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Why AI does not always enhance employee creativity: Metacognitive calibration and AI engagement in human–AI innovation systems

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Abstract

Artificial intelligence (AI) is widely assumed to enhance creativity in knowledge work, yet empirical findings reveal substantial variability in its effects. Addressing this inconsistency, the present study advances a metacognitive explanation by integrating metacognitive calibration theory with AI engagement research. We propose that calibration bias, the discrepancy between perceived and actual cognitive competence, influences creativity indirectly through behavioral engagement with AI systems as algorithmic support tools. Drawing on social cognitive theory, we develop a mediation model in which calibration bias predicts AI engagement, which in turn predicts supervisor-rated creativity. We further examine whether AI use intensity moderates this relationship. Using a time-lagged, multi-source design, data were collected from 437 employees nested within 58 supervisors in Islamic banking institutions and analyzed using Mplus-based structural modeling. Calibration bias positively predicts AI engagement, which in turn enhances creativity. Bootstrapped mediation analysis indicates a significant positive indirect effect of calibration bias on creativity through AI engagement, supporting partial mediation. However, AI use intensity does not significantly moderate the relationship between calibration bias and AI engagement. The findings contribute to theory by extending metacognitive calibration research into AI-augmented organizational contexts and reframing AI-assisted creativity as a metacognitively contingent process within AI-enabled work systems rather than a purely technological outcome. By identifying AI engagement as the behavioral mechanism linking metacognitive discrepancy to creative performance, this study advances a process-based understanding of human–AI collaboration.

Keywords: Artificial intelligence; Metacognition; Artificial intelligence engagement; Creativity; Human–artificial intelligence interaction; Process innovation; Developing countries

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1. Introduction

Artificial intelligence (AI) systems, as algorithmic support systems, are increasingly embedded in knowledge work, reshaping how employees search for information, generate ideas, and solve problems (Joksimovic *et al.*, 2023; Raisch & Fomina, 2025). From large language models to decision-support algorithms, AI is frequently framed as a cognitive augmenter capable of enhancing human creativity and performance within human–AI innovation processes (Boussieux *et al.*, 2024; Brynjolfsson & McAfee, 2014; Davenport & Ronanki, 2018). Recent empirical work, however, suggests that AI does not uniformly enhance creative outcomes. Instead, its impact varies across individuals and contexts (Bouschery *et al.*, 2023; Dell'Acqua *et al.*, 2026). This variability suggests that the effectiveness of AI depends not only on its technical capabilities but also on how individuals cognitively regulate their interaction with algorithmic outputs. These mixed findings raise a central question: why do some employees benefit from AI-assisted work while others do not?

Most prior research has examined AI from a technological affordance perspective, emphasizing system capabilities such as generative capacity, explainability, and interaction design (Faraj *et al.*, 2018; Raisch & Krakowski, 2021). While valuable, this perspective overlooks a critical metacognitive dimension: the metacognitive assumptions individuals bring to AI-mediated tasks. Human–AI collaboration is not merely a function of algorithmic capabilities but also of how individuals perceive and evaluate their own cognitive competence when interacting with intelligent systems (Jarrahi, 2018). Understanding this metacognitive layer is essential for explaining variability in AI-assisted creativity. One theoretically relevant construct is metacognitive calibration bias. Calibration refers to the degree of correspondence between perceived competence and objective ability (Kruger & Dunning, 1999; Lichtenstein & Fischhoff, 1982). Individuals often exhibit systematic discrepancies between self-assessments and actual performance, either overestimating or underestimating their capabilities. Calibration bias has been shown to influence learning behavior, feedback seeking, and performance regulation (Sitzmann & Yeo, 2013; Vancouver & Carlson, 2015). Yet, despite growing interest in AI-enabled work, little is known about how calibration bias shapes engagement with AI systems and subsequent creative performance.

This gap in the literature is consequential. AI systems function as algorithmic support systems that structure cognitive processing that can complement or substitute human judgments (Raisch & Krakowski, 2021). However, whether individuals treat AI as a complementary partner

or an auxiliary tool may depend on how accurately they assess their own cognitive strengths and limitations. This is particularly relevant in AI contexts where outputs are probabilistic and require iterative prompting, evaluation, and refinement. Conceptually, employees who overestimate their questioning and problem-framing abilities may underutilize AI input, whereas those who underestimate themselves may either over-rely on AI or disengage strategically. In either case, discrepancies between perceived and actual competence may shape patterns of AI engagement, thereby influencing creative outcomes. To address this gap, we integrate metacognitive calibration theory with research on AI engagement and creativity. Creativity involves the production of ideas that are both novel and useful (Amabile, 1988; Zhou & George, 2001). AI systems can expand ideational search spaces and recombine knowledge in novel ways, but such benefits are contingent upon active cognitive integration (Bouschery *et al.*, 2023; Hoßbach & Isaksen, 2025). We conceptualize AI engagement not as simple usage frequency but as the depth with which individuals incorporate AI into iterative problem-solving processes in interacting with algorithmic outputs. We propose that calibration bias influences this engagement process, which in turn shapes supervisor-rated creativity. Accordingly, our central research question is, how does metacognitive calibration bias influence AI-assisted creativity, and through what metacognitive mechanism does this occur?

