KNOWING AI OR BELIEVING IN IT? AI LITERACY, AI SELF-EFFICACY, AND EMPLOYEES' INNOVATIVE WORK BEHAVIOR IN SOUTHEAST ASIAN WORKPLACES

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ABSTRACT

Organizations are investing heavily in artificial intelligence (AI), yet the innovative value of AI depends on the employees who use it. Drawing on social cognitive theory, this study examines how two individual AI competencies, AI literacy (what employees know about AI) and AI self-efficacy (their confidence in using AI), relate to innovative work behavior, and which of the two carries more weight. Survey data were collected from 302 employees working in AI-enabled workplaces in Thailand, Vietnam, and Indonesia, and analyzed with partial least squares structural equation modeling in WarpPLS 8.0. The results show that AI literacy (β=0.446, $p<.001$, f^2=0.245) and AI self-efficacy (β=0.229, $p<.001$, f^2=0.096) were both positively related to innovative work behavior. Together with five control variables, they explained 36.9% of its variance. A bootstrapped path-difference test showed that the AI literacy path was significantly larger than the AI self-efficacy path. Among the controls, only job level was significant. The findings suggest that, in AI-enabled work, understanding AI and being able to judge its output may matter more for innovation than confidence alone.

Keywords: AI Literacy, AI Self-Efficacy, Innovative Work Behavior, Social Cognitive Theory

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INTRODUCTION

Firm-level adoption of artificial intelligence (AI) more than doubled between 2023 and 2025, reaching about 20% of firms across OECD countries (OECD, 2026). Generative AI tools, analytics platforms, and AI assistants are now part of daily work in marketing, finance, education, technology, and many other fields. Yet access to AI tools does not by itself turn into new ideas or better ways of working. Employees often report skill gaps, uncertainty, and low confidence when they use AI, which limits how far they bring it into everyday work (Savolainen et al., 2026). The value organizations gain from AI therefore depend on the employees who use it, and particularly on whether they use it to innovate rather than only to automate routine tasks.

Many factors may shape innovative work behavior, but this study focuses on the AI-related competencies of individual employees. Innovative work behavior refers to how employees explore, generate, promote, and implement new ideas at work (De Jong & Den Hartog, 2010; Janssen, 2000). It is the main way AI tools create new value through employees. This study examines two predictors of it. The first is AI literacy, the ability to understand, use, and critically evaluate AI (Long & Magerko, 2020; Wang et al., 2022). The second is AI self-efficacy, the confidence to use AI to reach work goals (Wang & Chuang, 2024). These two variables were selected for three reasons. First, they represent the two core drivers of action in social cognitive theory: what people are capable of and what they believe they can do (Bandura, 1997). Second, both are competencies that organizations can develop through training and practice, which makes the findings actionable. Third, they reflect the skill gaps and low confidence that employees most often report when working with AI (Savolainen et al., 2026).

However, most workplace AI research still focuses on adoption and acceptance, often through the technology acceptance model or the unified theory of acceptance and use of technology. These studies examine whether employees intend to use AI rather than what they do with it once they have it (Venkatesh, 2021). Studies on AI literacy and AI self-efficacy have grown quickly, but they usually examine each competency in isolation (Ding et al., 2025; Li et al., 2026). As a result, little is known about whether innovation depends more on *knowing* AI or on *believing* in one's ability to use it. This distinction matters for practice, because training that builds knowledge and programs that build confidence require different investments. Evidence from Southeast Asia, where AI adoption is rising quickly but workforce AI skills (Arias et al., 2025), is also scarce.

Thus, the purpose of this study is to examine how employees' AI literacy and AI self-efficacy relate to their innovative work behavior, drawing on social cognitive theory (Bandura, 1997). In particular, it tests the relationship of each competency with innovative work behavior and compares their relative strength, using partial least squares structural equation modeling (PLS-SEM) on survey data from 302 employees in AI-enabled workplaces in Southeast Asia. The central research question is: *Which carries more weight in explaining employees' innovative work behavior: knowing AI or believing in one's ability to use it?*

This study offers both theoretical and practical benefits. It extends social cognitive theory to workplace AI and helps managers decide whether to invest in employees' understanding of AI, their confidence in using it, or both. The remainder of the paper reviews the literature and develops the hypotheses, describes the research methodology, presents the findings, and closes with the discussion and conclusion.

