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Individual competencies driving innovative work behavior in generative AI–enabled environments: AI literacy, expertise and metacognition

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Abstract

Purpose – Drawing on innovation diffusion theory, this study examines how AI literacy (AIL) promotes innovative work behavior (IWB) in generative AI–enabled work environments and investigates the moderating roles of occupational expertise and metacognition.

Design/methodology/approach – This study examines the individual competencies that shape IWB in generative GAI–enabled work environments. Data were collected through an online survey using a stratified sampling method targeting employees with experience using GAI at work. A total of 600 valid responses were analyzed using hierarchical and moderated regression analyses.

Findings – The results of the analysis demonstrate that AIL has a positive effect on IWB. Moreover, this effect was moderated by both occupational expertise and metacognition. Specifically, the positive impact of AIL on IWB was stronger among individuals with higher occupational expertise. Similarly, the effect of AIL on IWB was amplified among those with higher metacognition levels. These findings have theoretical and practical implications for research and practice in organizational behavior, human resource management and human resource development.

Originality/value – This study makes a significant contribution to the relevant research field by identifying individual competencies that enhance employees' IWB in GAI-enabled work environments. Specifically, by highlighting the roles of AIL, occupational expertise and metacognition, this study provides a theoretical foundation for understanding how individual competencies influence IWB. Beyond its theoretical contributions, this study also offers practical guidance for managers and policymakers by suggesting strategies for talent development, selection and placement to promote sustainable growth and maintain a competitive advantage.

Keywords AI literacy, Innovative work behavior, Occupational expertise, Metacognition, Individual competencies

Paper type Research article

Introduction

With the advancement of AI technologies and their widespread application, AI is now being adopted and utilized across nearly all industries, supporting the overall work activities of organizational members (Almatrafi *et al.*, 2024). In particular, generative AI (GAI) provides

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customized knowledge and information and contributes to improved work efficiency and productivity by automating or optimizing routine tasks (Malik *et al.*, 2025). Furthermore, GAI offers greater opportunities for innovation within organizations by reducing the burden of routine tasks and enabling employees to focus on creative and strategic activities (Tambe *et al.*, 2019; Noy and Zhang, 2023; Vrontis *et al.*, 2023).

Meanwhile, as the AI era unfolds, the importance of employees' innovative work behavior (IWB) is becoming increasingly significant (Sedkaoui and Benaichouba, 2024). This is because, in the AI era, high efficiency and productivity alone are no longer sufficient for organizations to achieve sustainable growth and to maintain a competitive advantage. Even before the AI era, IWB had long been recognized as a behavior that plays a critical role in maintaining organizational sustainability and competitive advantage, and a substantial body of research has accumulated to identify its antecedents (AlEssa and Durugbo, 2022).

However, the rapid diffusion of GAI has created a new work environment that existing IWB research has not fully addressed. AlEssa and Durugbo (2022) emphasized that, in response to changes in the business environment, IWB research needs to be extended to new contexts (e.g. digital environments). This suggests that because most prior studies were conducted in work environments preceding the diffusion of GAI, there is still insufficient empirical evidence regarding the factors that promote IWB in GAI-enabled work environments. Accordingly, this study extends the scope of prior IWB research to the context of GAI-enabled work environments and seeks to identify the key factors that foster IWB in this setting.

Another gap in the existing literature is the limited understanding of which personal competencies effectively promote IWB in GAI-enabled work environments. The widespread adoption of GAI does not necessarily mean that all employees can use it effectively or immediately exhibit high IWB. Such differences may stem, in particular, from personal competencies related to interacting with the GAI. However, prior studies have mainly examined more general individual characteristics and competencies, such as motivation (Saether, 2019), personality (Woods *et al.*, 2018), and domain knowledge (Saeed *et al.*, 2019), which are limited in their ability to fully explain this phenomenon. Therefore, this study focuses on GAI-enabled work environments and seeks to identify key personal competencies that foster IWB.

Specifically, this study aimed to examine the role of AIL in fostering IWB in GAI-enabled work environments and to test the moderating effects of occupational expertise and metacognition. AIL is a core variable in this study. AIL goes beyond mere technical proficiency to encompass various dimensions, such as understanding AI technologies, using them effectively, critically evaluating their output, and considering ethical implications (Wang *et al.*, 2023). This competency enables users to adopt and proficiently utilize GAI. For innovative technologies to spread among users and translate into innovation, users must first adopt the technology and develop the relevant knowledge (Rogers *et al.*, 2014). Therefore, AIL can play a pivotal role in transforming innovative technologies into IWB. This is especially true for GAI, which relies heavily on natural language interfaces instead of rule-based interactions. Thus, understanding how to interact effectively with GAI is essential (Knoth *et al.*, 2024; Walter, 2024). As AIL includes this interaction capability, it can be considered a technical competency that promotes IWB.

Occupational expertise moderates the relationship between AIL and IWB. Occupational expertise refers to knowledge, experience, and problem-solving abilities within a specific domain. Employees with high levels of expertise are more capable of eliciting meaningful information from the GAI through sophisticated queries. Moreover, they can interpret and apply information within the context of their work, increasing the likelihood of converting it into actual IWB (Germain and Ruiz, 2009; Van der Heijden *et al.*, 2018).

Metacognition is expected to strengthen the relationship between AIL and IWB. Metacognition, defined as the ability to understand and regulate one's cognitive processes, plays a critical role in learning and problem solving (Flavell, 2024). Employees with high

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metacognitive skills can better identify the knowledge and information required for IWB. Consequently, they can use GAI to learn this information quickly and effectively (Lebuda and Benedek, 2025; Kim and Lee, 2018). Furthermore, they can select, modify, and adapt the ideas generated by GAI to fit the IWB context, thereby facilitating innovation (Acar *et al.*, 2020; Jia *et al.*, 2019).

This study contributes to the academic literature and managerial practice in several ways. First, by identifying the antecedents of IWB in GAI-enabled work environments, this study extends the scope of IWB research to reflect the changing nature of work in the AI era and fills gaps in the existing literature. Second, it identifies AIL as a novel antecedent of IWB, underscoring its significance for both scholars and practitioners seeking to understand and promote employees' IWB in the AI era. Finally, by empirically examining the interaction effects of AIL, occupational expertise, and metacognition, this study advances the understanding of the competencies required of employees in the AI era and provides practical guidance for organizations seeking to develop and support such talent.

Literature review and hypothesis development

AI literacy

The growing integration of AI technologies into everyday professional settings has heightened the demand for users to possess not only operational proficiency but also a deeper understanding of and critical engagement with AI systems. AIL has emerged as a critical competence for navigating, utilizing, and evaluating AI-driven processes and outputs (Ng *et al.*, 2021). AIL is not merely about technical knowledge or skillful usage; rather, it encompasses a multidimensional capacity that includes awareness, critical evaluation, ethical considerations, and adaptive application of AI tools (Wang *et al.*, 2023). This expanded view aligns with the broader trajectory of literacy studies, which have evolved from basic textual comprehension (Hock and Mellard, 2005) to encompass digital (van Laar *et al.*, 2017), media (Brown, 1998), and information literacies (Saranto and Hovenga, 2004) as necessary frameworks for understanding technologically mediated environments.

Wang *et al.* (2023) made a significant contribution by developing and validating an AIL scale that reflects this multidimensional nature. Their four-factor model includes AI Awareness, AI Interaction and Usage, AI Evaluation, and AI Ethics. Each dimension addresses essential user competencies: awareness refers to understanding AI's capabilities and limitations; interaction and usage measure practical skills in engaging with AI systems; evaluation assesses the ability to critically analyze AI outputs; and ethics gauges moral considerations in AI use. These domains are essential for responsible engagement with AI applications, particularly as such systems increasingly influence information production, communication, and decision-making in various contexts (Cetindamar *et al.*, 2022).

As recognition of the importance and necessity of AIL has expanded, a growing number of scholars have sought to define and conceptualize AIL and develop more refined instruments for its measurement (Ng *et al.*, 2021; Wang *et al.*, 2023). However, comparatively limited attention has been devoted to the role of AIL in enhancing organizational and job performance in actual workplace contexts, and empirical research on this issue is scarce. This is particularly notable, given the increasingly routine use of AI in everyday work environments. The lack of such discussions hinders a broader understanding of the role of AIL in organizational and job performance and limits its effective application in practice.

Although several studies conducted in organizational and occupational contexts have shown that AIL directly or indirectly improves outcomes such as job performance and job satisfaction (Liu *et al.*, 2025; Mughari *et al.*, 2024; Lee and Jeon, 2025), additional empirical evidence is needed to provide a more comprehensive understanding of its benefits. Shahid *et al.* (2026) argued that the advancement and expanded application of AI as a new technology impose new challenges and pressures on organizations in the form of AI-enabled employee innovation, and that employees' IWB through AI can enhance sustainable organizational

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performance. This line of reasoning suggests that AIL may play an important role in creating sustainable organizational performance in the AI era. In response, this study extends prior AIL research by examining the effect of AIL on IWB in the context of organizational and job performance.

AI literacy and complementary personal capabilities for innovative work behavior

Recent research further emphasizes that AIL should include the user's capacity for critical and ethical judgment, not just functional skills. For instance, studies have highlighted how users can be misled by algorithmic bias or manipulated by persuasive personalization unless they are equipped with evaluative and metacognitive tools (Celik, 2023; Ng *et al.*, 2021). This supports the conception of AIL that extends beyond usage to incorporate reflective thinking and domain-specific knowledge. As AI-generated content becomes increasingly prevalent, users' ability to judge its credibility and relevance is closely linked to their cognitive and ethical discernment capacities (Duffy, 2018; Wang *et al.*, 2025).

In the context of generative AI, such competencies are even more salient. Unlike traditional AI applications that rely on rule-based processing, generative AI uses natural language interfaces and deep learning to produce novel outputs, introducing new possibilities and risks (Orru *et al.*, 2023). Therefore, using generative AI tools such as ChatGPT requires more than just knowing how to prompt a system effectively; it necessitates the ability to critically assess the generated content, recognize potential limitations or biases, and apply the outputs in contextually appropriate ways (Knoth *et al.*, 2024; Walter, 2024).