We propose a mediation model in which calibration bias predicts AI engagement with algorithmic outputs, which, in turn, predicts creativity. We further explore whether AI use intensity moderates the first stage of this process, testing whether frequency-based interaction with AI systems strengthens or weakens the calibration–engagement relationship. Despite a growing body of AI augmentation research and its understanding in workplaces, a dominant assumption remains in both practice and emerging empirical research that access to AI systems and resources fundamentally enhances the generation of creative ideas and workplace performance (Jia *et al.*, 2024; Qin *et al.*, 2023; Xie *et al.*, 2026). However, augmentation is not an automatic technological property; AI augmentation is enacted through human cognition and the consistency and intensity of the efforts individuals put into the activities. If individuals differ in how they perceive their own cognitive competence, then AI effectiveness may fundamentally depend on metacognitive alignment rather than technological sophistication, specifically, the alignment between perceived and actual cognitive capability during interaction with algorithmic systems. This theoretical tension is between AI as a universal enhancer and AI as a metacognitively contingent resource

within algorithmic work systems.

This research offers several contributions to the literature. First, this study extends calibration theory into the domain of human–AI collaboration. Although calibration bias has been extensively studied in workplace judgments and learning contexts (Kruger & Dunning, 1999; Vancouver & Carlson, 2015), its significant role and implications for AI-assisted cognition remain underexplored in management research. In this study, we demonstrated that metacognitive discrepancies among employees shape how they engage with intelligent systems. Second, we contribute to the AI-creativity literature by identifying AI engagement as a metacognitive underlying mechanism that links individual cognition to their creative performance. Prior research on AI and the creativity of individuals has shown that AI can enhance productivity and idea generation (Dell'Acqua *et al.*, 2026), but less attention has been given to the individual-level differences in AI integration strategies. By positioning AI engagement as a mediator in our model, we shift the focus from the traditional technological exposure to the cognitive integration. Third, in this study, we introduced AI use as a first-stage boundary condition of the relationship between calibration bias and AI engagement; by doing so, we clarify the stability of this mechanism. If calibration bias influences AI engagement regardless of usage frequency, this would suggest that metacognitive accuracy is a relatively stable psychological resource in AI-enabled work environments. By integrating metacognitive theory with research on human–AI collaboration, this research contributes to the broader literature on digital cognition and technology-mediated performance.

2. Literature review and hypotheses development

2.1. Calibration bias and artificial intelligence engagement

Metacognitive theory states that individuals monitor and regulate their cognitive processes through self-evaluations of their competence (Flavell, 1979). Calibration refers to the degree of alignment between subjective self-assessment and objective ability (Lichtenstein & Fischhoff, 1982). When employees notice discrepancies between their subjective self-assessments and their objective abilities, they exhibit calibration bias, either overestimating or underestimating their actual competence (Kruger & Dunning, 1999). Therefore, calibration bias is not merely a perceptual error; it also influences employees' behavioral regulations, effort allocations, and information-seeking strategies (Vancouver & Carlson, 2015). Calibration bias differs from self-efficacy; self-efficacy explains generalized

confidence in one's capability to execute actions (Bandura, 1991), whereas calibration bias explains the discrepancy between perceived and objective ability of employees (Lichtenstein & Fischhoff, 1982). An individual may exhibit high self-efficacy yet be accurately calibrated, or alternatively, display inflated confidence relative to actual performance (Talsma *et al.*, 2019). The present research focuses on calibration bias as a metacognitive discrepancy rather than on global confidence, thereby emphasizing the accuracy of self-assessment rather than motivational belief alone.

Self-regulation theory further suggests that perceived capability shapes how individuals approach complex tasks (Bandura, 1991). Employees who believe that they have higher levels of task-related abilities are more likely to engage in proactive exploration of activities at workplaces, seek feedback from others at workplaces, and experiment with new and novel approaches more than others at work (Bouffard-Bouchard, 1990; Zhang & Xu, 2025). On the other hand, employees with lower levels of perceived competence may reduce their cognitive effort, avoid uncertainty, or rely on rigid workplace strategies (Sitzmann & Yeo, 2013). Thus, subjective competence assessment of individuals is either accurate or biased, and in both cases, it serves as a motivational driver that influences their engagement and persistence with external cognitive resources. In AI-enabled task contexts, these computer-aided intelligent working systems function as cognitive augmentation tools (Raisch & Krakowski, 2021). Augmenting cognitive activities requires deliberate integration of individual thoughts and understandings. Human–AI collaboration depends on whether the employees perceive the value of AI in interacting with the algorithmic suggestions (Jarrahi, 2018). Employees with higher levels of perceived questioning, understanding, and problem-framing and problem-understanding abilities may see AI systems as a complementary extension of their own cognition. Instead of substituting their personal judgments, the employees may engage deeply with the AI outputs to refine and expand the raw ideas it generates. Calibration bias, therefore, is most likely to influence AI engagement because the perceived competence of employees shapes how they regulate cognitive effort and leverage external aids. When employees exhibit positive calibration bias, perceiving themselves as more capable of performing an activity, they may engage more assertively and strategically with AI systems. Such engagement reflects cognitive integration rather than passive reliance. Thus, we propose here:

Hypothesis 1: Calibration bias is positively related to AI engagement.