LITERATURE REVIEW

Social Cognitive Theory

Social cognitive theory explains human behavior as the product of continuous interaction between personal factors, behavior, and the environment (Bandura, 1986). Within the

personal factors, two elements carry particular weight. The first is capability: the knowledge and skills a person has acquired. The second is self-efficacy: a person's belief that he or she can use those capabilities to organize and carry out the actions needed to reach a goal (Bandura, 1997). Capability sets the range of actions that are possible, while self-efficacy shapes which actions people choose to attempt, how much effort they invest, and how long they persist when they face difficulties.

Applied to organizations, the theory explains why employees with similar resources differ in what they attempt and achieve at work (Wood & Bandura, 1989). Self-efficacy has been shown to relate strongly to work performance (Stajkovic & Luthans, 1998), and its technology-specific form, computer self-efficacy, has long been used to explain how employees use new information systems (Compeau & Higgins, 1995). Bandura (1997) also noted that self-efficacy grows mainly through mastery experiences, which means capability and belief tend to develop together. Social cognitive theory suits this study because AI literacy and AI self-efficacy map directly onto its two core personal elements: what employees know about AI and what they believe they can do with it.

AI Literacy

AI literacy is a set of competencies that allows individuals to understand, use, and critically evaluate AI technologies, and to work with them effectively while following ethical standards (Long & Magerko, 2020; Wang et al., 2022). The concept emerged as AI moved from specialist systems into everyday tools, turning ordinary users from "AI immigrants" into "AI natives" (Wang et al., 2022). Scholars describe AI literacy in terms of three related dimensions (Long & Magerko, 2020; Ng et al., 2021). The cognitive dimension covers an understanding of data, algorithms, and what AI can and cannot do. The technical dimension covers the practical use of AI tools. The critical dimension covers the ability to evaluate AI output for bias, uncertainty, and ethical risk.

For employees, AI literacy goes beyond knowing how to operate a tool. It allows them to interpret AI-generated insights, judge when to rely on them, and integrate them into decisions (Pinski & Benlian, 2023). This critical element is increasingly important with generative AI, whose output can be fluent but wrong. Held and Heubeck (2025) found that the capability to evaluate generative AI, rather than simply to use it, distinguished employees who turned AI into innovative behavior.

AI Self-Efficacy

AI self-efficacy is an individual's belief in his or her ability to interact with and use AI technologies effectively to achieve specific goals (Wang & Chuang, 2024). It applies the general concept of Bandura (1997) to the AI context and extends earlier work on computer self-efficacy (Compeau & Higgins, 1995). Wang and Chuang (2024) identified four aspects of AI self-efficacy: confidence in using AI for assistance, comfort with human-like interaction, general ease with technology, and basic technical skill. AI self-efficacy therefore covers both confidence and comfort, including the ability to cope with the uncertainty that comes with AI-generated results.

Employees with high AI self-efficacy approach AI tasks as manageable challenges rather than threats. Han et al. (2025)found that AI use reshapes employees' self-efficacy and their willingness to take risks at work, and Li et al. (2026) treated AI self-efficacy as a personal resource that supports proactive behavior. Because self-efficacy affects effort and persistence, it is especially relevant when employees face new and fast-changing AI tools.

Innovative Work Behavior

Innovative work behavior is the intentional creation, promotion, and implementation of new ideas within a work role to benefit the individual, group, or organization (Janssen, 2000; Scott & Bruce, 1994). It differs from creativity, which concerns only idea generation, because it also includes promoting ideas to others and putting them into practice (De Jong & Den

Hartog, 2010). De Jong and Den Hartog (2010) describes four stages: exploring opportunities, generating ideas, championing them, and implementing them.