Accordingly, this study extends the validated model proposed by Wang *et al.* (2023) by contextualizing AIL in relation to IWB and, more importantly, by examining the strengthening roles of metacognition and occupational expertise in this relationship. While prior research has primarily established the effectiveness of the technical and educational dimensions of AIL, this study highlights that the influence of AIL in real-world professional settings may not be uniform but rather contingent on employees' additional personal capabilities. In workplaces where generative AI is actively utilized, employees are required not only to understand and use AI effectively, but also to generate contextually appropriate outputs and critically evaluate, interpret, and apply those outputs within the scope of their work. From this perspective, metacognition and occupational expertise are expected to strengthen the positive relationship between AIL and IWB by enabling employees to produce more appropriate AI-generated outputs and assess and leverage such outputs more reflectively and effectively in job-related problem-solving. This study addresses an important gap in the literature by moving beyond a simple direct association between multidimensional AIL and IWB and empirically testing the moderating roles of metacognition and occupational expertise among employees.

AI literacy and innovative work behavior

IWB is defined as "the intentional creation, introduction and application of new ideas within a work role, group or organization, in order to benefit role performance, the group, or the organization" (Janssen, 2000, p. 288). Specifically, Scott and Bruce (1994) and Janssen (2000) conceptualized IWB as a multidimensional construct that includes three different types of behavioral tasks: generating new ideas, promoting them to potential supporters to gain their endorsement, and ultimately realizing innovation in practice.

IWB is widely recognized as a critical factor in securing competitive advantage for organizations. Accordingly, continuous efforts have been made to identify various individual, environmental, and institutional factors that contribute to enhancing IWB (Bos-Nehles *et al.*, 2017). Previous studies have reported that IWB is facilitated by a variety of personal characteristics (e.g. creativity, openness, motivation, and self-efficacy), job characteristics (e.g., job complexity and autonomy), and environmental factors (e.g. climate for innovation and supervisor support) (Hammond *et al.*, 2011). However, with recent advancements in

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digital and AI technologies, GAI has drawn attention as a new factor that may promote IWB (Smothers *et al.*, 2024).

The GAI is capable of learning from diverse data sources and providing tailored feedback in response to user queries (Li *et al.*, 2024). From this perspective, Rafique *et al.* (2025) argue that AIL serves as a catalyst for innovation by equipping individuals with the tools and confidence to explore novel ideas. In other words, employees can utilize GAI to generate new ideas more easily and quickly, which serve as the foundation for IWB, as well as explore effective strategies for implementing those ideas. Although GAI is recognized as a useful tool that complements employees' capabilities and promotes IWB (Sedkaoui and Benaichouba, 2024), not all employees demonstrate enhanced IWB through the use of GAI. This is because not all employees actively use GAI in their work, nor are they necessarily able to use it effectively (Steinhauser and Heid, 2026). This means that for this useful tool to contribute to IWB, it is essential that employees accept this innovative technology and use it consistently and effectively in their work.

According to the Diffusion of Innovation Theory proposed by Rogers *et al.* (2014), the adoption and diffusion of innovation proceeds through the stages of knowledge, persuasion, decision, implementation, and confirmation. Specifically, the theory explains that a high level of understanding and knowledge about an innovation forms positive attitudes toward it, which subsequently leads to its adoption and continued use. In addition, Mumtaz *et al.* (2025) emphasized that relative advantage is an important antecedent in shaping users' positive attitudes toward innovative tools and facilitating their adoption. From this perspective, AIL can serve as an important background factor in determining the acceptance and sustained use of the GAI. This is because employees with high AIL levels have a better understanding of the functionality and structure of GAI and can quickly acquire the know-how required to use it effectively (Ji *et al.*, 2025; Wang *et al.*, 2023). Consequently, individuals with high AIL actively adopt GAI, use it consistently in their work, and engage more in activities that involve generating and implementing new ideas through its use. Steinhauser and Heid (2026) examined the effects of AI use on R&D activities and innovation capability and found that individuals with higher AIL levels were better able to utilize AI, which in turn improved their R&D activities and enhanced their innovation capability.

Furthermore, employees with high AIL levels can acquire more advanced knowledge and information necessary for IWB. Effective interaction with the GAI is essential to obtain such outcomes (White *et al.*, 2023). The quality and accuracy of GAI output depend on the quality of the prompts provided by the user, such as questions or instructions (Wei *et al.*, 2022; White *et al.*, 2023). Haugsbaken and Hagelia (2024) pointed out that for generative AI to function effectively and accurately, users must possess the skill to formulate instructions in ways that the system can properly interpret and understand. Otherwise, generative AI may produce undesirable outputs or hallucinations, leading to inefficient communication and suboptimal performance. Accordingly, employees with high levels of AIL tend to have a better understanding of the technical characteristics of GAI and therefore make greater efforts to provide it with more refined questions and instructions. As a result, they are more likely to obtain higher-quality knowledge and information, which contributes to higher levels of IWB.

H1. AI literacy has a positive effect on innovative work behavior.

Moderation effect of occupational expertise

Expertise is generally defined as "the combination of knowledge, experience, and skills held by a person in a specific domain" (Germain and Ruiz, 2009). Occupational expertise refers to domain-specific competence related to one's job or tasks and is understood as the ability to perform successfully in work-related contexts (Van der Heijde and Van der Heijden, 2006). It reflects a range of individual capabilities, including knowledge, skills, experience, and problem-solving ability (Germain and Ruiz, 2009; Van der Heijden *et al.*, 2018).

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Occupational expertise plays a critical role in facilitating the transformation of AIL into IWB. Specifically, it offers substantial advantages in the generation and implementation of creative ideas. First, occupational expertise is closely and positively associated with individuals' information-seeking behavior (Khosrowjerdi and Iranshahi, 2011), as prior knowledge enables individuals to locate relevant information more rapidly and efficiently. For instance, Khosrowjerdi and Iranshahi (2011) found that prior knowledge, comprising domain expertise and past experience, was positively related to graduate students' information-seeking behavior.

This function of occupational expertise can also be applied to the GAI usage environments. As discussed earlier, to obtain high-quality knowledge and information from GAI, users must input high-quality prompts. These prompts should include contextual details, examples, reasoning processes, relevant information, and background knowledge (Wei *et al.*, 2022; White *et al.*, 2023). This suggests that individuals with high occupational expertise are better equipped to formulate effective and informative prompts. Consequently, members who possess both AIL and high levels of occupational expertise are more likely to acquire the necessary knowledge and information for idea generation more easily and efficiently.

Beyond idea generation, occupational expertise plays an important role in implementing ideas derived from GAI. Chiu (2025) emphasized that AI is always applied within a specific context and that effective AI expertise in any domain—such as education, healthcare, law, finance, engineering, or the arts—requires a deep understanding of the knowledge, practices, terminology, and challenges specific to that field. For instance, the effective use of healthcare AI tools depends not only on technical familiarity with AI systems but also on medical expertise to understand their intended purpose, accurately interpret their outputs and identify potential clinical risks or biases.

In this regard, the value of the outputs generated through AIL is likely to increase when they are integrated with domain-specific occupational expertise. In organizational settings, employees with higher levels of occupational expertise are more likely to recognize which AI-generated ideas are relevant and feasible, adapt those ideas to task-specific demands, and translate them into practical solutions. Therefore, occupational expertise is expected to strengthen the positive effect of AIL on IWB by enhancing employees' ability to convert AI-generated knowledge and suggestions into contextually appropriate and practically implementable IWB.

H2. Occupational expertise moderates the relationship between AI literacy and innovative work behavior.

Moderation effect of metacognition

Metacognition refers to "thinking about thinking" or "cognition about cognition" (Lebuda and Benedek, 2025). Specifically, it comprises two components: cognitive knowledge and regulation. Cognitive knowledge involves awareness and understanding of one's own cognitive processes and outputs, as well as related information. In contrast, cognitive regulation refers to the deliberate regulation (including active monitoring, consequent regulation, and orchestration of cognitive processes) of these cognitive processes to achieve specific goals (Harrison and Vallin, 2018; Flavell, 2024).

In other words, metacognition enables individuals to regulate their cognitive processes and strategies to navigate unfamiliar or problem-solving situations effectively (Yadav *et al.*, 2022). It allows individuals to recognize the knowledge they already possess, understand how various pieces of information and knowledge are interconnected, and plan the acquisition of new knowledge (Kim and Lee, 2018).

Recent research has emphasized the importance of metacognition alongside AIL in the use of generative AI. Sidra and Mason (2026) argued that metacognition is essential for the use of generative AI because AI itself does not possess human-like self-awareness or situational awareness. Consequently, when using generative AI, individuals must rely on metacognitive capabilities to guide effective communication, adjustment, and monitoring, including

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information verification and error detection. In this sense, the effective use of generative AI depends on both AIL and metacognitive capabilities (Sidra and Mason, 2024, 2026).

This suggests that metacognition can facilitate the transformation of AIL into IWB. Individuals with high metacognition are more adept at identifying the knowledge and information required for IWB, enabling them to acquire the insights and data needed for creative idea generation through GAI more effectively. (Lebuda and Benedek, 2025; Kim and Lee, 2018).

Moreover, metacognition significantly contributes to the implementation of ideas generated through GAI (Jia *et al.*, 2019). The process monitoring theory proposed by MacGregor *et al.* (2001) posits that creative problem-solving involves continuously monitoring the gap between the current and desired goal states and adjusting cognitive strategies accordingly. This perspective can be directly applied to the role of metacognitive regulation in adopting and implementing GAI-generated ideas. Although GAI offers vast amounts of information and facilitates idea generation through data-driven insights, not all ideas are immediately actionable. Selecting, modifying, and tailoring ideas to fit IWB contexts requires careful judgment, a process that depends largely on an individual's metacognitive capacity (Acar *et al.*, 2020).

Ultimately, even individuals with high AIL may struggle to learn from the GAI or implement its outputs effectively if they lack sufficient metacognitive skills. In such cases, the practical impact of AIL on IWB may be reduced. In contrast, individuals with high metacognitive ability can better monitor, evaluate, and adapt GAI-generated outputs to their work context, thereby strengthening the positive effect of AIL on IWB. Therefore, metacognition is expected to strengthen the positive effect of AIL on IWB by enhancing employees' ability to monitor, evaluate, and adapt AI-generated outputs in a manner that supports IWB.

H3. Metacognition moderates the relationship between AI literacy and innovative work behavior.

The three hypotheses suggest that AIL positively affects IWB, and that this effect is strengthened by occupational expertise and metacognition. Based on these hypotheses, Figure 1 presents the research model.