2.2. Artificial intelligence engagement and creativity

Creativity, the generation of novel and useful ideas (Amabile, 1988; Zhou & George, 2001), depends on divergent thinking, recombination of information, and iterative refinement (Aldabbas *et al.*, 2025; Mumford & Gustafson, 1988). Researchers have found that flexibility and exposure to diverse informational resources enhance employees' ability to generate creative ideas (Hundscheil *et al.*, 2022). Employees, when connected to diverse individuals, information, and new ideas, increase their knowledge base and enhance their divergent thinking (Rawlings *et al.*, 2025; Swartz, 2009). AI systems, by virtue of their structure, are designed to expand ideational search spaces for the users by making a large volume of diverse information and by generating alternative framing (Bouschery *et al.*, 2023; Brynjolfsson & McAfee, 2014). Some users have described their experience of using AI systems as discussing and seeking help from an expert (Chen *et al.*, 2025). However, technological capability alone does not guarantee a learning experience and creative enhancement (Adeel, Batool, *et al.*, 2023). Previous research on the topic of human-AI interaction and collaboration has shown that AI outcomes depend heavily on the depth of user engagement (Adeel, Batool, *et al.*, 2023; Dell'Acqua *et al.*, 2026). Passive acceptance of the output generated by AI systems may enhance the efficiency of the individuals overall, but active cognitive integration, evaluating, refining, and recombining AI suggestions, supports creativity. From the perspective of cognitive absorption and augmentation, AI works as a cognitive partner of the users rather than a replacement mechanism (Raisch & Krakowski, 2021). Employee engagement with AI reflects the extent to which individuals incorporate AI-generated insights into the iterative problem-solving processes. When users critically engage with AI outputs and challenge AI outcomes without passively accepting them, they may access diverse, non-obvious knowledge, different opinions, and associations, and explore alternative solution paths, thereby enhancing the novelty and usefulness of their ideas. Thus, deeper AI engagement should positively influence creative performance. Accordingly, we propose here:

Hypothesis 2: AI engagement is positively related to creativity.

2.3. The mediating role of artificial intelligence engagement

The relationship between metacognitive calibration and performance outcomes is rarely direct. Calibration bias influences the regulatory behavior of individuals, which in turn affects their task-related performance (Vancouver

& Carlson, 2015). Social cognitive theory explains how cognition influences the behavior of individuals, and how behavior mediates performance outcomes (Bandura, 1991). In AI-assisted work environments, calibration bias may shape how individuals deploy and use available organizational AI tools, but individual-level employee creativity emerges from the behavioral enactment of that deployment and use. If calibration bias increases AI engagement, and AI engagement enhances employees' creative output, then AI engagement constitutes the behavioral pathway linking metacognitive discrepancy to employee creativity. This reasoning aligns with the process innovation (Ettlie & Reza, 1992) and process models of creativity, these process models emphasize that cognitive strategies of individuals and resource utilization in creative work mediate individual differences in creative performance (Ettlie & Reza, 1992; Mumford *et al.*, 2002). Calibration bias shapes the regulatory orientation; AI engagement represents the enacted cognitive strategy of individuals; creativity reflects the outcome.

Taken together, the preceding arguments suggest a process mechanism linking calibration bias to employee creativity through AI engagement. Calibration bias shapes how employees regulate their cognitive efforts and external resource utilization during creative activities. In AI-enabled environments, such regulation manifests as differential engagement with intelligent systems. Creativity does not emerge directly from the metacognitive bias; rather, employee creativity results from how that bias influences the behavioral integration of AI input. Accordingly, AI engagement constitutes an intervening process mechanism through which calibration bias translates into creative outcomes for employees. Therefore, AI engagement should transmit the effect of calibration bias to creative performance. Accordingly, we proposed here:

Hypothesis 3: AI engagement positively mediates the relationship between calibration bias and creativity.

2.4. Artificial intelligence use intensity as a boundary condition

While AI engagement reflects the qualitative cognitive integration of employees with AI systems, AI use intensity reflects the frequency of interaction with them. Technology acceptance workplace research suggests that repeated exposure to technology enhances familiarity and perceived ease of use (Davis, 1989). Greater frequency of use may strengthen users' skill acquisition and learning. From an experiential learning perspective, frequent interaction with AI systems may amplify the behavioral implications of metacognitive beliefs. Employees with stronger perceived competence may be more likely to engage in repeated

exposure to AI systems and to enact their regulatory orientations more consistently. Thus, AI use intensity is proposed as a first-stage moderator in this study as it could strengthen the positive relationship between calibration bias and AI engagement. However, calibration-driven engagements may also operate independently of frequency if strategic integration reflects a stable metacognitive orientation rather than exposure level. To examine this theoretical possibility, we test whether AI use intensity conditions the calibration–engagement relationship. Accordingly, we propose here:

Hypothesis 4: AI use intensity positively moderates the relationship between calibration bias and AI engagement, such that the positive relationship is stronger at higher levels of AI use intensity.