Innovative work behavior is discretionary and carries a risk of failure, so it goes beyond routine job requirements (AlEssa & Durugbo, 2021). Employees who show it tend to challenge the status quo, seek new methods, and persist until their ideas are adopted. Prior studies link innovative work behavior to better individual performance (Pham et al., 2024) and to organizational competitiveness. In AI-enabled workplaces, it is the behavior through which AI tools are most likely to produce new products, processes, and ways of working.

Relationship between AI Literacy and Innovative Work Behavior

From a social cognitive perspective, knowledge sets the range of actions a person can attempt (Bandura, 1986). For innovation, this matters at every stage. Employees who understand what AI can and cannot do are better placed to spot tasks and processes that AI could improve, which supports opportunity exploration. When they know how to prompt, combine, and refine AI output, they can turn AI suggestions into workable ideas. When they can evaluate AI output critically, they are better able to judge which ideas are sound enough to champion and implement (Pinski & Benlian, 2023). AI literacy also lowers the cognitive cost of experimenting with new tools, freeing attention for higher-level problem-solving.

Empirical studies support this link. Ding et al. (2025) found that AI literacy was positively related to the innovative work behavior of Chinese designers. Held and Heubeck (2025) reported that, among 439 consultants, the capability to evaluate generative AI was related to innovative work behavior, whereas the capability merely to use it was not. Zhang et al. (2025) also found that AI use was positively related to employees' innovation behavior, particularly when employees were open to new experiences. Together, these findings suggest that employees who understand AI more deeply are more likely to use it as a source of new ideas. Therefore:

H1: AI literacy is positively related to employees' innovative work behavior.

Relationship between AI Self-Efficacy and Innovative Work Behavior

Social cognitive theory also holds that people undertake and persist in challenging activities when they believe they can succeed (Bandura, 1997). Innovation is risky and optional, so self-efficacy is especially relevant to it. Employees with high creative self-efficacy are more likely to engage in creative work (Tierney & Farmer, 2002). In the AI context, employees who feel confident with AI are more likely to experiment with new applications, persist when results are uncertain, and present AI-supported ideas to colleagues and managers. By contrast, employees with low AI self-efficacy may avoid AI-related tasks or use AI only for safe, routine work.

Evidence supports this reasoning. Li et al. (2026) found that AI self-efficacy was positively related to innovative work behavior ($\beta = 0.34$) among 300 hospitality and tourism employees. Han et al. (2025) showed that AI use strengthens employees' self-efficacy and their willingness to take risks, a precondition for innovation. Wang and Chuang (2024) also noted that AI self-efficacy reflects the ability to adapt to new AI features and handle the uncertainty of AI-generated results. Therefore:

H2: AI self-efficacy is positively related to employees' innovative work behavior.

In addition to testing these two hypotheses, this study explores which of the two competencies shows the stronger relationship with innovative work behavior. Gender, age, educational level, job level, and work experience are included as control variables because prior research links them to technology use and innovative behavior (Morris & Venkatesh, 2000; Theurer et al., 2018). Figure 1 presents the conceptual framework.