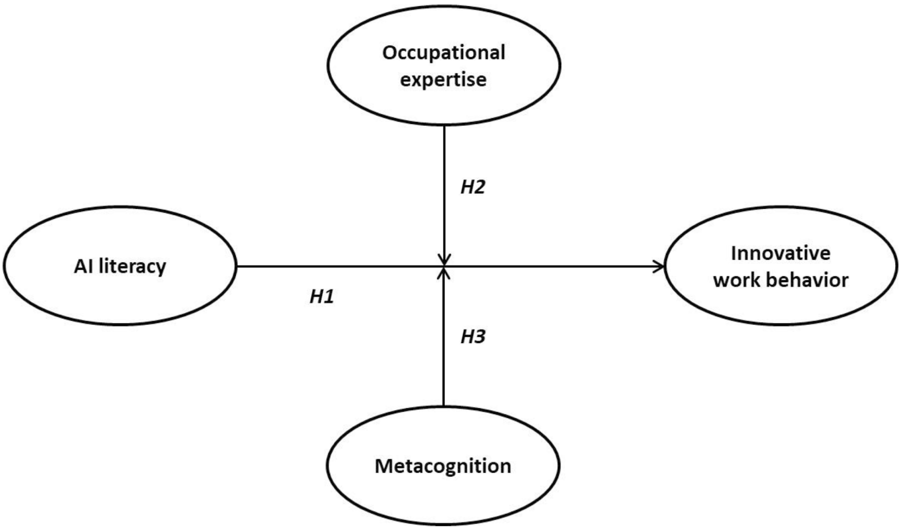

Figure 1. Research model. Source(s): Authors' own work

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Methods

Participants and procedure

To test the proposed hypotheses, data were collected through an online survey conducted from October 9 to 16, 2024, targeting employees in Korean companies and institutions. As this study aimed to examine the relationships among AIL, IWB, occupational expertise, and metacognition in generative AI–based work environments, respondents who did not use generative AI were excluded from the survey.

South Korea provides an appropriate context for testing the present hypotheses because generative AI has been rapidly adopted and actively used in workplace settings in the country. According to Microsoft's AI Economy Institute, South Korea recorded the largest increase in global AI adoption rankings in the second half of 2025, rising from 25th to 18th place, while generative AI usage grew from approximately 26% to over 30% of the population. In addition, the Bank of Korea reported that 51.8% of Korean workers use generative AI for work and 17.1% use it regularly, suggesting that generative AI has already become embedded in everyday work practices. These trends indicate that Korean employees are actively incorporating generative AI into their work and that Korean organizations are operating in environments in which AI-related capabilities are increasingly relevant. Accordingly, data collected from employees in Korean organizations provide a suitable empirical basis for testing the present hypotheses in a generative AI–enabled work context.

Prior to administering the survey, a rigorous double-translation procedure was employed to enhance measurement accuracy. Given that this study was conducted in South Korea, ensuring linguistic and cultural accuracy in the translation process was essential. Initially, the questionnaire was translated from English to Korean by the research team. A professional bilingual translatorfluent in both English and Korean independently backtranslated the Korean version into English. The back-translated version was reviewed and confirmed to be semantically equivalent to the original English version of the questionnaire. This comparison revealed no significant discrepancies, affirming the fidelity of the Korean translation, which was subsequently used in the survey.

The survey was administered through Invite, a reputable research company in South Korea. The survey targeted individuals employed by companies or organizations in South Korea who had prior experience with or were currently using GAI. The survey consisted of 33 items measuring participants' perceptions of the study variables—AIL, IWB, occupational expertise, and metacognition—as well as six items capturing demographic characteristics. The demographic items included gender, age, education, position, tenure, and prior experience with AI-related training. A stratified random sampling method was employed to achieve demographic representativeness. Selected respondents were invited at random within each demographic stratum (e.g., gender and age) from the existing research panel, thereby minimizing selection bias and ensuring a balanced sample. Participation was voluntary, and the respondents received a small incentive for their involvement.

A total of 633 responses were collected, of which 600 were deemed valid and included in the final analysis. The remaining 33 responses were excluded due to indicators of careless or insincere responding, such as providing identical ratings to both positively and negatively worded items or selecting only the extreme ends of the scale (e.g., only 1s or 5s) throughout the questionnaire. The detailed demographic characteristics of the final sample are summarized in Table 1.

Measures

The constructs examined in this study—AIL, IWB, occupational expertise, and metacognition—were assessed using validated multi-item scales derived from the existing literature. The detailed questions are included in the Appendix 1. Each item was rated on a five-point Likert scale ranging from (1) strongly disagree to (5) strongly agree.

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Table 1. Demographic characteristics of participants

	Frequency	Percent (%)
Gender		
Male	304	50.7
Female	296	49.3
Age		
20s	145	24.2
30s	153	25.5
40s	145	24.2
50s and above	157	26.2
Education		
High school diploma and below	49	8.2
Two-year college degree	51	8.5
Four-year college degree	396	66.0
Master's or Doctoral degree	104	17.3
Position		
Staff	134	22.3
Assistant manager	174	29.0
Manager	184	30.7
Director	79	13.2
Executive	29	4.8
Tenure		
Less than 3 years	121	20.2
3 years to less than 6 years	112	18.7
6 years to less than 9 years	80	13.3
9 years to less than 12 years	81	13.5
12 years to less than 15 years	59	9.8
Over 15 years	147	24.5
Experience of AI related training		
Experienced	226	37.7
Inexperienced	374	62.3
	600	100

Source(s): Authors' own work

AI Literacy. To evaluate AIL, this study employed the Artificial Intelligence Literacy Scale developed by Wang *et al.* (2023). The scale comprises 12 items, with three items allocated to each of the four dimensions: awareness, usage, evaluation, and ethical considerations. The items assess employees' competencies in recognizing AI, effectively using AI applications, critically evaluating AI's capabilities and limitations, and adhering to ethical standards in the use of AI. The example items include "I can identify the AI technology employed in the applications and products I use," "I can use AI applications or products to improve my work efficiency," "I can evaluate the capabilities and limitations of an AI application or product after using it for a while," and "I always comply with ethical principles when using AI applications or products." In Wang *et al.*'s (2023) study, the reliability coefficients (Cronbach's alpha) of the measurements were 0.73 for awareness, 0.75 for usage, 0.78 for evaluation, and 0.73 for ethics. In the current study, the Cronbach's alpha values were 0.70, 0.74, 0.75, and 0.72, respectively.

Innovative Work Behavior. To evaluate IWB, this study used the IWB scale employed in Janssen's (2000) study. The measurement consists of nine items, including three items each on three dimensions: idea generation, idea promotion, and idea realization. The items assess employees' behaviors related to the generation of ideas and the promotion and realization of

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these ideas within the organization. The example items include "I am capable of creating new ideas for difficult issues in my work," "I actively engage in mobilizing support for innovative ideas from my colleagues," and "I am effective in transforming innovative ideas into useful applications in my work." The Cronbach's alpha value for the overall scale reported in Janssen's (2000) study was 0.95. In this study, Cronbach's alpha was 0.91.

Occupational expertise. To evaluate occupational expertise, this study used a five-item unidimensional scale developed by Van der Heijden *et al.* (2018). This scale was originally proposed as a subdimension of employability. The items assess employees' self-perceived competence in performing job-related tasks accurately and thoughtfully. The example items include "I was, in general, competent to perform my work accurately and with few mistakes" and "I consider myself competent to weigh up and reason out the 'pros' and 'cons' of particular decisions on working methods, materials, and techniques in my job domain." The Cronbach's alpha value reported by Van der Heijden *et al.* (2018) was 0.87. In this study, Cronbach's alpha was 0.80.

Metacognition. To evaluate metacognition, this study used the Metacognitive Awareness Inventory developed by Harrison and Vallin (2018). The measurement consists of 19 items, including eight items on knowledge of cognition and 11 items on the regulation of cognition. The items assess employees' metacognitive ability to understand and effectively regulate their own cognitive processes. The example items include "I know when each strategy I use will be most effective" and "I think about what I really need to learn before I begin a task." The Cronbach's alpha values reported in Harrison and Vallin's (2018) study were 0.78 for knowledge of cognition and 0.82 for the regulation of cognition. In this study, Cronbach's alpha values were 0.86 and 0.85, respectively.

Control variables. To control for potential demographic effects that could influence the study outcomes, several background characteristics were included as control variables. These variables included gender, age, educational background, organizational position, and tenure. These factors are commonly employed as control variables in prior research examining employees' attitudes and perceptions within organizational contexts (Nielsen and Raswant, 2018). This study also included prior experience with AI-related training as a control variable. This factor may influence the development of AIL, which, in turn, can have a considerable impact on overall research outcomes.

Analysis

A total of 600 valid responses were analyzed using AMOS 24.0 and SPSS 24.0. This study included several reverse-worded questions. Therefore, before conducting the analysis, these items were reverse-coded to ensure a consistent interpretation of the instruments. The analysis procedure consisted of three steps. First, a confirmatory factor analysis (CFA) was conducted to examine the convergent validity of the measurements. Second, a bivariate correlation analysis was performed to explore the relationships among the research variables. Third, a hierarchical regression analysis was conducted to test the proposed hypotheses.

Hierarchical regression was conducted in four steps: demographic control variables were entered in Step 1, followed by independent variables in Step 2, the moderator variable in Step 3, and the interaction term in Step 4. In Steps 2–4, the demographic variables were included as control variables. The interaction term entered in Step 4 was computed using the mean-centered values of the independent and moderator variables to reduce the multicollinearity.

Finally, to further examine the direction and strength of the moderating effect, a simple slope test was performed following Aiken *et al.* (1991) recommended procedure. The analysis compared two groups: one representing a low level (mean − 1 SD) and the other representing a high level (mean +1 SD) of the moderator, to determine how AIL influenced IWB across these conditions.

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Validity

Confirmatory factor analysis (CFA) was conducted to examine the construct validity of the measurement instruments using AMOS 24.0. The analysis followed a structured procedure as described below. Initially, both first- and second-order CFAs were performed on the constructs of AIL, IWB, and metacognition, all of which were conceptualized as multidimensional constructs. The results demonstrated that the factor loadings, critical ratio (C.R.), average variance extracted (AVE), and composite reliability (CR) met or exceeded the recommended thresholds. Furthermore, the model fit indices indicated satisfactory levels of overall model fit, supporting the adequacy of the measurement models (Fornell and Larcker, 1981; Hu and Bentler, 1999).

First, both first- and second-order CFA were conducted for AIL, which includes three dimensions: awareness, usage, evaluation, and ethics. For the first-order CFA of the AIL, all items exhibited acceptable standardized factor loadings ranging from 0.623 to 0.767. The C. The R. values ranged from 11.915 to 15.813, all exceeding the threshold of 1.965. The AVE values ranged from 0.572 to 0.610, and the CR values ranged from 0.799 to 0.824. The model demonstrated an acceptable fit: χ^2/df = 3.342, CFI = 0.955, GFI = 0.956, AGFI = 0.929, RMSEA = 0.063, and SRMR = 0.046.