In summary, we proposed a model in which calibration bias positively predicts AI engagement, AI engagement positively predicts creativity, and AI engagement mediates the relationship between calibration bias and creativity. We further examine whether AI use intensity moderates the first stage of this process. Figure 1 presents the conceptual framework of the proposed relationships.

3. Method

3.1. Study design and context

In this study, we used a multi-source, time-lagged research design to examine whether employees' metacognitive calibration bias influences supervisor-rated creativity through AI engagement, and whether this mechanism is contingent upon AI use intensity. This time-lagged, multi-source research approach reduced the chances of common method variance by temporally dividing predictor and

outcome variables (Podsakoff *et al.*, 2003). Subordinates provided data on the predictors; however, supervisors rated their subordinates' creativity, mitigating the risk of perceptual inflation. Data for this research were collected from employees of an Islamic banking institution operating in the Dera Ghazi Khan Division of South Punjab, Pakistan. Islamic banking combines compliance-driven decision processes with discretionary judgment under normative constraints, making it a theoretically relevant context for examining AI-assisted cognition and creativity.

In such workplace environments, discrepancies between the perceived and actual cognitive competence may meaningfully shape reliance on AI systems as cognitive scaffolds. Before any data collection, the first and second authors visited the bank's regional office and explained the purpose and significance of the study to the regional manager, in the presence of the regional operations manager. After a thorough discussion, they allowed us to collect data from employees of the regional office, area offices, and branch banking offices under the Dera Ghazi Khan region's jurisdiction. An introductory email describing confidentiality assurances and voluntary participation was distributed to all branches in the division from the regional human resources coordinator. The second author, along with a field coordinator, then visited regional office employees, area office employees, and employees working in individual branches to collect survey data in person. Initially, 759 subordinates and 63 supervisors agreed to participate; however, at Time 1 (T1), the researchers collected 573 subordinate questionnaires and 61 usable supervisor responses, representing 75.5% and 96.8%, respectively. After four weeks, at Time 2 (T2), 58 supervisors provided data for their 489 subordinates'

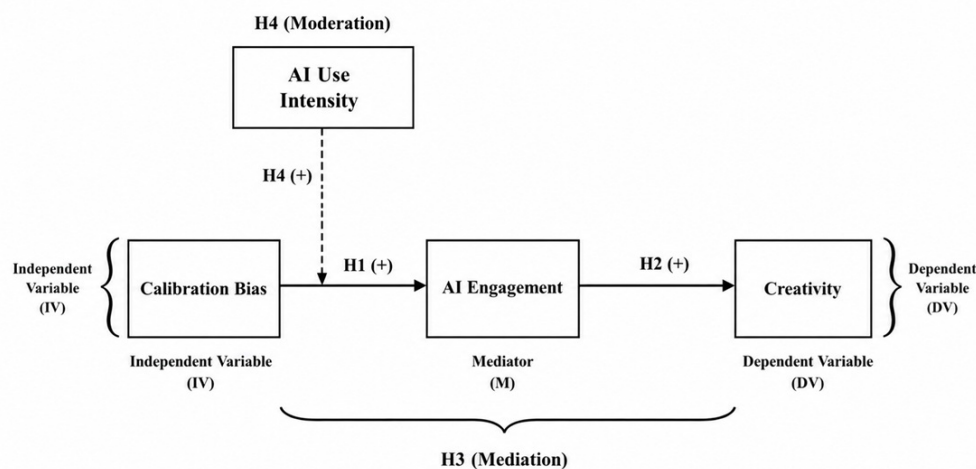


Figure 1. Proposed research model

Note: Solid arrows represent direct effects; dashed arrow represents moderating effect.

Abbreviation: AI: Artificial intelligence.

creativity ratings, 64.4% and 92%, respectively. After excluding data with missing records and mismatched responses, our final sample yielded responses from 437 subordinates and their 58 supervisors, 57.6% and 92%, respectively. This final dataset was used in all analyses of this research. The employees were nested into different workgroups with an average cluster size of approximately 7.5 subordinates per supervisor. Given the nested structure of the data, multilevel robustness checks were conducted (Bliese, 2000). Because employees were nested within supervisors (58 supervisors; mean cluster size = 7.53), we also calculated the interclass correlation coefficient (ICC[1]) for creativity. The intraclass correlation was $ICC(1) = 0.0019$, indicating that only 0.19% of the variance in creativity was attributable to supervisor-level clustering. Random-intercept multilevel models yielded substantively identical results, indicating that the mediation findings are robust to clustering.

3.2. Measures

All perceptual constructs were measured using five-point Likert-type scales (1 = strongly disagree; 5 = strongly agree). Separate survey instruments were used for supervisors and subordinates to reduce potential common method bias.

