Environment and Social Psychology (2025) Volume 10 Issue 7 ISSN: 2424-8975 (O)
doi: 10.59429/esp.v10i7.3892 2424-7979 (P)

Research Article

Knowledge management and research motivation in higher education: Exploring the moderating role of AI proficiency

Thi Lua Mai[1], Nguyen Quang Vinh [2,*], Manh Hien Luc[3]

[1] *University of Economics - Technology for Industries*

[2] *Thuongmai University*

[3] *University of Labour and Social Affairs*

*** Corresponding author:** Nguyen Quang Vinh, vinh.nq@tmu.edu.vn.

ABSTRACT

In the context of higher education's growing emphasis on research productivity and digital transformation, this study investigates how knowledge management (KM) infrastructure and KM processes influence university lecturers' research motivation, with research self-efficacy serving as a mediator and AI proficiency acting as a moderator. Drawing on Social Cognitive Theory and Task–Technology Fit Theory, a conceptual model was developed and empirically tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) with data collected from 295 academic staff members at public and private universities in Vietnam. The findings reveal that both KM infrastructure and KM processes significantly enhance research motivation, both directly and indirectly through research self-efficacy. Moreover, AI proficiency not only has a direct positive effect on research motivation and self-efficacy but also strengthens the relationship between research self-efficacy and research motivation. These results underscore the critical importance of fostering institutional KM systems, cultivating psychological capabilities, and equipping faculty with digital competencies—particularly AI literacy—to drive sustainable academic engagement. The study offers theoretical contributions to the literature on knowledge management and academic motivation, as well as practical implications for higher education institutions aiming to build research-capable environments in the digital era.

Keywords: knowledge management; research motivation; research self-efficacy; AI proficiency; higher education; PLS-SEM

1. Introduction

In the era of the knowledge economy, knowledge management (KM) has become an indispensable strategic function for higher education and research institutions seeking to enhance research performance and sustain academic competitiveness [1-3] Universities are no longer viewed merely as teaching institutions but are increasingly evaluated based on their research capacity and scholarly outputs. However, in many developing countries—such as Vietnam—research activities in universities have not been prioritized to the same extent as teaching and enrollment. Academic performance is still largely assessed based on teaching hours rather than scientific contributions, which hinders the development of a robust research culture [4,5]. As

ARTICLE INFO
Received: 10 May 2025 | Accepted: 16 July 2025 Available online: 28 July 2025

CITATION
Mai TL, Vinh NQ, Luc MH. Knowledge management and research motivation in higher education: Exploring the moderating role of AI proficiency. *Environment and Social Psychology* 2025; 10(7): 3892 doi:10.59429/esp.v10i7.3892

a result, Vietnamese lecturers often lag behind their regional peers in countries like Singapore, Malaysia, and Thailand in terms of research output and recognition [6], [7].

In this context, effective knowledge management is seen not only as a driver of institutional innovation but also as a critical enabler of faculty research motivation (RM)—a construct that plays a decisive role in fostering academic creativity, productivity, and international integration [8]. Previous studies have demonstrated that KM infrastructure (KMI) and KM processes (KMP) positively influence organizational learning and individual innovation [5]. However, despite the growing interest in KM's role within academic institutions, the mechanisms through which KM translates into research motivation remain underexplored, particularly in developing higher education systems. Notably, the mediating role of research self-efficacy (RSE)—defined as an individual's belief in their capacity to conduct academic research—has received limited empirical attention in the KM–RM relationship[9].

At the same time, the Fourth Industrial Revolution, spearheaded by Artificial Intelligence (AI), is transforming how knowledge is created, disseminated, and applied within academic settings. As AI tools become increasingly integrated into research workflows—from data analysis and literature review automation to writing assistance—AI proficiency (AIP) emerges as a new form of digital competence that may shape researchers' confidence and motivation [10], [11]. While prior research has acknowledged AI's potential to enhance productivity and efficiency in various domains [11], its moderating role in psychological processes related to research behavior—such as its interaction with RSE to influence RM—remains empirically untested.

These contextual and theoretical considerations reveal several research gaps. First, it is still unclear whether KM exerts a direct impact on research motivation or whether its influence is primarily channeled through research self-efficacy. Second, existing studies often treat KM as a unified construct, without differentiating the relative contributions of KM infrastructure versus KM processes. Third, although digital competency is increasingly essential in academic environments, the role of AI proficiency as a boundary condition—amplifying or attenuating the effect of self-efficacy on research motivation—has yet to be confirmed through empirical evidence.

To address these gaps, this study develops and tests an integrated structural model that links KM infrastructure, KM processes, research self-efficacy, and research motivation, while also assessing the moderating role of AI proficiency. Drawing on Social Cognitive Theory [12] and knowledge-based organizational perspectives, we posit that research self-efficacy functions as a psychological mechanism through which KM enhances motivation, and that this mechanism is strengthened by high levels of AI proficiency.