For the second-order CFA of AIL, the four sub-dimensions—awareness, usage, evaluation, and ethics—demonstrated factor loadings of 0.569, 0.849, 0.959, and 0.786, respectively. The C.R. values were 8.684, 13.221, 13.254, and 12.065, respectively. The AVE value was 0.912 and the CR value was 0.996. The model also showed a good fit to the data: χ^2/df = 3.253, CFI = 0.955, GFI = 0.956, AGFI = 0.931, RMSEA = 0.061, and SRMR = 0.046.

Next, both first-order and second-order CFA were conducted for IWB, which includes three dimensions: idea generation, idea promotion, and idea realization. For the first-order CFA, the standardized factor loadings ranged from 0.609 to 0.853, all of which were statistically significant. The C.R. values ranged from 13.871 to 22.25, clearly exceeding the threshold of 1.965. The AVE values ranged from 0.599 to 0.702, and the CR values ranged from 0.817 to 0.876. The model fit indices confirmed an excellent model fit: χ^2/df = 2.924, CFI = 0.983, GFI = 0.974, AGFI = 0.952, RMSEA = 0.057, and SRMR = 0.025.

For the second-order CFA of IWB, the three sub-dimensions—idea generation, idea promotion, and idea realization—demonstrated factor loadings of 0.719, 0.943, and 0.922, respectively. The C.R. values were 13.871, 22.250, and 21.565, respectively. The AVE value was 0.936 and the CR value was 0.978. The model also showed a good fit to the data: χ^2/df = 2.924, CFI = 0.983, GFI = 0.974, AGFI = 0.952, RMSEA = 0.057, and SRMR = 0.025.

Subsequently, both first- and second-order CFA were conducted to assess metacognition, which comprises the cognitive knowledge and cognitive regulation sub-dimensions. For the first-order CFA, standardized factor loadings ranged from 0.512 to 0.704, and the C.R. values ranged from 10.812 to 15.951, all surpassing the 1.965 threshold. For the metacognition construct, the AVE and CR values for cognitive knowledge were 0.609 and 0.926, respectively, while those for cognitive regulation were 0.478 and 0.909. Although the AVE value for cognitive regulation fell slightly below the recommended threshold of 0.50, it was not substantially lower, and the corresponding CR value exceeded 0.90, indicating a strong internal consistency (Fornell and Larcker, 1981). Therefore, the construct was deemed acceptable in terms of convergent validity. In addition, the model fit indices confirmed an excellent model fit: χ^2/df = 3.059, CFI = 0.921, GFI = 0.921, AGFI = 0.901, RMSEA = 0.059, and SRMR = 0.046.

For the second-order CFA of metacognition, the two sub-dimensions—cognitive knowledge and cognitive regulation—demonstrated standardized factor loadings of 0.947 and 0.912, respectively, with C.R. values of 15.951 and 10.812. The AVE and CR values were 0.971 and 0.985, respectively. The model fit indices confirmed an excellent model fit: χ^2/df = 3.059, CFI = 0.921, GFI = 0.921, AGFI = 0.901, RMSEA = 0.059, and SRMR = 0.046.

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Finally, a CFA was conducted on the overall measurement model, which included all constructs. All items demonstrated standardized factor loadings between 0.517 and 0.853, with C.R. values ranging from 10.196 to 22.318, exceeding the recommended threshold of 1.965. The AVE values ranged from 0.530 to 0.669, and the CR values ranged from 0.867 to 0.955. The model fit indices for the final measurement model were as follows: χ^2/df = 2.029, CFI = 0.922, TLI = 0.914, GFI = 0.868, AGFI = 0.848, RMSEA = 0.041, and SRMR = 0.044. While some indices, such as GFI and AGFI, were marginally below the ideal cutoff of 0.9, the overall fit indices were within acceptable thresholds, confirming the adequacy of the measurement model. A detailed summary of the CFA results for all constructs is provided in Appendix 2.

Common method bias

This study employed a self-report survey method to measure variables and capture participants' subjective perceptions. Although this method is effective for assessing perceptual constructs, it may introduce the risk of a common method bias. To further assess the potential presence of such bias, three additional post hoc analyses were conducted (Lee and Roh, 2025; Liang *et al.*, 2026). First, Harman's single-factor test was conducted to examine the extent to which a single factor accounts for the overall variance in the data (Podsakoff *et al.*, 2003). Specifically, an exploratory factor analysis (EFA) was performed on all measurement items by constraining the extraction to one factor. The analysis revealed that the first factor accounted for 32.607% of the total variance, which was well below the recommended threshold of 50%.

Second, following Kock and Lynn (2012), a full collinearity assessment was conducted to simultaneously evaluate multicollinearity and the potential for common method bias. The results showed that the variance inflation factor (VIF) values ranged from 1.538 to 2.725, all of which were well below the recommended threshold of 3.3.

Finally, the fit of the proposed model was compared with that of several competing models (Doty and Glick, 1998). Specifically, confirmatory factor analysis was used to compare the fit of the proposed four-factor model with alternative three-, two-, and one-factor models in which some constructs were combined. The results indicated that the originally proposed model demonstrated a better fit than the alternative models. Taken together, these additional analyses indicate that common method bias is unlikely to pose a serious threat to the validity of the findings of this study.

Results

Descriptive statistics and correlations

Table 2 presents the descriptive statistics and correlations for all variables. Table 2 shows that the mean scores for the research variables ranged from 3.458 to 3.697. AIL was positively correlated with IWB, occupational expertise, and metacognition. Similarly, occupational expertise was positively correlated with IWB, and metacognition was also positively correlated with IWB.

Hierarchical and moderated regression analyses

Hierarchical regression analysis was conducted to test the proposed hypotheses. The analyses followed a stepwise procedure in which demographic characteristic variables, independent variables, moderator variables, and interaction terms were entered in sequence. As two moderators were examined, six models were generated. The results of the hierarchical regression analysis are presented in Table 3.

Model 2 in Table 3 reports the test of Hypothesis 1, which proposes that AIL has a positive effect on IWB. The results show that AIL has a significant positive effect on IWB ($\beta = 0.526$, $p < 0.001$). Therefore, Hypothesis 1 was supported.

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Table 2. Descriptive statistics and correlations

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10
1. Gender	0.507	0.500	1									
2. Age	3.523	1.122	0.012	1								
3. Education	2.925	0.762	−0.018	0.152**	1							
4. Position	2.492	1.119	0.172**	0.614**	0.296**	1						
5. Tenure	3.477	1.872	0.057	0.744**	0.222**	0.702**	1					
6. Experience	0.377	0.485	−0.072	0.002	0.117**	0.046	0.048	1				
7. AIL	3.684	0.510	−0.045	−0.124**	0.095*	−0.057	−0.081*	0.213**	1			
8. IWB	3.458	0.638	0.059	0.014	0.111**	0.071	0.041	0.268**	0.550**	1		
9. OE	3.631	0.577	−0.011	0.115**	0.143**	0.128**	0.150**	0.202**	0.511**	0.617**	1	
10. MC	3.697	0.451	−0.037	0.048	0.121**	0.069	0.078	0.185**	0.680**	0.680**	0.703**	1

Note(s): $n = 621$; $^{*}p < 0.05$, $^{**}p < 0.01$ (two-tailed tests); gender 0 = female, 1 = male; age 1 = 20s, 2 = 30s, 3 = 40s, 4 = 50s and above; education 1 = high school diploma and below, 2 = two-year college degree, 3 = four-year college degree, 4 = master’s or doctoral degree; position 1 = staff, 2 = assistant manager, 3 = manager, 4 = director, 5 = executive; tenure 1 = less than 3 years, 2 = 3 years to less than 6 years, 3 = 6 years to less than 9 years, 4 = 9 years to less than 12 years, 5 = 12 years to less than 15 years, 6 = over 15 years; Experience = experience of AI related training 0 = inexperience, 1 = experience; AIS = AI Literacy; IWB = Innovative Work Behavior; OE=Occupational Expertise; MC = Metacognition

Source(s): Authors’ own work

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Table 3. Results of the hierarchical regression analysis

Variable	Innovative work behavior Model 1 β (SE)	Model 2 β (SE)	Model 3 β (SE)	Model 4 β (SE)	Model 5 β (SE)	Model 6 β (SE)
Gender	0.073 (0.052)	0.087* (0.044)	0.083** (0.039)	0.085** (0.039)	0.092** (0.038)	0.093** (0.038)
Age	−0.018 (0.034)	0.049 (0.029)	0.011 (0.026)	0.014 (0.026)	0.006 (0.025)	0.008 (0.025)
Education	0.074 (0.035)	0.025 (0.030)	0.005 (0.027)	0.010 (0.026)	0.012 (0.026)	0.016 (0.026)
Job Position	0.041 (0.034)	0.041 (0.028)	0.036 (0.025)	0.038 (0.025)	0.036 (0.025)	0.038 (0.025)
Tenure	−0.007 (0.023)	0.001 (0.019)	−0.046 (0.017)	−0.049 (0.017)	−0.035 (0.017)	−0.038 (0.017)
Experience	0.264*** (0.052)	0.158*** (0.045)	0.121*** (0.041)	0.115*** (0.041)	0.140*** (0.039)	0.128*** (0.040)
AIL		0.526*** (0.043)	0.302*** (0.045)	0.313*** (0.045)	0.143*** (0.051)	0.154*** (0.051)
OE			0.439*** (0.040)	0.433*** (0.040)		
AIL x OE				0.083** (0.056)		
MC					0.559*** (0.057)	0.558*** (0.057)
AIL x MC						0.086** (0.065)
R^2	0.086	0.343	0.476	0.483	0.504	0.512
ΔR^2	0.086	0.257	0.133	0.007	0.161	0.007
F	9.252***	44.161***	67.140***	61.201***	75.201***	68.684***

Note(s): $n = 621$; *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; Experience = Experience of AI related training, AIL = AI Literacy, IB=Innovative Behavior, OE=Occupational Expertise, MC = Metacognition
Source(s): Authors' own work

Next, Model 4 tested Hypothesis 2, which proposed that occupational expertise moderates the relationship between AIL and IWB. The interaction term between AIL and occupational expertise showed a significant positive effect on IWB ($\beta = 0.083$, $p < 0.01$), supporting Hypothesis 2.

Finally, Model 6 tested Hypothesis 3, which proposed that metacognition moderates the relationship between AIL and IWB. The interaction term between AIL and metacognition also had a significant positive effect on IWB ($\beta = 0.086$, $p < 0.01$). Thus, Hypothesis 3 was also supported.