Self-Assessed Question-Asking Ability (SQAA) captured subordinates' perceived ability to formulate diagnostic and generative questions during work tasks. Prior researchers have measured overconfidence and metacognitive monitoring (Kruger & Dunning, 1999); validated measures of workplace question-asking competence remain limited. Therefore, for this study, a five-item scale was developed following established scale development procedures (Anderson & Gerbing, 1988). Items were generated based on prior metacognitive and problem-framing literature and reviewed by subject matter experts for content validity. Sample item includes "I am skilled at asking questions that uncover hidden problems" and "My questions often lead to innovative solutions." ($\alpha = 0.921$) (Table A1). For objective ability and calibration bias, the objective domain ability was measured using supervisor-rated competence indicators relevant to banking operations (e.g., task accuracy, problem-solving effectiveness). Both SQAA and objective ability scores were standardized. Calibration bias was operationalized as: $\text{Calibration bias} = Z(\text{SQAA}) - Z(\text{objective ability})$. Positive values of the score indicate overestimation, whereas negative values indicate underestimation. This operationalization aligns with metacognitive calibration research examining discrepancies between perceived and actual competence. AI engagement reflects the cognitive depth with which employees integrate AI tools into their problem-solving processes through interaction with

algorithmic outputs. Importantly, this construct captures qualitative engagement rather than mere exposure frequency, including iterative prompting, evaluation, and refinement of AI-generated responses. Sample items include "I actively use AI tools to refine my ideas" and "I rely on AI systems to explore alternative solutions." ($\alpha = 0.884$). This approach is consistent with prior metacognitive research operationalizing discrepancies between perceived and actual competence. AI use intensity was measured using two items assessing the frequency and regularity of AI use in daily work tasks. This variable was included as both a control and a hypothesized moderator. ($\alpha = 0.661$). Creativity was assessed at T2 by the supervisor; supervisors rated their subordinates for novelty and usefulness, consistent with the consensual assessment perspective (Amabile, 1988; Zhou & George, 2001).

The overall creativity score was computed as the mean of the novelty and usefulness ratings. ($\alpha = 0.815$). Inter-item correlation (r) for creativity was 0.693, and for AI use intensity was 0.493; Spearman-Brown coefficient for creativity was 0.819, and for AI use intensity was 0.661.

3.3. Control variables

In this study, we used subordinates' tenure, AI familiarity, and domain knowledge as control variables, as these factors may independently influence AI engagement and creative performance. AI use intensity was also included as a control in the mediation models.

4. Results

4.1. Measurement model

Data were analyzed using Mplus (v8.11, Muthén & Muthén, USA). Data for this study were collected from employees of Islamic banking who were nested into different workgroups. The likelihood of standard error underestimation increases with such nested data, according to researchers (Muthén *et al.*, 2016). We used random-coefficient models in Mplus. This research approach is also appropriate for non-independence of the observations, and it is appropriate for supervisor-subordinate dyadic designs (Olsen & Kenny, 2006). Before any formal analysis, we performed confirmatory factor analysis (CFA) to assess the measurement model. The results of CFA are presented in Table 1. We also compared the hypothesized measurement model with alternative models (e.g., one-factor and combined-factor models), and the hypothesized model demonstrated superior fit. As shown in the table, all constructs demonstrated strong internal consistency, with Cronbach's α and composite reliability exceeding the recommended threshold of 0.70. Convergent validity was supported, as the average variance extracted for each construct exceeded 0.50. Together, these results indicate

an acceptable and reliable measurement model (Fornell & Larcker, 1981). All continuous predictors were mean-centered prior to analysis. In Table 1, the hypothesized measurement model demonstrated excellent fit to the data ($\chi^2/\text{degree of freedom} = 1.11$; comparative fit index = 0.99; Tucker–Lewis Index = 0.99; root mean square error of approximation = 0.01; standardized root mean square residual = 0.02). All the standardized loadings were significant. Reliability and convergent validity were also satisfactory. For SQAA, Cronbach's $\alpha = 0.921$, composite reliability [CR] = 0.922, and average variance extracted [AVE] = 0.702. For AI engagement, Cronbach's $\alpha = 0.884$, CR = 0.886, and AVE = 0.608. All CR values exceeded 0.70, and all AVE values exceeded 0.50, indicating adequate internal consistency and convergent validity. To assess common method variance, we conducted Harman's single-factor test. The first factor accounted for less than 50% of the total variance, suggesting that common method bias is unlikely to substantially affect the results.

Table 1. Measurement model fit and reliability/validity

Statistic	Value
χ^2	37.93
Df	34
p	0.295
CFI	0.999
TLI	0.998
RMSEA	0.016
SRMR	0.025
SQAA	
Cronbach's α	0.921
CR	0.922
AVE	0.702
AI engagement	
Cronbach's α	0.884
CR	0.886
AVE	0.608

Notes: CFA fit for the hypothesized measurement model; Conventional benchmarks: CFI/TLI ≥ 0.90 (preferably ≥ 0.95), RMSEA ≤ 0.08 (preferably ≤ 0.06), SRMR ≤ 0.08 . Cronbach's $\alpha \geq 0.70$ indicates internal consistency; CR ≥ 0.70 and AVE ≥ 0.50 support convergent validity; All standardized factor loadings were significant ($p < 0.001$). Abbreviations: AI: Artificial intelligence; AVE: Average variance extracted; CFI: Comparative fit index; CR: Composite reliability; Df: Degree of freedom; RMSEA: Root mean square error of approximation; SRMR: Standardized root mean square residual; TLI: Tucker–Lewis Index.

