risk of common method variance (Podsakoff et al., 2003). Further, we focused on the moderating effects of metacognitive strategies, and research shows that "interaction effects cannot be artifacts of CMV" (Siemsen et al., 2010, p. 456).

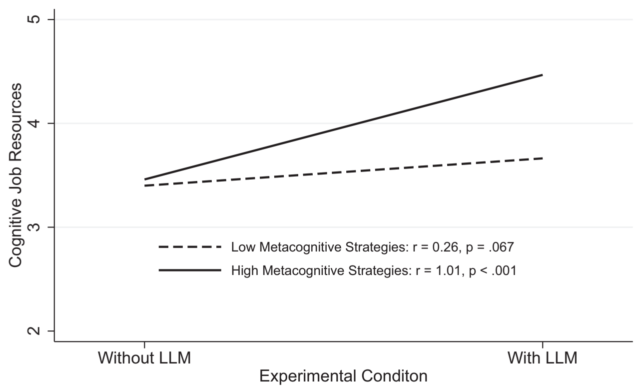
Second, while our findings show that metacognitive strategies moderate whether employees can use LLMs to acquire cognitive job resources for creativity, future research should explore additional individual-difference moderators. Complementing our cognitive perspective, motivational factors may also shape how employees engage with LLMs to enhance cognitive job resources and, in turn, creativity. For instance, learning goal orientation—the motivation to develop new skills and master new situations (Dweck, 1986)—may also moderate the relationship between LLM assistance and cognitive job resources. Individuals high in learning goal orientation are eager to acquire new knowledge (Vandewalle et al., 2019) and may use LLMs more effectively to gather information, thereby boosting their creative potential. Similarly, promotion focus—the motivation to

Table 3
Multilevel Regressions for Hypothesis Testing

Variable	Model 1: Cognitive job resources	Model 2: Creativity (supervisor rating)	Model 3: Novelty (external raters' rating)	Model 4: Usefulness (external raters' rating)	Model 5: Creativity (supervisor rating)	Model 6: Novelty (external raters' rating)	Model 7: Usefulness (external raters' rating)	Model 8: Cognitive job resources	Model 9: Creativity (supervisor rating)	Model 10: Novelty (external raters' rating)	Model 11: Usefulness (external raters' rating)
Intercept	3.43*** (0.07)	3.17*** (0.08)	2.82*** (0.09)	2.93*** (0.08)	2.47*** (0.22)	2.22*** (0.27)	2.16*** (0.24)	3.43*** (0.07)	2.40*** (0.23)	2.27*** (0.28)	2.17*** (0.24)
LLM assistance condition	**0.66*** (0.10)**	**0.84*** (0.10)**	**0.25* (0.13)**	**0.17 (0.11)**	0.71*** (0.11)	0.13 (0.13)	0.02 (0.12)	0.63*** (0.10)	0.70*** (0.11)	0.13 (0.13)	0.02 (0.12)
Cognitive job resources					**0.21** (0.06)**	**0.17* (0.08)**	**0.22** (0.07)**		**0.23*** (0.06)**	**0.16* (0.08)**	**0.22** (0.07)**
Metacognitive strategies								0.05 (0.15)	0.01 (0.15)	−0.51** (0.19)	−0.43** (0.16)
LLM Assistance Condition × Metacognitive Strategies								**0.62*** (0.16)**	−0.17 (0.17)	0.45* (0.21)	0.32 (0.18)
Heuristic task characteristics: Unclear means	0.13 (0.11)	−0.01 (0.11)	−0.01 (0.13)	0.15 (0.12)	−0.03 (0.10)	−0.04 (0.13)	0.12 (0.12)	0.11 (0.11)	−0.03 (0.10)	−0.02 (0.13)	0.14 (0.11)
Heuristic task characteristics: Unclear ends	0.01 (0.10)	−0.02 (0.10)	0.01 (0.12)	−0.17 (0.11)	−0.02 (0.10)	0.01 (0.12)	−0.17 (0.11)	0.03 (0.10)	−0.02 (0.10)	0.00 (0.12)	−0.18 (0.11)
Past job performance	0.01 (0.02)	0.02 (0.02)	0.02 (0.02)	0.02 (0.02)	0.01 (0.01)	0.02 (0.02)	0.02 (0.02)	0.01 (0.01)	0.01 (0.01)	0.03 (0.02)	0.02 (0.02)
Job insecurity	−0.02 (0.06)	0.01 (0.06)	0.02 (0.07)	0.04 (0.06)	0.01 (0.05)	0.02 (0.07)	0.05 (0.06)	0.01 (0.06)	0.01 (0.06)	−0.00 (0.07)	0.02 (0.06)
Creative self-efficacy	0.09 (0.06)	0.50*** (0.06)	0.13 (0.08)	0.16* (0.07)	0.48*** (0.06)	0.12 (0.08)	0.14* (0.07)	0.11 (0.06)	0.47*** (0.06)	0.13 (0.08)	0.15* (0.07)
Intrinsic motivation	0.27*** (0.07)	0.00 (0.07)	0.04 (0.09)	0.02 (0.08)	−0.05 (0.07)	−0.01 (0.09)	−0.04 (0.08)	0.12 (0.10)	−0.03 (0.10)	0.20 (0.13)	0.15 (0.11)
Variance (Level 3 intercept)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Variance (Level 2 intercept)	0.00 (0.02)	0.04 (0.03)	0.00 (0.02)	0.00 (0.00)	0.03 (0.03)	0.00 (0.02)	0.00 (0.00)	0.01 (0.02)	0.03 (0.04)	0.00 (0.00)	0.00 (0.00)
Variance (Level 1 residual)	0.60 (0.06)	0.56 (0.05)	0.88 (0.08)	0.69 (0.07)	0.53 (0.05)	0.87 (0.08)	0.66 (0.06)	0.55 (0.05)	0.53 (0.05)	0.84 (0.08)	0.64 (0.06)
Pseudo R^2	0.14	0.22	0.02	0.01	0.04	0.02	0.04	0.06	0.05	0.02	0.04

Note. $N = 250$. Standard errors are presented in parentheses. LLM assistance condition: 0 = control (no LLM assistance), 1 = experimental (with LLM assistance). All continuous variables are mean centered. Values in presented in bold are relevant to hypothesis testing. LLM = large language model.
$^{*} p < .05$. $^{**} p < .01$. $^{***} p < .001$.