Additionally, simple slope tests were conducted to visually examine the direction and intensity of the moderating effects and assess the moderating roles of occupational expertise and metacognition. The results of each test are shown in Figures 2 and 3.

Figure 2 illustrates that the slope for the group with high occupational expertise is steeper than that for the group with low occupational expertise. This suggests that the positive effect of AIL on IWB becomes stronger as the level of occupational expertise increases.

Similarly, Figure 3 shows that the slope for the group with high metacognition is steeper than that for the group with low metacognition. This result also indicates that the positive effect of AIL on IWB strengthens as metacognition increases.

Conclusion

This section summarizes the results of the hypothesis tests and discusses their implications for theory and practice. First, AIL had a significant positive effect on the IWB. This indicates that employees with higher AIL levels demonstrate higher IWB levels. As an innovative

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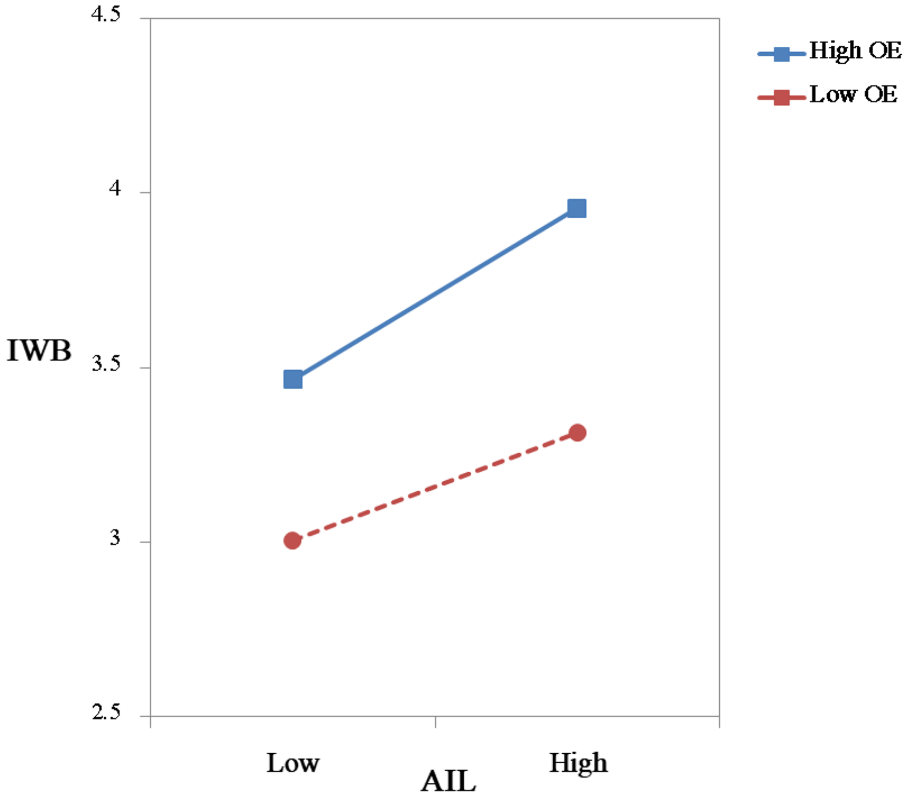

Figure 2. Moderating effect of occupational expertise on the relationship between AI literacy and innovative work behavior. Source(s): Authors' own work

technology, GAI is more likely to be adopted and utilized by individuals with greater AIL (Rogers *et al.*, 2014). Moreover, employees with high AIL are better able to understand the functions of GAI and use it effectively, for example, by submitting well-structured prompts (Ji *et al.*, 2025; Wang *et al.*, 2023). Consequently, they leverage the high-quality information and knowledge obtained through GAI to exhibit greater IWB.

Second, the effect of AIL on IWB was strengthened by occupational expertise in this study. This suggests that occupational expertise is necessary for employees with high AIL to demonstrate higher levels of IWB. To acquire high-quality knowledge and information via GAI, well-formulated prompts must be provided. Employees with high occupational expertise can incorporate contextual details, examples, and background knowledge into their questions (Wei *et al.*, 2022; White *et al.*, 2023). Furthermore, they can interpret and apply GAI outputs appropriately to their specific work contexts. Consequently, employees with both high AIL and occupational expertise exhibit higher IWB.

Third, the effect of AIL on IWB was strengthened by metacognition. This implies that metacognition aids employees with high AIL in engaging in higher levels of IWB. Employees with both high AIL and high metacognitive awareness are able to quickly identify the information and knowledge required for IWB and easily acquire it using GAI (Lebuda and Benedek, 2025; Kim and Lee, 2018). In addition, employees with high metacognition can evaluate whether the ideas or outputs generated by GAI are applicable in their current situations

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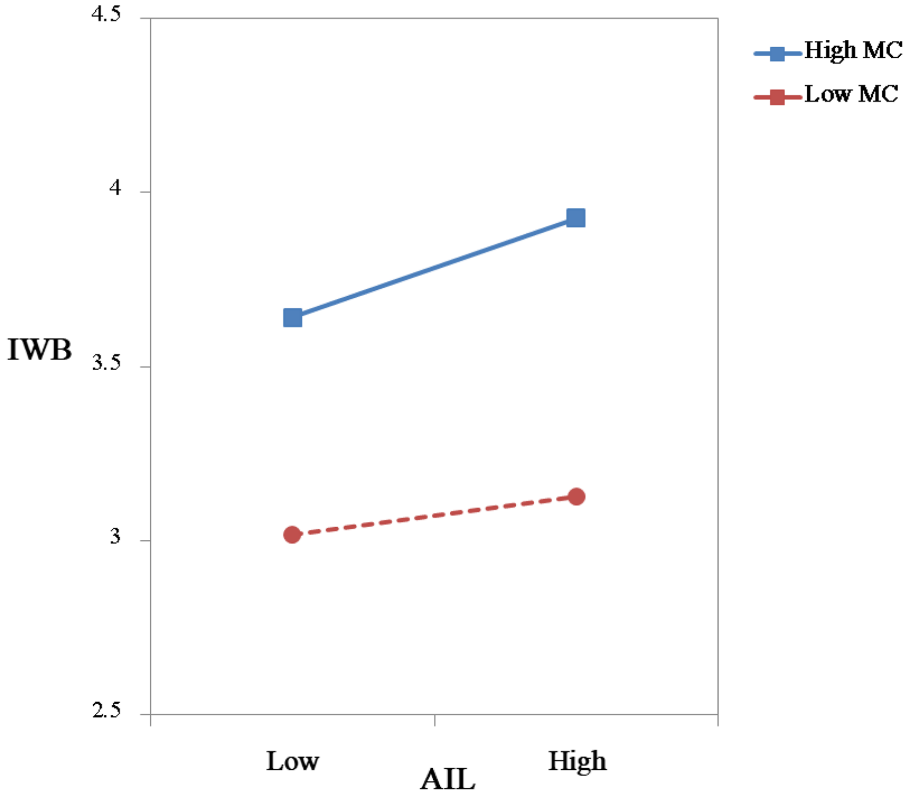

Figure 3. Moderating effect of metacognition on the relationship between AI literacy and innovative work behavior. Source(s): Authors' own work

and can modify and apply them appropriately (MacGregor *et al.*, 2001; Jia *et al.*, 2019). Consequently, those with both high AIL and metacognition exhibit higher levels of IWB.

These findings provide meaningful insights into understanding the individual capabilities that promote IWB in the AI era, where AIL is increasingly emphasized. AIL plays a crucial role in converting GAI use into an IWB. However, AIL alone is insufficient to ensure the execution of high-level IWB. To generate and implement innovative ideas quickly, high levels of occupational expertise and metacognition are necessary. Ultimately, to foster high-level IWB in the age of AI, it is important to enhance individuals' AIL, expertise, and metacognition.

Discussion

Theoretical implications

The findings of this study offer several important theoretical implications for research on human resource management, human resource development, and organizational behavior. More specifically, this study extends research on IWB and AIL to generative AI–enabled work environments, positions AIL as a strategic individual capability for workplace innovation, and explains how complementary human capabilities, particularly occupational expertise and metacognition, shape the translation of AIL into IWB in contemporary organizations.

First, this study contributes to the IWB literature by extending its scope to generative AI–enabled work environments. Prior IWB research has identified a wide range of antecedents of

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IWB, but much of this work was conducted in organizational contexts preceding the widespread diffusion of generative AI, thereby offering limited insight into what drives IWB in AI-enabled work settings (AlEssa and Durugbo, 2022). In addition, prior studies have mainly emphasized relatively general antecedents, such as motivation, personality, and broad competencies or domain knowledge (Saether, 2019; Woods *et al.*, 2018; Saeed *et al.*, 2019). By empirically demonstrating that AIL positively influences IWB in GAI-enabled work environments, this study helps address important gaps in the existing literature and extends the IWB literature to a new technological context in which human–AI interaction has become an important part of employees' daily work.

Second, this study contributes to the AIL literature by extending its theoretical relevance beyond conceptualization and measurement to innovation-related behavior in organizational contexts. As discussed in the literature review, prior AIL research has largely focused on defining the construct, refining its dimensions and developing measurement instruments (Ng *et al.*, 2021; Wang *et al.*, 2023). Even when organizational implications were considered, empirical attention was directed primarily toward general outcomes, such as job performance and job satisfaction (Liu *et al.*, 2025; Mughari *et al.*, 2024; Lee and Jeon, 2025). Thus, although the importance of AIL has been increasingly recognized, relatively little is known about whether AIL contributes to employee behaviors directly related to workplace innovation. By showing that AIL is positively associated with IWB, this study addresses this gap and repositions AIL not merely as a technical or educational competence but as a strategically important individual capability that can foster innovation-oriented behavior in organizations.

Finally, this study contributes to the literature by offering a more integrated theoretical framework for understanding employee innovation in the age of generative AI. Drawing on innovation diffusion theory, this study proposes that AIL facilitates the understanding, acceptance, and effective use of generative AI, thereby increasing the likelihood that employees will engage in IWB (Rogers *et al.*, 2014). Simultaneously, the findings show that the effect of AIL on IWB is not uniform but becomes stronger when employees also possess occupational expertise and metacognition. This suggests that employees are more likely to translate AIL into IWB when they have the domain-specific expertise needed to contextualize AI-generated outputs and the metacognitive ability to monitor, evaluate, and adapt those outputs appropriately. Therefore, this study extends innovation diffusion theory from a technology adoption perspective to a behavioral outcome perspective by explaining not only why employees adopt and use generative AI but also under what personal capability conditions such use is more likely to be converted into IWB. This study provides a richer theoretical foundation for future research on how AI-related and complementary human capabilities jointly shape employee behavior and organizational outcomes in AI-enabled work environments.