4.2. Descriptive statistics

Means, standard deviations, and correlations are reported in Table 2. Calibration bias was positively associated with AI engagement ($r = 0.329$, $p < 0.001$) and creativity ($r = 0.350$, $p < 0.001$). AI engagement was strongly associated with creativity ($r = 0.615$, $p < 0.001$). Most correlations were below 0.70, except for the association between domain knowledge and calibration bias, suggesting that multicollinearity is unlikely to be a concern. The strong negative correlation between domain knowledge and calibration bias reflects that higher domain expertise is associated with more accurate self-assessment. Despite this association, multicollinearity diagnostics indicated acceptable variance inflation factors, suggesting that multicollinearity is unlikely to bias the regression estimates.

4.3. Tests of hypotheses

We first tested the mediation model using ordinary least squares regression with bootstrapped confidence intervals (5,000 resamples). We first regressed AI engagement on calibration bias, controlling for all the control variables. Calibration bias was positively related to AI engagement ($\beta = 0.409$, $p < 0.001$), indicating that greater calibration bias is associated with higher AI engagement. Next, we regressed creativity on calibration bias, controlling for AI engagement and all other control variables. AI engagement was positively related to creativity ($\beta = 0.500$, $p < 0.001$), and calibration bias also remained a significant predictor ($\beta = 0.279$, $p < 0.001$). The bootstrapped indirect effect was significant ($\beta = 0.204$, 95% confidence interval: [0.154, 0.260]). Because the confidence interval excludes zero, the indirect effect is statistically significant, and the significant direct and indirect effects indicate partial mediation. We then tested the moderating role of AI use intensity on the relationship between calibration bias and AI engagement. We entered the interaction term (calibration bias $\times$ AI use intensity) in the first-stage regression model. The interaction term was not significant ($\beta = -0.006$), indicating that AI use intensity does not moderate the effect of calibration bias on AI engagement. Among the control variables, domain knowledge significantly predicted AI engagement ($\beta = 0.351$, $p < 0.001$), whereas AI familiarity ($\beta = 0.029$) and tenure ($\beta = -0.034$) were not significant. The insignificant results of the moderating role of AI use intensity on the relationship between calibration bias and AI engagement suggest that the calibration–engagement relationship may not be contingent on usage frequency in the present sample. In other words, metacognitive discrepancy appears to influence engagement depth independently of exposure frequency. This finding refines theoretical expectations by indicating that qualitative integration, rather than mere repetition, appears to shape the calibration–engagement

Table 2. Descriptive statistics and correlations

Variable	M	SD	1	2	3	4	5	6
1. Calibration bias (Z)	0.000	1.416						
2. AI engagement	3.902	0.866	0.329***					
3. AI use intensity	3.875	0.945	0.056	0.010				
4. Creativity (supervisor-rated)	3.786	0.889	0.350***	0.615***	0.043			
5. AI familiarity	3.823	0.943	−0.016	0.027	−0.143**	0.034		
6. Domain knowledge	4.294	0.758	−0.707***	−0.059	0.010	−0.013	0.009	
7. Tenure (years)	10.812	5.659	−0.020	−0.033	−0.057	−0.079	−0.011	0.035

Notes: $n = 437$; Supervisors = 58; Correlations are Pearson's r ; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (two-tailed), computed from r and n . Abbreviations: AI: Artificial intelligence; M: Mean; SD: Standard deviation.

relationship. Mediation analysis results are presented in Table 3, and the results of the moderation test and multilevel diagnostics are presented in Table 4.

5. Research contributions

5.1. Theoretical contributions

This study develops a metacognitive explanation of human–AI collaboration, contributes to a more nuanced, theory-driven understanding of it, and advances theory at the intersection of metacognition, creativity, and human–AI collaboration in several important ways. First, prior calibration research has mainly focused on judgment accuracy, learning environment, and forecasting performance (Kruger & Dunning, 1999; Vancouver & Carlson, 2015). By integrating calibration bias within AI environments, this research found that calibration bias influences how individuals engage with AI systems, thereby shaping the behavioral pathway through which technology affects their performance, extending calibration theory beyond self-regulation in isolated cognitive tasks and positions it as a foundational construct in human–AI collaboration with these, this research extends metacognitive calibration research into AI-enabled work contexts into AI research rather than treating AI outcomes as purely technological artifacts (Jarrahi, 2018; Raisch & Krakowski, 2021).