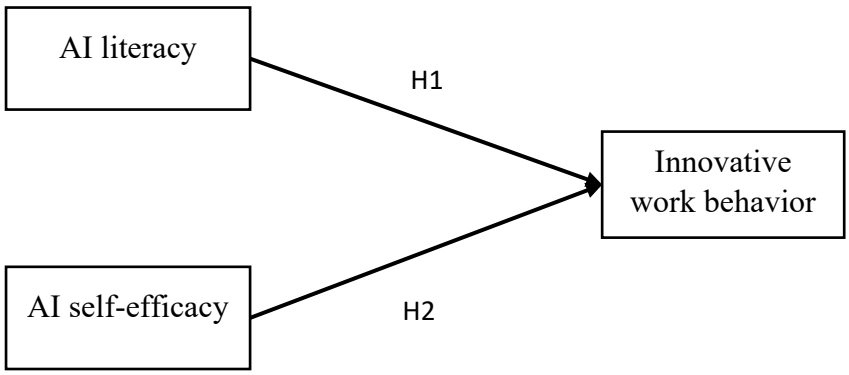

Figure 1 Conceptual Framework

RESEARCH METHODOLOGY

This study adopted a quantitative, cross-sectional survey design. The target population was employees who use AI tools or AI-supported systems in their daily work. Because no sampling frame of such employees exists, convenience sampling was used. The data were collected as part of a larger survey project; a separate study examines different relationships using the same dataset. Two screening questions confirmed that each respondent used AI tools at work and that his or her organization encouraged or required this use; respondents who did not meet both criteria were excluded.

The questionnaire was prepared in English and Vietnamese on Microsoft Forms and was available from February to May 2026. Two channels were used. First, 870 invitations were sent through email, social media, and professional networks; 215 responses were received (response rate 24.71%) and 208 were usable (usable response rate 23.91%). Respondents in this channel could enter a lucky draw in which 40 participants received rewards. Second, 540 invitations were sent to eligible participants through the Prolific research platform. Prolific is a well-known online research platform that helps researchers find verified participants who meet specific criteria (Palan & Schitter, 2018). A total of 255 responses were received (response rate 47.22%) and 94 were usable after screening (usable response rate 17.41%). Responses were excluded if they were incomplete or failed the screening questions. In total, 1,410 invitations produced 470 responses and 302 usable questionnaires, giving an overall response rate of 33.33% and a usable response rate of 21.42%. Participation was voluntary, and anonymity and confidentiality were assured. Because the two channels differed in recruitment method and incentive structure, each response was coded with a dummy variable for sample source (1=Prolific, 0=direct channel). This variable was used in a robustness check as an additional control variable.

All constructs were measured with established scales, adapted to the workplace AI context and rated on a five-point Likert scale (1=strongly disagree, 5=strongly agree).

- **AI literacy** was measured with 13 items adapted from Pinski and Benlian (2023) and Wang et al. (2022) covering knowledge of AI technologies, their use cases, and the interpretation of AI output (e.g., "I have knowledge of using AI output and interpreting it").
- **AI self-efficacy** was measured with 11 items from Wang and Chuang (2024), covering confidence in using AI for assistance, comfort with human-like interaction, general ease with the technology, and basic technical skill (e.g., "Interacting with AI is easy for me").
- **Innovative work behavior** was measured with six items from Hai Yen et al. (2025), covering the exploration, generation, promotion, and implementation of new ideas (e.g., "I sought out new techniques and methods").

To improve convergent validity, items with low loadings were removed: two AI literacy items (AIL5, AIL13) and five AI self-efficacy items (AISE1, AISE2, AISE9, AISE10, AISE11), leaving 11 and 6 items, respectively. Five control variables were included: gender

(1=male, 0=female), age in years, educational level (1=below bachelor's degree to 4=doctoral degree), job level (1=entry level to 5=director or executive level), work experience (1=0-2 years to 4=more than 10 years).

The research model was analyzed with PLS-SEM in WarpPLS 8.0, using the Stable3 resampling method to estimate standard errors and p-values (Kock, 2025). PLS-SEM was appropriate because the study focuses on explaining and predicting innovative work behavior, and because all latent variables departed from normality under the Jarque-Bera and robust Jarque-Bera tests (Hair, Risher, et al., 2019). The analysis followed two stages. First, the measurement model was assessed for reliability, convergent validity, and discriminant validity. Second, the structural model was assessed through model fit indices, path coefficients, effect sizes (f^2), the coefficient of determination (R^2), and predictive relevance (Q^2). Common method bias was assessed with the full collinearity test (Kock, 2017). As a robustness check, the model was re-estimated with sample source (1=Prolific, n=94; 0=direct channel, n=208) as an additional control variable. To test whether the two hypothesized paths differed significantly, the latent variable scores obtained in WarpPLS were analyzed in IBM SPSS Statistics 27. Innovative work behavior was regressed on AI literacy and the sum of AI literacy and AI self-efficacy, together with the control variables, so that the coefficient of AI literacy equals the difference between the two paths. This coefficient was bootstrapped with 5,000 resamples, and the difference was considered significant when the 95% bias-corrected and accelerated (BCa) confidence interval excluded zero (Efron & Tibshirani, 1994).