Practical implications

In addition to its theoretical contributions, this study also provides practical implications for organizational leaders, HR policymakers, HR managers, HRD practitioners, and managers responsible for digital transformation and AI implementation. More specifically, the findings offer guidance for these stakeholders on how to foster employees' IWB in generative AI–enabled work environments by investing in AI literacy development, supporting employees' continuous learning and experimentation with AI, cultivating complementary human capabilities such as occupational expertise and metacognition, and using these capabilities as criteria for talent development, allocation, and recruitment.

First, it highlights the importance of enhancing employees' AIL to promote IWB through the use of a GAI. This is especially critical in the current environment, where the use of AI is rapidly expanding and the value of the IWB is increasingly emphasized. Therefore, organizations and managers should develop and implement AI-related education and training programs to improve employees' AIL. Previous studies have reported the effectiveness of AI training in enhancing AIL (Almatrafi *et al.*, 2024), and in this study, the correlation analysis

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also indicates a positive relationship between AIL and AI-related education (see Table 2). Moreover, organizations can enhance the effectiveness of AI-related education by linking training outcomes to performance management and reward systems. For example, improvements in AI-related competencies may be reflected in performance evaluations, developmental feedback, promotion considerations, or incentive structures, thereby encouraging employees to engage more consistently with AI learning and application.

Second, organizations should focus on enhancing AIL not only through formal training but also by promoting employees' learning agility and providing organizational support. Prior research suggests that individuals with high learning agility are more likely to adapt quickly to new AI applications, develop AIL more rapidly, and achieve better work outcomes (Lee and Jeon, 2025). This implies that AIL should not be treated as a fixed individual trait but rather as a capability that can be developed under appropriate learning conditions. In this regard, managers can foster learning agility by strengthening employees' goal orientation, enhancing achievement motivation, and assigning developmental or challenging tasks that encourage experimentation and continuous learning (Lombardo and Eichinger, 2000). Simultaneously, organizations should provide supportive conditions that enable employees to actively engage with AI in their work, such as access to relevant AI applications, opportunities for repeated use, and a work environment that supports learning and experimentation (Day *et al.*, 2012; Lee and Jeon, 2025). Such efforts can help employees develop higher AIL levels and apply AI more effectively in ways that support IWB.

Third, this study emphasizes the importance of occupational expertise and metacognition. Although GAI can be an effective tool in facilitating IWB, higher levels of IWB may require additional competencies. Therefore, instead of focusing solely on improving AIL, organizations and managers should adopt a balanced approach that also promotes other relevant competencies such as occupational expertise and metacognitive skills. Providing employees with educational and training programs is a key strategy for enhancing these competencies. Although occupational expertise can be developed through practical work experience, the process may be more effective when supported by structured training programs (Clark, 2008). Additionally, Downing *et al.* (2009) emphasized the role of problem-based learning, which focuses on reflection and application, in developing metacognitive abilities.

Finally, the findings of this study can be strategically applied to internal talent allocation and recruitment. For example, departments such as R&D or product and service development often require employees to demonstrate high IWB levels. Therefore, in these departments, AIL, occupational expertise, and metacognitive ability may be considered key evaluation criteria when hiring or assigning members.

Limitation and future research directions

This study had several limitations. First, it primarily focused on the effect of AIL in promoting IWB and did not examine its impact on other outcomes. However, AIL may also contribute to various organizational outcomes beyond IWB, such as employee engagement, adaptive performance, and knowledge-sharing behavior. Future studies should investigate the broader impact of AIL on diverse performance indicators to expand our understanding of its role within organizations.

Second, this study focused on individual competencies in facilitating IWB and did not account for the interaction effects between AIL and environmental factors. The influence of AIL on IWB may vary depending on the job context or workplace characteristics. For example, Park *et al.* (2004) argued that the implementation of knowledge management technologies is affected by organizational culture and that a supportive culture is essential for the success of such initiatives. Similarly, Nusrat *et al.* (2025) showed that the interaction between entrepreneurial leadership and AI enhances organizational innovativeness, suggesting that the effects of AI-related capabilities may be amplified when favorable organizational conditions support them. In addition, future research should examine whether

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organizational-level variables, such as digitalization capability and digital dynamic capabilities, shape the extent to which AIL is translated into IWB. Prior studies have shown that organizational digital capabilities play an important role in enabling firms to respond effectively to changing environments and achieve superior outcomes (Lee and Roh, 2025; Liang *et al.*, 2026). This suggests that even employees with high AIL may demonstrate different levels of IWB depending on the level of digital support and capability embedded in their organizations. Therefore, future research should examine the differentiated effects of AIL on IWB in various work environments and conditions, ideally through multilevel designs that jointly consider individual- and organizational-level factors.

Third, this study was conducted in South Korea and therefore did not sufficiently account for cross-national sociocultural differences. South Korea is characterized by a high and rapidly increasing level of generative AI use, which may reflect relatively active attitudes toward adopting and utilizing AI technologies. Such sociocultural characteristics may play an important role in shaping employees' AIL. For example, Lee and Jeon (2025) suggested that frequent experience with AI use may function as a form of learning, which can contribute to the development of higher levels of AIL. Therefore, future research should conduct comparative studies across countries with distinct sociocultural and technological environments to examine whether the relationships among AIL, occupational expertise, metacognition, and IWB differ depending on the national context. Such comparative work would help assess the contextual boundary conditions of the present findings and enhance the generalizability of this research.

Finally, the data used in this study were collected through a self-report survey, which raises the possibility of common method biases. To address this concern, this study conducted several post hoc statistical checks, including Harman's single-factor test, a full collinearity assessment, and comparisons with competing measurement models. The results consistently suggest that the likelihood of serious common method bias is low. Nevertheless, such post hoc tests cannot completely rule out the possibility of methodological bias. Therefore, future research should adopt more rigorous methodological strategies, such as conducting additional post hoc analyses using marker variables or collecting data from multiple sources to separate the sources of measurement for predictors, moderators, and outcomes (Doty and Glick, 1998; Lee and Roh, 2025; Liang *et al.*, 2026). In addition, longitudinal or time-lagged research designs would be particularly valuable for clarifying the causal ordering among AIL, complementary competencies, and IWB, thereby providing a more robust test of the relationships proposed in this study's hypotheses.

Data availability statement
The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Appendix 1
Survey questionnaire

AI Literacy

Awareness

(1) I can distinguish between smart devices and non-smart devices.

(2) I do not know how AI technology can help me. (R)

(3) I can identify the AI technology employed in the applications and products I use.

Usage

(1) I can skillfully use AI applications or products to help me with my daily work.

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(2) It is usually hard for me to learn to use a new AI application or product. (R)

(3) I can use AI applications or products to improve my work efficiency.

Evaluation

(1) I can evaluate the capabilities and limitations of an AI application or product after using it for a while.

(2) I can choose a proper solution from various solutions provided by a smart agent.

(3) I can choose the most appropriate AI application or product from a variety for a particular task.

Ethics

(1) I always comply with ethical principles when using AI applications or products.

(2) I am never alert to privacy and information security issues when using AI applications or products. (R)

(3) I am always alert to the abuse of AI technology.

Innovative work behavior

Idea generation

(1) Creating new ideas for difficult issues

(2) Searching out new working methods, techniques, or instruments

(3) Generating original solutions for problems

Idea promotion

(1) Mobilizing support for innovative ideas

(2) Acquiring approval for innovative ideas

(3) Making important organizational members enthusiastic for innovative ideas

Idea realization

(1) Transforming innovative ideas into useful applications

(2) Introducing innovative ideas into the work environment in a systematic way

(3) Evaluating the utility of innovative ideas

Metacognition

Knowledge of cognition

(1) I know what kind of information is most important to learn.

(2) I know what the teacher expects me to learn.

(3) I have control over how well I learn.

(4) I am a good judge of how well I understand something.

(5) I am aware of what strategies I use when I study.

(6) I find myself using helpful learning strategies automatically.

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Regulation of cognition dimension

(1) I think about what I really need to learn before I begin a task.

(2) I set specific goals before I begin a task.

(3) I try to translate new information into my own words.

(4) I use the organizational structure of the text to help me learn.

(5) I ask myself if what I'm reading is related to what I already know.

(6) I periodically review to help me understand important relationships.

(7) I summarize what I've learned after I finish.

(8) I ask myself if I learned as much as I could have once I finish a task.

(9) I change strategies when I fail to understand.

(10) I re-evaluate my assumptions when I get confused.

(11) I stop and go back over new information that is not clear.

Occupational expertise

(1) I was, in general, competent to perform my work accurately and with few mistakes.

(2) I was, in general, competent to take prompt decisions with respect to my approach to work.

(3) In general, I am competent to distinguish main issues from side issues and to set priorities.

(4) I consider myself competent to weigh up and reason out the "pros" and "cons" of particular decisions on working methods, materials, and techniques in my job domain.

(5) How would you rate the quality of your skills overall?

Appendix 2

Table A1. Results of reliability analysis and confirmatory factor analysis

Variable		β	B	S.E.	C.R.	p	AVE	CR
AIL	Awareness 1	0.648	1				0.596	0.946
	Awareness 2	0.656	0.866	0.066	13.113	***		
	Awareness 3	0.693	1.146	0.084	13.661	***		
	Usage 1	0.767	1					
	Usage 2	0.676	0.879	0.056	15.802	***		
	Usage 3	0.654	0.733	0.048	15.267	***		
	Evaluation 1	0.678	1					
	Evaluation 2	0.722	1.082	0.070	15.385	***		
	Evaluation 3	0.712	1.109	0.073	15.198	***		
	Ethics 1	0.618	1					
	Ethics 2	0.761	1.184	0.094	12.587	***		
	Ethics 3	0.692	1.093	0.090	12.180	***		

(*continued*)