Second, this research contributes to the emerging research on AI and workplace creativity by clarifying how metacognitive regulation shapes the integration of AI outputs into creative processes (Batool *et al.*, 2024). Limited research on the topic has evaluated the role of AI in increasing productivity or generating creative ideas (Bouschery *et al.*, 2023; Dell'Acqua *et al.*, 2026), often treating AI exposures as a uniform intervention. Our research

contributes to this stream by explaining how creativity emerges not from AI presence or absence per se, but from how the individuals integrate AI outputs into iterative problem-solving at work. Third, this research identified AI engagement as a behavioral mechanism linking individual cognition to creative performance. Creativity research has long emphasized the importance of cognitive strategies and resource utilization (Amabile, 1988; Mumford *et al.*, 2002). However, by explaining the mediating role of AI engagement in the relationship between calibration bias and creativity, this research clarifies how AI, as an external cognitive resource, introduces new complexity and how metacognitive discrepancies translate into performance outcomes in technology-mediated environments. This underlying process aligns with the social cognitive theory, which posits that cognitive beliefs influence behavior, and is consistent with self-regulation theory, which emphasizes monitoring and control of cognitive processes during task execution, which in turn affects performance and is consistent with self-regulation theory, which emphasizes monitoring and control of cognitive processes during task execution (Bandura, 1991).

Finally, this research introduced AI use intensity as a potential moderator, contributing to boundary condition theorizing by indicating that calibration-driven engagement operates relatively independently of usage frequency. The insignificant results of moderation suggest that the impact of calibration bias on AI engagement may not be contingent on usage frequency in the present context, but rather a refinement of the augmentation theory. Additionally, by integrating calibration theory, creativity research, and AI augmentation frameworks, this research bridges the organizational behavior theories of self-regulation with digital technology research on AI collaboration. This research showed that AI systems

Table 3. Mediation analysis

Effect	Estimate	SE	<i>p</i> /95% CI	Significance
Calibration bias (Z) → AI engagement (a)	0.408	0.044	<0.001	***
AI engagement → Creativity (b)	0.500	0.039	<0.001	***
Calibration bias (Z) → Creativity (c')	0.279	0.039	<0.001	***
Indirect effect (a × b)	0.204	–	[0.154, 0.260]	–

Notes: *n* = 437; Supervisors = 58; Unstandardized coefficients reported; Indirect effect is reported with bootstrapped 95% CIs; An indirect effect is statistically significant when its confidence interval excludes zero; ****p* < 0.001.

Abbreviations: AI: Artificial intelligence; CI: Confidence intervals; SE: Standard error.

Table 4. First-stage moderation model and multilevel diagnostics

Predictor	Estimate	SE	<i>p</i>	Significance
Calibration bias (Z)	0.409	0.044	<0.001	***
AI use intensity (Z)	–0.024	0.045	0.593	–
Calibration bias (Z) × AI use intensity	–0.006	0.031	0.855	–
AI familiarity (Z)	0.029	0.044	0.517	–
Domain knowledge (Z)	0.351	0.062	<0.001	***
Tenure (Z)	–0.034	0.044	0.440	–
ICC(1) for creativity	0.0019	–	–	–
Supervisors (clusters)	58	–	–	–
Mean cluster size	7.53	–	–	–

Notes: *n* = 437; Supervisors = 58; First-stage moderation model predicting AI engagement; The interaction term tests whether AI use intensity moderates the calibration bias → AI engagement relationship; ICC(1) indicates the proportion of variance in creativity attributable to supervisor-level clustering; The non-significant interaction indicates no moderation effect; ****p* < 0.001.

Abbreviations: AI: Artificial intelligence; ICC(1): Interclass correlation coefficient; SE: Standard error.

operate within human regulatory processes at workplaces, and that individual cognition and cognitive-regulatory characteristics shape how AI tools are endorsed within organizational processes. This integration of behavioral, calibration, and AI research advances management literature by positioning AI as embedded within human regulatory systems.

5.2. Practical contributions

This study offers distinct implications for organizations implementing AI systems and for enhancing their employees'

creativity in knowledge-intensive environments. First, this research found that calibration bias, as a metacognitive orientation, shapes how employees engage with AI systems in their organizations, indicating that AI effectiveness depends not only on the quality of AI systems but also on users' self-regulatory characteristics. Organizations may design training for their employees that includes exercises to help them develop calibrated awareness of their strengths and limitations in AI-supported tasks, integrated into AI adoption initiatives (Adeel, Ahmed, *et al.*, 2023). For such training, in addition to internal organizational