Figure 3
The Moderating Patterns of Metacognitive Strategies: Simple Slopes



Note. LLM = large language model.

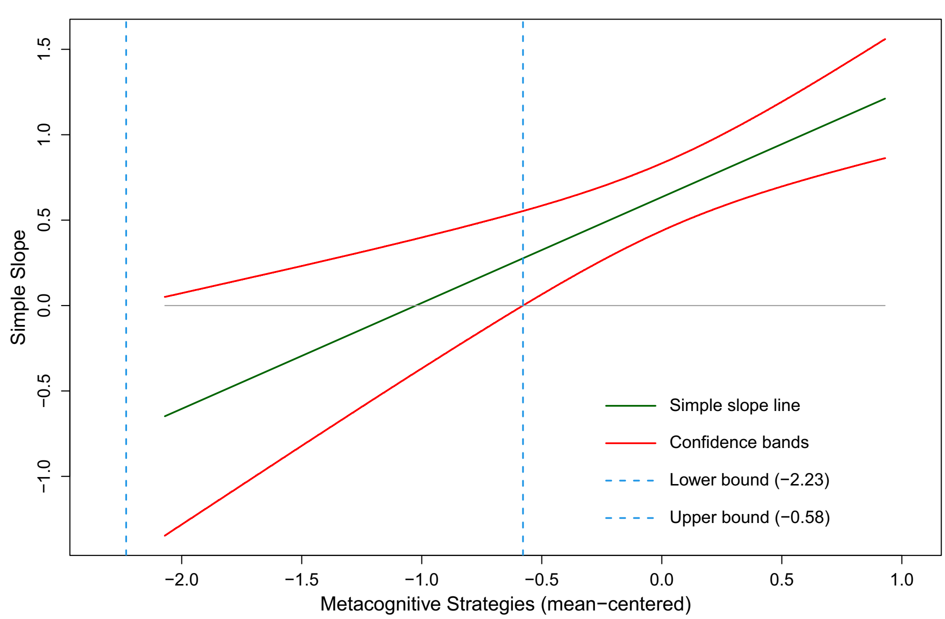
pursue advancement and positive outcomes (Higgins, 1997)—may encourage employees to proactively leverage LLMs to tackle complex problems, thereby increasing creative potential. Moreover, given the moderating role of metacognitive strategies observed in our experiment, future research could also examine whether motivational factors influence the use of metacognitive strategies, thus shaping the impact of LLMs on cognitive job resources and creative outcomes.

Third, our field experiment was conducted within a single organization in China. Although our theory is not tied to a specific organization or culture, the generalizability of our findings remains an open empirical question. Individuals from different cultures may differ in their attitudes toward AI (Yam, Tan, et al., 2023), and LLM outputs can reflect cultural tendencies embedded in the training data or shaped by the language of prompts (e.g., English vs. Chinese; Lu et al., in press). This raises questions about the reinforcement of cultural norms through LLMs, which is an important topic for future research.

Fourth, organizations are multilevel, with individuals nested within teams and broader organizational systems. Because cognition and behavior are shaped by contexts (Johns, 2018), future research should examine how team- and organizational-level factors influence the cognition-based mechanisms in our model. For example, team or organizational environments that emphasize active thinking—such as those involving explorations, errors, or challenge stressors—may foster metacognitive strategies (Keith & Frese, 2005; Sun, 2024). Additionally, organizational and team norms around LLM use may shape employees' attitudes toward adoption and usage (Kodapanakkal et al., 2020; Qin et al., in press), ultimately impacting their ability to access cognitive job resources critical for creativity.

Finally, future research should explore the long-term effects of extended LLM use. The Matthew effect (Rigney, 2010) suggests that individuals with initial advantages, such as strong metacognitive strategies, may experience compounding benefits over time. However, prolonged reliance on LLMs may also carry downsides. For instance, employees who initially enhance creativity through LLM-assisted cognitive job resources may become increasingly

Figure 4
The Moderating Patterns of Metacognitive Strategies: Regions of Significance Using the Johnson–Neyman Technique



Note. Simple slopes for cognitive job resources between the lower bound (−2.23) and the upper bound (−0.58) are not statistically significant, as the confidence bands contain zero within this range. The plot indicates that simple slopes become significant when mean-centered metacognitive strategies reach or exceed −0.58 (equivalent to a raw score of 3.49). See the online article for the color version of this figure.

dependent on these tools, potentially reducing autonomy, learning, and networking—factors essential for sustaining creativity over time. These contrasting possibilities underscore the need to identify conditions under which such divergent outcomes may emerge. Longitudinal studies tracking cohorts of employees over extended periods would enable researchers to examine not only changes in creativity but also whether patterns of LLM use contribute to skill development or overreliance that impairs independent thinking. These questions await future research.

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Received November 28, 2024
Revision received March 31, 2025
Accepted April 7, 2025 ■