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Table A1. Continued

Variable		β	B	S.E.	C.R.	p	AVE	CR
IWB	Generation 1	0.731	1				0.669	0.948
	Generation 2	0.639	0.859	0.058	14.787	***		
	Generation 3	0.726	1.089	0.065	16.799	***		
	Promotion 1	0.795	1					
	Promotion 2	0.853	1.060	0.047	22.318	***		
	Promotion 3	0.756	0.999	0.051	19.426	***		
	Realization 1	0.820	1					
	Realization 2	0.817	0.976	0.044	22.117	***		
	Realization 3	0.724	0.860	0.045	18.978	***		
OE	OE1	0.595	1				0.567	0.867
	OE2	0.661	1.073	0.084	12.705	***		
	OE3	0.667	1.079	0.084	12.794	***		
	OE4	0.744	1.168	0.085	13.751	***		
	OE5	0.653	1.190	0.094	12.600	***		
MC	Knowledge 1	0.647	1				0.530	0.955
	Knowledge 2	0.630	1.085	0.081	13.474	***		
	Knowledge 3	0.629	1.105	0.082	13.468	***		
	Knowledge 4	0.643	1.038	0.076	13.714	***		
	Knowledge 5	0.657	1.042	0.066	15.872	***		
	Knowledge 6	0.682	1.159	0.081	14.400	***		
	Knowledge 7	0.640	1.127	0.083	13.651	***		
	Knowledge 8	0.704	1.207	0.082	14.773	***		
	Regulation 1	0.609	1					
	Regulation 2	0.617	1.077	0.085	12.670	***		
	Regulation 3	0.628	0.941	0.073	12.837	***		
	Regulation 4	0.567	0.906	0.076	11.852	***		
	Regulation 5	0.587	0.952	0.078	12.179	***		
	Regulation 6	0.600	1.076	0.087	12.397	***		
	Regulation 7	0.517	1.008	0.092	10.983	***		
	Regulation 8	0.579	1.131	0.094	12.053	***		
	Regulation 9	0.570	1.003	0.084	11.890	***		
	Regulation 10	0.541	0.934	0.082	11.380	***		
	Regulation 11	0.605	0.970	0.078	12.471			

Note(s): $n = 600$; ***$p < 0.001$; AIL = AI Literacy, IWB = Innovative Work Behavior, OE = Occupational Expertise, MC = Metacognition

References

Acar, S., Runco, M.A. and Park, H. (2020), "What should people be told when they take a divergent thinking test? A meta-analytic review of explicit instructions for divergent thinking", *Psychology of Aesthetics, Creativity, and the Arts*, Vol. 14 No. 1, pp. 39-49, doi: 10.1037/aca0000256.

Aiken, L.S., West, S.G. and Reno, R.R. (1991), *Multiple Regression: Testing and Interpreting Interactions*, Sage Publications, Thousand Oaks, CA.

AlEssa, H.S. and Durugbo, C.M. (2022), "Systematic review of innovative work behavior concepts and contributions", *Management Review Quarterly*, Vol. 72 No. 4, pp. 1171-1208, doi: 10.1007/s11301-021-00224-x.

Almatrafi, O., Johri, A. and Lee, H. (2024), "A systematic review of AI literacy conceptualization, constructs, and implementation and assessment efforts (2019-2023)", *Computers and Education Open*, Vol. 6, 100173, doi: 10.1016/j.caeo.2024.100173.

Bos-Nehles, A., Renkema, M. and Janssen, M. (2017), "HRM and innovative work behaviour: a systematic literature review", *Personnel Review*, Vol. 46 No. 7, pp. 1228-1253, doi: 10.1108/PR-09-2016-0257.

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Brown, J.A. (1998), "Media literacy perspectives", *Journal of Communication*, Vol. 48 No. 1, pp. 44-57, doi: 10.1111/j.1460-2466.1998.tb02736.x.

Celik, I. (2023), "Exploring the determinants of artificial intelligence (AI) literacy: digital divide, computational thinking, cognitive absorption", *Telematics and Informatics*, Vol. 83, 102026, doi: 10.1016/j.tele.2023.102026.

Cetindamar, D., Kitto, K., Wu, M., Zhang, Y., Abedin, B. and Knight, S. (2022), "Explicating AI literacy of employees at digital workplaces", *IEEE Transactions on Engineering Management*, Vol. 71, pp. 810-823, doi: 10.1109/TEM.2021.3138503.

Chiu, T.K. (2025), "AI literacy and competency: definitions, frameworks, development and future research directions", *Interactive Learning Environments*, Vol. 33 No. 5, pp. 3225-3229, doi: 10.1080/10494820.2025.2514372.

Clark, R.C. (2008), *Building Expertise: Cognitive Methods for Training and Performance Improvement*, John Wiley and Sons, San Francisco, CA.

Day, A., Paquet, S., Scott, N. and Hambley, L. (2012), "Perceived information and communication technology (ICT) demands on employee outcomes: the moderating effect of organizational ICT support", *Journal of Occupational Health Psychology*, Vol. 17 No. 4, pp. 473-491, doi: 10.1037/a0029837.

Doty, D.H. and Glick, W.H. (1998), "Common methods bias: does common methods variance really bias results?", *Organizational Research Methods*, Vol. 1 No. 4, pp. 374-406, doi: 10.1177/109442819814002.

Downing, K., Kwong, T., Chan, S.W., Lam, T.F. and Downing, W.K. (2009), "Problem-based learning and the development of metacognition", *Higher Education*, Vol. 57 No. 5, pp. 609-621, doi: 10.1007/s10734-008-9165-x.

Duffy, B. (2018), *The Perils of Perception*, Atlantic Books, London.

Flavell, J.H. (2024), "Metacognitive aspects of problem solving", in Resnick, L.B. (Ed.), *The Nature of Intelligence*, Routledge, London.

Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18 No. 1, pp. 39-50, doi: 10.1177/002224378101800104.

Germain, M.L. and Ruiz, C.E. (2009), "Expertise: myth or reality of a cross-national definition?", *Journal of European Industrial Training*, Vol. 33 No. 7, pp. 614-634, doi: 10.1108/03090590910985381.

Hammond, M.M., Neff, N.L., Farr, J.L., Schwall, A.R. and Zhao, X. (2011), "Predictors of individual-level innovation at work: a meta-analysis", *Psychology of Aesthetics, Creativity, and the Arts*, Vol. 5 No. 1, pp. 90-105, doi: 10.1037/a0018556.

Harrison, G.M. and Vallin, L.M. (2018), "Evaluating the metacognitive awareness inventory using empirical factor-structure evidence", *Metacognition and Learning*, Vol. 13 No. 1, pp. 15-38, doi: 10.1007/s11409-017-9176-z.

Haugsbaken, H. and Hagelia, M. (2024), "A new AI literacy for the algorithmic age: prompt engineering or educational promptization?", *2024 4th International Conference on Applied Artificial Intelligence (ICAPAI)*, IEEE, pp. 1-8, doi: 10.1109/ICAPAI61893.2024.10541229.

Hock, M. and Mellard, D. (2005), "Reading comprehension strategies for adult literacy outcomes", *Journal of Adolescent & Adult Literacy*, Vol. 49 No. 3, pp. 192-200, doi: 10.1598/JAAL.49.3.3.

Hu, L.T. and Bentler, P.M. (1999), "Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives", *Structural Equation Modeling: A Multidisciplinary Journal*, Vol. 6 No. 1, pp. 1-55, doi: 10.1080/10705519909540118.

Janssen, O. (2000), "Job demands, perceptions of effort-reward fairness and innovative work behaviour", *Journal of Occupational and Organizational Psychology*, Vol. 73 No. 3, pp. 287-302, doi: 10.1348/096317900167038.

Ji, Y., Zhong, M., Lyu, S., Li, T., Niu, S. and Zhan, Z. (2025), "How does AI literacy affect individual innovative behavior: the mediating role of psychological need satisfaction, creative self-efficacy,

Downloaded from ftp.nowpublishers.com/apjba/article-pdf/doi/10.1108/APJBA-10-2025-0781/11828982/apjba-10-2025-0781en.pdf by guest on 09 September 2026

and self-regulated learning”, *Education and Information Technologies*, Vol. 30 No. 11, pp. 1-30, doi: 10.1007/s10639-025-13437-4.

Jia, X., Li, W. and Cao, L. (2019), “The role of metacognitive components in creative thinking”, *Frontiers in Psychology*, Vol. 10, p. 2404, doi: 10.3389/fpsyg.2019.02404.

Khosrowjerdi, M. and Iranshahi, M. (2011), “Prior knowledge and information-seeking behavior of PhD and MA students”, *Library & Information Science Research*, Vol. 33 No. 4, pp. 331-335, doi: 10.1016/j.lisr.2010.04.008.

Kim, D. and Lee, D. (2018), “Impacts of metacognition on innovative behaviors: focus on the mediating effects of entrepreneurship”, *Journal of Open Innovation: Technology, Market, and Complexity*, Vol. 4 No. 2, p. 18, doi: 10.3390/joitmc4020018.

Knoth, N., Tolzin, A., Janson, A. and Leimeister, J.M. (2024), “AI literacy and its implications for prompt engineering strategies”, *Computers and Education: Artificial Intelligence*, Vol. 6, 100225, doi: 10.1016/j.caeai.2024.100225.

Kock, N. and Lynn, G. (2012), “Lateral collinearity and misleading results in variance-based SEM: an illustration and recommendations”, *Journal of the Association for Information Systems*, Vol. 13 No. 7, pp. 546-580, doi: 10.17705/1jais.00302.

Lebuda, I. and Benedek, M. (2025), “Contributions of metacognition to creative performance and behavior”, *The Journal of Creative Behavior*, Vol. 59 No. 1, e652, doi: 10.1002/jocb.652.

Lee, J.H. and Jeon, J.H. (2025), “Examining the impact of AI literacy and its antecedents on job performance in the context of South Korea”, *Asia Pacific Business Review*, pp. 1-25, doi: 10.1080/13602381.2025.2487780.

Lee, M.J. and Roh, T. (2025), “Digitalization capability and sustainable performance in emerging markets: mediating roles of in/out-bound open innovation and coopetition strategy”, *Management Decision*, Vol. 63 No. 8, pp. 2796-2824, doi: 10.1108/MD-10-2022-1398.

Li, T., Ji, Y. and Zhan, Z. (2024), “Expert or machine? Comparing the effect of pairing student teacher with in-service teacher and ChatGPT on their critical thinking, learning performance, and cognitive load in an integrated-STEM course”, *Asia Pacific Journal of Education*, Vol. 44 No. 1, pp. 45-60, doi: 10.1080/02188791.2024.2305163.

Liang, Y., Kim, T.H. and Lee, M.J. (2026), “Digital dynamic capabilities and environmental sustainability: the role of circular supply chain practices”, *Corporate Social Responsibility and Environmental Management*, Vol. 33 No. 4, pp. 5434-5452, doi: 10.1002/csr.70458.

Liu, X., Zhang, L. and Wei, X. (2025), “Generative artificial intelligence literacy: scale development and its effect on job performance”, *Behavioral Sciences*, Vol. 15 No. 6, p. 811, doi: 10.3390/bs15060811.

Lombardo, M.M. and Eichinger, R.W. (2000), “High potentials as high learners”, *Human Resource Management*, Vol. 39 No. 4, pp. 321-329.