RESEARCH RESULTS

Respondents' Profiles

Table 1 summarizes the employees' profile. Slightly more than half of the respondents were male (54.6%). The sample was well educated, with 52.6% holding a master's or doctoral degree. Most respondents were early-to-mid-career professionals (57.6%), with a mean age of 32.99 years (SD = 9.47). All respondents worked in Thailand, Vietnam, or Indonesia. By nationality, most were Vietnamese (33.1%) or Indonesian (31.5%), followed by Thai (4.3%); the remaining 31.1% were nationals of other countries, such as Malaysia, Philippines and Singapore, working in the three target countries. Respondents came from a wide range of industries; technology (22.8%), marketing (14.2%), and education (13.2%) were the largest.

Table 1 Descriptive statistics of sample (n = 302)

Characteristic	Category	Frequency	Percentage
Gender	Male	165	54.6
	Female	137	45.4
Age (years)	Range	19-73 years	
	Mean	32.99 years	
	S.D.	9.47	-
Educational level	Below bachelor's degree	9	3.0
	Bachelor's degree	134	44.4
	Master's degree	152	50.3
	Doctoral degree	7	2.3
Work experience	0-2 years	54	17.9
	3-5 years	91	30.1
	6-10 years	72	23.8
	More than 10 years	85	28.1
Job level	Entry level	78	25.8
	Mid level	96	31.8
	Senior level	59	19.5

Characteristic	Category	Frequency	Percentage
	Managerial level	48	15.9
	Director or executive level	21	7.0
Industry	Technology	69	22.8
	Marketing	43	14.2
	Education	40	13.2
	Creative and media	29	9.6
	Other industries	121	40.1

Measurement Model

The reliability of the three constructs innovative work behavior, AI literacy and AI self-efficacy was assessed using Cronbach's alpha coefficient (α) and composite reliability (CR), as presented in Table 2. All Cronbach's alpha **(α)** values exceeded the 0.70 threshold, thereby confirming the internal consistency and reliability of each construct (Hair, Black, et al., 2019; Nunnally & Bernstein, 1994).

Table 2 Cronbach's alpha and Composite Reliability test

Constructs	IWB	AIL	AISE
Cronbach's alpha (α)	0.89	0.90	0.80
Composite reliability	0.91	0.92	0.86

Notes: IWB=innovative work behavior, AIL=AI literacy, AISE=AI self-efficacy

All constructs were modeled as reflective. Discriminant validity was assessed with two criteria. First, Table 3 shows that the square root of each construct's AVE exceeded its correlations with the other constructs (Fornell & Larcker, 1981). Second, all heterotrait-monotrait (HTMT) ratios presented in Table 4 were below the conservative threshold of 0.85 (Henseler et al., 2015).

Table 3 The Correlations and the Square Roots of AVE

Constructs	IWB	AIL	AISE
IWB	(0.80)		
AIL	0.55***	(0.72)	
AISE	0.42***	0.42***	(0.71)

Notes: IWB=innovative work behavior, AIL=AI literacy, AISE=AI self-efficacy, *** p-value <0.001

Table 4 Heterotrait-Monotrait Ratio (HTMT) assessment

HTMT ratios *(good if < 0.90, best if < 0.85)*	IWB	AIL	AISE
IWB			
AIL	0.61***		
AISE	0.49***	0.48***	

Notes: IWB=innovative work behavior, AIL=AI literacy, AISE=AI self-efficacy, *** p-value <0.001

Convergent validity of innovative work behavior (IWB), AI literacy (AIL), and AI self-efficacy (AISE) was assessed through factor loadings. As shown in Table 5, every item's factor loading exceeded 0.50.