arrangements, external experts with a management-IT background should be hired for their rich experience and practical exposure for employees. For example, the use of AI in the education sector (Amoozegar *et al.*, 2025; Wang *et al.*, 2024) will also enhance the learning experience. Similarly, both in-house and external workshops should be arranged by the organizations on calibration or structured reflection protocols, particularly in Islamic financial institutions characterized by strong regulatory and ethical compliance frameworks, where decision quality and compliance to Islamic standards are of priority for the management, which may encourage calibrated self-awareness and prevent both the overreliance and the underutilization of AI systems. Second, the results of this research indicated that creative outcomes are driven by depth of engagement rather than mere exposure to AI systems. The organizations should shift their evaluation and reward criteria from employees from “how often employees use AI” to “how employees use AI.” This may include structured prompt-evaluation protocols, human-in-the-loop review processes, and training on iterative refinement of AI-generated outputs. These changes should involve assessing whether employees critically evaluate AI outputs and structured prompts; for practical exposure, collaborative AI-integrated sessions, and reflective debriefings may enhance their qualitative engagement in routine organizational tasks and increase organizational performance accordingly. Third, this study reinforces the augmentation perspective of AI implementation in workplaces by showing that the benefits of AI for employee creativity are greater when AI serves as an interactive algorithmic partner rather than a replacement for routine work-related activities. Organizations, thus, should communicate clearly to their employees through their internal portals, discussion groups, and informal communication channels that the AI facilities provided at workplaces are intended to extend their reasoning at work rather than replace their professional judgments in their routine activities. Finally, in organizational setting where organizations, like Islamic financial institutions, operate under the strict compliance and ethical framework, developing AI governance frameworks that include guidelines for reflective use, cognitive accountability, and human oversight and policies must include guidelines for reflective use, cognitive accountability, and human oversight explained in dedicated training programs should also emphasize how AI outputs can stimulate alternative perspectives while preserving human evaluative authority. Supervisors’ role remained very important for creativity (Song *et al.*, 2025). Supervisors can also encourage their subordinates to engage effectively with AI by fostering psychologically safe environments where they feel

comfortable experimenting with AI tools and discussing their cognitive strategies. Human resources should incorporate criteria in the performance appraisal systems that reward thoughtful AI integration.

6. Limitations and future research directions

Although this study offers some distinct contributions, it also has several limitations that open avenues for future research. First, data for this research were collected from an Islamic banking organization operating in Pakistan. However, the context of this Islamic banking sector was valuable and was characterized by regulatory rigor, knowledge-intensive work, and emerging AI adoption. Future researchers may use other knowledge-driven, technology-oriented public and private sector organizations to determine whether these patterns of results repeat in those organizations, too. Second, calibration bias was operationalized through self-assessed question-asking ability, and AI engagement was measured through self-reported depth of interaction. Future researchers may further refine these measurements by incorporating experimental calibration tasks or behavioral accuracy indices and combining perceptual measures. Additionally, a true longitudinal or experimental design may help researchers examine whether calibration bias changes over time as employees gain experience within their organizations and with the AI systems they use. Finally, in this study, we explored AI use intensity as a potential moderator, but it was statistically insignificant. Future researchers should examine psychological safety, technological trust, algorithmic transparency, or task complexity as theoretically relevant moderators. Additionally, Future researchers should also examine whether calibration bias and AI engagement jointly influence broader performance indicators, particularly in highly regulated sectors where accuracy and compliance are as critical as novelty.

7. Conclusion

Artificial intelligence has now become an integral component of organizational work processes; therefore, understanding the psychological foundations of human-AI collaborations in contemporary workplaces is critical. Using a process-based explanation of AI-assisted creativity, integrating metacognitive calibration theory with augmentation perspectives of artificial intelligence, and positioning AI engagement as the behavioral central mechanism linking metacognitive discrepancy to creative output, this research contributes to a more psychologically grounded understanding of digital augmentation. We found that calibration bias shapes how employees engage

with AI systems at work, and that this engagement, in turn, influences their creative performance. Instead of treating AI as a uniform technological enhancer for employees, this research highlighted that workplace creative gains depend on employees' cognitive orientations and the depth of integration with AI systems provided by organizations. Access to AI does not automatically augment employees' creativity; the benefits of AI for creativity emerge when employees actively incorporate algorithmic inputs into iterative problem-solving processes, enhancing the creative pool for organizations and increasing their radical and process innovation.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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Ethics approval and consent to participate

This study was approved by the Ethical Committee of the University of Chenab (Ref: 1207BE25). Informed consent was obtained from all individual participants included in the study.

Consent for publication

Verbal informed consent was obtained from all

participants, documented, and approved by the relevant ethics committee. No identifiable personal data or images are disclosed in this publication.

Availability of data

The data supporting the findings of this study are available from the corresponding author upon reasonable request. To support transparency and replicability, simulated replication datasets that mirror the statistical properties of the empirical data have been generated and are available for verification and methodological purposes. Due to ethical considerations and confidentiality agreements with participating organizations, the original raw survey data are not publicly available.

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Appendix

Table A1. Newly developed scale items

Construct	Item
Self-assessed question-asking ability (SQAA)	I am skilled at asking questions that uncover hidden problems.
	I can frame questions that stimulate deeper thinking.
	My questions often lead to innovative solutions.
	I know how to ask questions that clarify complex issues.
Artificial intelligence (AI) engagement	I frequently ask questions that challenge assumptions.
	I actively use AI tools to refine my ideas.
	I rely on AI systems to explore alternative solutions.
	AI helps me expand my thinking during complex tasks.
	I use AI to test and evaluate different approaches.
	AI systems enhance my creative problem-solving process.

Notes: All items were measured on five-point Likert-type scales (1 = strongly disagree, 5 = strongly agree); Items were developed based on metacognitive and problem-framing literature and reviewed by subject matter experts.