MacGregor, J.N., Ormerod, T.C. and Chronicle, E.P. (2001), “Information processing and insight: a process model of performance on the nine-dot and related problems”, *Journal of Experimental Psychology: Learning, Memory, and Cognition*, Vol. 27 No. 1, pp. 176-201, doi: 10.1037/0278-7393.27.1.176.

Malik, A., Lirio, P., Budhwar, P., Nguyen, M. and Fauzi, M.A. (2025), “Guest editorial: artificial intelligence (AI) in the world of work: bibliometric insights and mapping opportunities and challenges”, *Personnel Review*, Vol. 54 No. 3, pp. 781-799, doi: 10.1108/PR-12-2024-1061.

Mughari, S., Rafique, G.M. and Ali, M.A. (2024), “Effect of AI literacy on work performance among medical librarians in Pakistan”, *The Journal of Academic Librarianship*, Vol. 50 No. 5, 102918, doi: 10.1016/j.acalib.2024.102918.

Mumtaz, S., Ali, A. and Abbas, M. (2025), “I want to embrace it: how diffusion of innovation drives employee attitude and intention toward data analytics adoption?”, *Asia-Pacific Journal of Business Administration*, Vol. 18 No. 5, pp. 1222-1239, doi: 10.1108/APJBA-02-2025-0120.

Ng, D.T.K., Leung, J.K.L., Chu, S.K.W. and Qiao, M.S. (2021), “Conceptualizing AI literacy: an exploratory review”, *Computers and Education: Artificial Intelligence*, Vol. 2, 100041, doi: 10.1016/j.caeai.2021.100041.

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Nielsen, B.B. and Raswant, A. (2018), "The selection, use, and reporting of control variables in international business research: a review and recommendations", *Journal of World Business*, Vol. 53 No. 6, pp. 958-968, doi: 10.1016/j.jwb.2018.05.003.

Noy, S. and Zhang, W. (2023), "Experimental evidence on the productivity effects of generative artificial intelligence", *Science*, Vol. 381 No. 6654, pp. 187-192, doi: 10.1126/science.adh2586.

Nusrat, A., Zongming, Z., Li, J. and Muhammad Muneeb, F. (2025), "Thriving big data artificial intelligence: entrepreneurial leadership, proactive personality and affective commitment to innovate micro and small family businesses", *Asia-Pacific Journal of Business Administration*, Vol. 17 No. 5, pp. 1185-1204, doi: 10.1108/APJBA-05-2024-0280.

Orru, G., Piarulli, A., Conversano, C. and Gemignani, A. (2023), "Human-like problem-solving abilities in large language models using ChatGPT", *Frontiers in Artificial Intelligence*, Vol. 6, 1199350, doi: 10.3389/frai.2023.1199350.

Park, H., Ribière, V. and Schulte, W.D. (2004), "Critical attributes of organizational culture that promote knowledge management technology implementation success", *Journal of Knowledge Management*, Vol. 8 No. 3, pp. 106-117, doi: 10.1108/13673270410541079.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y. and Podsakoff, N.P. (2003), "Common method biases in behavioral research: a critical review of the literature and recommended remedies", *Journal of Applied Psychology*, Vol. 88 No. 5, pp. 879-903, doi: 10.1037/0021-9010.88.5.879.

Rafique, G.M., Mughari, S. and Khan, H.A. (2025), *Exploring the Impact of AI Literacy on Innovative Behavior: Insights from Medical Head Librarians in Pakistan*, Information Discovery and Delivery, doi: 10.1108/IDD-12-2024-0196.

Rogers, E.M., Singhal, A. and Quinlan, M.M. (2014), "Diffusion of innovations", in *An Integrated Approach to Communication Theory and Research*, Routledge, New York, NY.

Saeed, B.B., Afsar, B., Cheema, S. and Javed, F. (2019), "Leader-member exchange and innovative work behavior: the role of creative process engagement, core self-evaluation, and domain knowledge", *European Journal of Innovation Management*, Vol. 22 No. 1, pp. 105-124, doi: 10.1108/EJIM-11-2017-0158.

Saether, E.A. (2019), "Motivational antecedents to high-tech R&D employees' innovative work behavior: self-determined motivation, person-organization fit, organization support of creativity, and pay justice", *The Journal of High Technology Management Research*, Vol. 30 No. 2, 100350, doi: 10.1016/j.hitech.2019.100350.

Saranto, K. and Hovenga, E.J. (2004), "Information literacy—what it is about?: literature review of the concept and the context", *International Journal of Medical Informatics*, Vol. 73 No. 6, pp. 503-513, doi: 10.1016/j.ijmedinf.2004.03.002.

Scott, S.G. and Bruce, R.A. (1994), "Determinants of innovative behavior: a path model of individual innovation in the workplace", *Academy of Management Journal*, Vol. 37 No. 3, pp. 580-607, doi: 10.5465/256701.

Sedkaoui, S. and Benaichouba, R. (2024), "Generative AI as a transformative force for innovation: a review of opportunities, applications and challenges", *European Journal of Innovation Management*, Vol. ahead-of-print No. 3, pp. 677-701, doi: 10.1108/EJIM-02-2024-0129.

Shahid, M.K., Mahmood, K., Altayyar, R.S. and Abdullah, H. (2026), "Role of AI capabilities in sustainable firm performance: mediating role of innovative work behavior and the moderating effect of environmental dynamism", *International Journal of Productivity and Performance Management*, Vol. 75 No. 2, pp. 651-671, doi: 10.1108/IJPPM-02-2025-0114.

Sidra, S. and Mason, C. (2024), "Reconceptualizing AI literacy: the importance of metacognitive thinking in an artificial intelligence (AI)-enabled workforce", *2024 IEEE Conference on Artificial Intelligence (CAI)*, IEEE, pp. 1181-1186, doi: 10.1109/CAI59869.2024.00211.

Sidra, S. and Mason, C. (2026), "Generative AI in human-AI collaboration: validation of the collaborative AI literacy and collaborative AI metacognition scales for effective use", *International Journal of Human–Computer Interaction*, Vol. 42 No. 7, pp. 5084-5108, doi: 10.1080/10447318.2025.2543997.

Downloaded from ftp.nowpublishers.com/apjba/article-pdf/doi/10.1108/APJBA-10-2025-0781/11828982/apjba-10-2025-0781en.pdf by guest on 09 September 2026

Smothers, J., Viktora-Jones, M., Ferreira, F. and Jankuhn, N. (2024), "Managing generative AI innovation: the impact of proactive personality and LMX on work outcomes", *Journal of Behavioral and Applied Management*, Vol. 24 No. 2, pp. 90-102, doi: 10.21818/001c.122144, available at: https://jbam.scholasticahq.com/article/122144.pdf

Steinhauser, S. and Heid, P. (2026), "Organizational readiness, AI literacy, and the new Frontier of R&D: how generative AI shapes innovation capacity", *R&D Management*, Vol. 56 No. 4, pp. 559-578, doi: 10.1111/radm.70038.

Tambe, P., Cappelli, P. and Yakubovich, V. (2019), "Artificial intelligence in human resources management: challenges and a path forward", *California Management Review*, Vol. 61 No. 4, pp. 15-42, doi: 10.1177/0008125619867910.

Van der Heijde, C.M. and Van der Heijden, B.I.J.M. (2006), "A competence-based and multidimensional operationalization and measurement of employability", *Human Resource Management*, Vol. 45 No. 3, pp. 449-476, doi: 10.1002/hrm.20119.

Van der Heijden, B.I., Notelaers, G., Peters, P., Stoffers, J.M., De Lange, A.H., Froehlich, D.E. and Van der Heijde, C.M. (2018), "Development and validation of the short-form employability five-factor instrument", *Journal of Vocational Behavior*, Vol. 106, pp. 236-248, doi: 10.1016/j.jvb.2018.02.003.

Van Laar, E., Van Deursen, A.J., Van Dijk, J.A. and De Haan, J. (2017), "The relation between 21st-century skills and digital skills: a systematic literature review", *Computers in Human Behavior*, Vol. 72, pp. 577-588, doi: 10.1016/j.chb.2017.03.010.

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A. and Trichina, E. (2023), "Artificial intelligence, robotics, advanced technologies and human resource management: a systematic review", *International Journal of Human Resource Management*, Vol. 33 No. 6, pp. 1237-1266, doi: 10.1080/09585192.2020.1871398.

Walter, Y. (2024), "Embracing the future of artificial intelligence in the classroom: the relevance of AI literacy, prompt engineering, and critical thinking in modern education", *International Journal of Educational Technology in Higher Education*, Vol. 21 No. 1, p. 15, doi: 10.1186/s41239-024-00448-3.

Wang, B., Rau, P.L.P. and Yuan, T. (2023), "Measuring user competence in using artificial intelligence: validity and reliability of artificial intelligence literacy scale", *Behaviour & Information Technology*, Vol. 42 No. 9, pp. 1324-1337, doi: 10.1080/0144929X.2022.2072768.

Wang, C., Wang, H., Li, Y., Dai, J., Gu, X. and Yu, T. (2025), "Factors influencing university students' behavioral intention to use generative artificial intelligence: integrating the theory of planned behavior and AI literacy", *International Journal of Human–Computer Interaction*, Vol. 41 No. 11, pp. 6649-6671, doi: 10.1080/10447318.2024.2383033.

Wei, J., Wang, X., Schuurmans, D., Bosma, M., Xia, F., Chi, E. and Zhou, D. (2022), "Chain-of-thought prompting elicits reasoning in large language models", *Advances in Neural Information Processing Systems*, Vol. 35, pp. 24824-24837, available at: https://proceedings.neurips.cc/paper_files/paper/2022/file/9d5609613524ecf4f15af0f7b31abca4-Paper-Conference.pdf

White, J., Fu, Q., Hays, S., Sandborn, M., Olea, C., Gilbert, H. and Schmidt, D.C. (2023), "A prompt pattern catalog to enhance prompt engineering with ChatGPT", arXiv preprint, arXiv: 2302.11382, doi: 10.48550/arXiv.2302.11382.

Woods, S.A., Mustafa, M.J., Anderson, N. and Sayer, B. (2018), "Innovative work behavior and personality traits: examining the moderating effects of organizational tenure", *Journal of Managerial Psychology*, Vol. 33 No. 1, pp. 29-42, doi: 10.1108/JMP-01-2017-0016.

Yadav, A., Ocak, C. and Oliver, A. (2022), "Computational thinking and metacognition", *TechTrends*, Vol. 66 No. 3, pp. 405-411, doi: 10.1007/s11528-022-00695-z.

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