Table 5 Factor Loadings

Items	IWB	AIL	AISE
IWB1	(0.80)		
IWB2	(0.79)		
IWB3	(0.77)		
IWB4	(0.82)		
IWB5	(0.78)		
IWB6	(0.82)		
AIL1		(0.74)	
AIL2		(0.74)	
AIL3		(0.77)	
AIL4		(0.63)	
AIL6		(0.55)	
AIL7		(0.77)	
AIL8		(0.76)	
AIL9		(0.79)	
AIL10		(0.77)	
AIL11		(0.71)	
AIL12		(0.65)	
AISE3			(0.60)
AISE4			(0.68)
AISE5			(0.66)
AISE6			(0.73)
AISE7			(0.76)
AISE8			(0.79)

Notes: IWB=innovative work behavior, AIL=AI literacy, AISE=AI self-efficacy

The average variance extracted (AVE) assessment following item purification indicated that the results were 0.64 for innovative work behavior, 0.52 for AI literacy, and 0.50 for AI self-efficacy. The AVEs of each latent variable are greater than 0.5, therefore, the data pass the convergent validity (Fornell & Larcker, 1981). The AVE results are presented in Table 6.

Table 6 The AVE Assessment

Construct	IWB	AIL	AISE
AVE	**0.64**	**0.52**	**0.50**

Notes: IWB=innovative work behavior, AIL=AI literacy, AISE=AI self-efficacy

As reported in Table 7, full collinearity variance inflation factors (VIFs) ranged from 1.04 to 2.14 across all latent and control variables, below the 3.3 threshold. This suggests that common method bias is unlikely to be a serious concern (Kock, 2017).

Table 7 Full Variance Inflation Factor (VIF) of overall model

Constructs	IWB	AIL	AISE	GEN	EDU	AGE	JOBL	EXP
Full Collin. VIF	1.58	1.60	1.31	1.06	1.04	1.96	1.71	2.14

Notes: IWB=innovative work behavior, AIL=AI literacy, AISE=AI self-efficacy, GEN=gender, EDU=educational level, AGE=age, JOBL=job level, EXP=work experience.

Finalized Structural Model and Hypothesis Analysis

The structural model met all ten fit and quality criteria in WarpPLS (Kock, 2025): average path coefficient (APC)=0.14 (p=.004), average R^2 (ARS)=0.37 (p<.001), average adjusted R^2

(AARS)=0.35 (p<.001), average block VIF (AVIF)=1.48 ideally, average full collinearity VIF (AFVIF)=1.55 ideally, Tenenhaus GoF=0.55 (large), Simpson's paradox ratio (SPR)=0.71 acceptable, R^2 contribution ratio (RSCR)=1.00 acceptable, statistical suppression ratio (SSR)=0.86 acceptable, and nonlinear bivariate causality direction ratio (NLBCDR)=0.93 acceptable.

Figure 2 presents the results of the hypothesis tests. AI literacy was positively and significantly related to innovative work behavior (β=0.45, p<.001); therefore, H1 was supported. AI self-efficacy was also positively and significantly related to innovative work behavior (β=0.23, p<.001); therefore, H2 was supported. However, the two relationships differ in size. Following Cohen (1988), the effect size was medium for AI literacy (f^2=0.25) but small for AI self-efficacy (f^2=0.10). This suggests that although AI self-efficacy contributes to innovative work behavior, its practical contribution is more modest. A bootstrapped path-difference test indicated that the path from AI literacy was significantly larger than the path from AI self-efficacy (Δβ=0.22, bootstrap SE=0.10, 95% BCa CI [0.03, 0.41], p=.023). Among the control variables, only job level was significant (β=0.16, p=.003). Finally, the R^2 of innovative work behavior is 0.369 (Adj. R^2=0.354). This means that the seven predictors in the model (AI literacy, AI self-efficacy, gender, age, educational level, job level, and work experience) together explain 36.9% of the variance in innovative work behavior. The Q^2 value of 0.372 indicated predictive relevance (Hair, Black, et al., 2019).

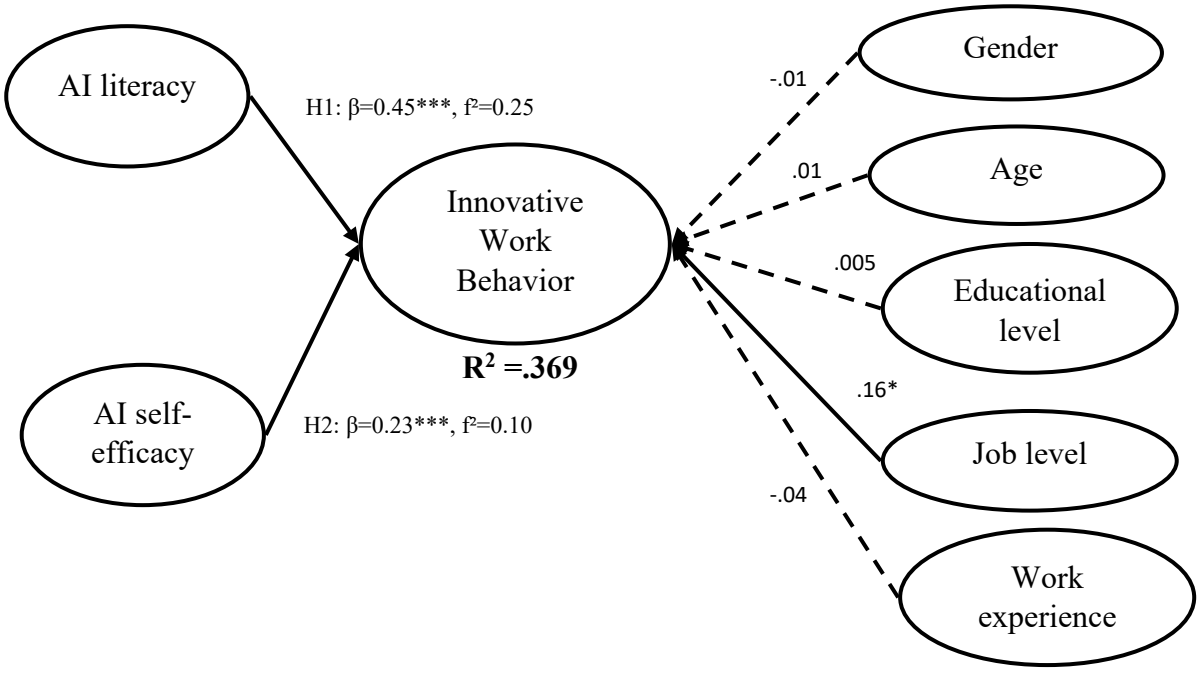

Figure 2 Finalized Model
Notes: *** p<.001, ** p<.01, * p<.05.
Standardized beta coefficients are reported.
Dashed lines represent non-significant paths.

Robustness to Sample Source

To examine whether pooling the two data-collection channels affected the results, the model was re-estimated with sample source as an additional control variable. Sample source was not significantly related to innovative work behavior (β=0.04, p=.22), and the hypothesized paths remained virtually unchanged (H1: β=0.45, p<.001; H2: β=0.23, p<.001). The explained

variance increased only marginally (R^2=0.370 vs. 0.369). Because the dummy variable introduced an additional Simpson's paradox instance in a non-significant control path (SPR=0.63), the more parsimonious model without it was retained as the main model. These results indicate that the findings are robust to the data-collection channel.

DISCUSSION AND CONCLUSION

This study examined how employees' AI literacy and AI self-efficacy relate to their innovative work behavior. Both hypotheses were supported. Employees who know more about AI, and those who feel more confident using it, report more innovative work behavior. These results are consistent with earlier evidence linking AI literacy and AI self-efficacy to innovative behavior (Ding et al., 2025; Li et al., 2026). Moreover, the results extend that evidence to a multi-country sample of employees in Southeast Asian workplaces.

The most notable result concerns the comparison between the two competencies. AI literacy showed a larger relationship with innovative work behavior than AI self-efficacy, with an effect size more than twice as large. A bootstrapped test confirmed that this difference was statistically significant ($\Delta\beta$=0.22, 95% BCa CI [0.03, 0.41]). In this sample, therefore, knowing AI carried more weight for innovation than believing in one's ability to use it, although the lower bound of the confidence interval suggests that this advantage is modest. This pattern raises questions about the common expectation in social cognitive research that self-efficacy is the strongest personal driver of discretionary behavior (Bandura, 1997; Tierney & Farmer, 2002).

One explanation lies in the nature of AI-supported innovation. Generating new ideas with AI is now relatively easy; the harder task is judging which AI-generated ideas are accurate, useful, and worth promoting. This task depends on understanding how AI works and where it fails, which is the core of AI literacy. The interpretation agrees with Held and Heubeck (2025), who found that the capability to evaluate generative AI, not the capability to use it, was related to innovative work behavior. Confidence without that understanding may lead employees to use AI often but not necessarily in new or better ways.

AI self-efficacy still showed a meaningful relationship with innovative work behavior. Its role may be to help employees act on what they know, try new applications, persist when AI output is disappointing, and present AI-supported ideas to others. The moderate correlation between the two competencies (r=0.42) is consistent with the view that capability and mastery experience feed self-efficacy beliefs. Finally, the positive relationship between job level and innovative work behavior suggests that employees in senior roles have more autonomy and resources to turn ideas into practice (Theurer et al., 2018).

This study makes three theoretical contributions. First, it applies social cognitive theory to workplace AI and examines its two core personal elements, capability and self-efficacy, side by side rather than separately. Second, it suggests that for an emerging technology such as AI, the knowledge element may carry more weight than the belief element in explaining innovative behavior. Accordingly, models of AI-enabled work may need to treat AI literacy, and especially its critical evaluation component, as a central predictor rather than as a background condition for self-efficacy. Third, it responds to calls to move beyond adoption and acceptance models by focusing on what employees do with AI once they have it (Venkatesh, 2021).

The findings offer three implications for managers and human resource professionals. First, AI training should go beyond tool operation and prompting. Programs should build employees' understanding of how AI works, where it fails, and how to evaluate its output critically, because this understanding showed the larger association with innovation in this sample. Second, organizations can strengthen AI self-efficacy through hands-on experimentation, peer demonstrations, and visible early successes, while making clear that

mistakes during experimentation are acceptable. Third, because job level was positively related to innovative work behavior, managers may need to give employees in junior roles more autonomy, time, and support to develop and implement AI-supported ideas. For policymakers in Southeast Asia, where AI adoption is outpacing workforce skills (Arias et al., 2025), these results support national and industry AI literacy programs that emphasize critical understanding, not only tool use.

This study has several limitations. First, the cross-sectional, self-reported design means that the relationships should be read as associations rather than causal effects; longitudinal or experimental designs could test their direction. Second, convenience sampling and the uneven distribution of respondents across nationalities, with few Thai nationals (4.3%), limit generalizability, although a robustness check showed that sample source did not affect the results. Future studies should use more balanced samples across countries. Third, innovative work behavior was self-reported; supervisor ratings would reduce the risk of common method bias. Finally, future research could test whether AI self-efficacy mediates the relationship between AI literacy and innovative work behavior, and whether factors such as leadership support or job autonomy moderate these relationships.

Grounded in social cognitive theory, this study shows that both AI literacy and AI self-efficacy are positively related to employees' innovative work behavior, with AI literacy showing the larger relationship. The answer to the central research question is therefore that, in this sample, knowing AI showed a significantly larger relationship with innovative work behavior than believing in one's ability to use it ($\Delta\beta=0.22$, $p=.023$). For organizations seeking innovation from AI, helping employees understand and critically evaluate AI may be more important than building their confidence alone, although both matter.

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