Using Partial Least Squares Structural Equation Modeling (PLS-SEM) and a sample of lecturers from Vietnamese higher education institutions, this study offers three major contributions: (1) it advances theoretical understanding of KM and motivation in academia; (2) it introduces AI proficiency as a novel moderator in the research motivation process; and (3) it provides practical guidance for university leaders and policymakers on strengthening.

2. Literature review

2.1. Knowledge management

Over the past decades, scholars have proposed various approaches to understanding knowledge and knowledge management. Among the most influential perspectives, [13]] conceptualized knowledge as a dynamic combination of beliefs and commitment, emphasizing its tacit and contextual nature in organizational contexts. Regarding the definition of KM, the one proposed by [14] is considered highly comprehensive and has been widely adopted in academic literature. According to Smith, "Knowledge management is a process consisting of activities such as acquiring and accumulating knowledge for the organization; organizing, distributing, and applying knowledge to organizational operations; facilitating knowledge sharing and protecting the rights of knowledge creators; and implementing motivational mechanisms to sustain valuable knowledge within the organization." From this definition, it is evident that the core activities of KM include: (1) knowledge acquisition and accumulation, (2) knowledge sharing within the organization, (3) employee motivation, (4) knowledge transformation and dissemination, and (5) protection of intellectual property rights for knowledge creators. A synthesis by [15] further revealed that although different studies may categorize KM processes slightly differently, there is a general consensus around four fundamental components: knowledge acquisition, knowledge transfer, knowledge application, and knowledge protection or retention.

Recent scholarship on KM frameworks in higher education converges on four core processes that foster a culture of knowledge sharing and collaboration. [16] identify: (1) making knowledge visible, (2) intensifying knowledge flows, (3) building KM infrastructure, and (4) nurturing a knowledge-sharing culture through appropriate incentives. From an academic standpoint, learning communities should originate at the individual level, generate intra-departmental knowledge, evolve into inter-departmental communities of practice, and finally expand into institution-wide and inter-organizational knowledge networks. Empirical studies consistently include five KM components in university settings—knowledge creation, acquisition, storage, application, and dissemination [17]. Recent evidence further supports a three-part mechanism: KM infrastructure acts as an environmental "lever," RSE functions as the psychological "engine," and AIP serves as an "amplifier" (or attenuator) of this relationship. At the organizational level, a survey of 273 faculty members from 18 Jordanian private universities showed that KM systems exert a strong direct effect on institutional research performance ($\beta = 0.317$, $p < 0.001$) and an additional indirect effect via intellectual capital ($\beta = 0.221$, $p < 0.001$), underscoring the strategic value of knowledge infrastructure [18]. At the individual level, a German study of 2,359 students found that RSE was the strongest predictor of both academic achievement and motivation, mediating the link between autonomous motivation and outcomes [19]. Complementary evidence from Austria showed that 86 % of 286 undergraduates valued AI tools for research, yet 45 % expressed concerns about reliability; higher AI literacy enhanced self-efficacy, whereas insufficient AI skills diminished output quality [20]. Collectively, these findings imply that transforming KM infrastructure and processes into effective research motivation requires simultaneous investment in both RSE and AI literacy. Universities that focus solely on IT platforms or knowledge-sharing routines—without parallel capacity-building in self-efficacy and AI proficiency—risk information overload and, ultimately, reduced research motivation.

2.2. Research motivation

Motivation is widely recognized as a critical psychological driver that prompts individuals to exert sustained effort toward achieving their goals [19]. It reflects a person's intrinsic tendency to learn, explore, and pursue challenges as a means of expanding their competence and fulfilling their potential [21]. In the context of knowledge work, especially in academia, research motivation is not only linked to professional performance but is also shaped by the organizational environment, particularly through KM practices.

Several empirical studies have established a positive relationship between KM and employee motivation [22], [23] found that effective KM systems contribute to increased motivation by enabling knowledge sharing, learning opportunities, and a sense of empowerment. Specifically in academic settings, [18] demonstrated that well-executed KM practices can enhance faculty members' motivation to conduct research, especially when these practices promote accessibility, collaboration, and recognition [24], [25]. Further support comes from [26] whose study confirmed that KM positively influences research motivation among university lecturers. These findings suggest that KM is not merely a strategic function for organizational innovation, but also a vital psychological enabler for individual academic engagement. However, despite these insights, research on the influence of KM on research motivation in the context of higher education remains relatively scarce, especially in developing countries. Most existing studies tend to generalize KM's impact on organizational outcomes without isolating its specific effects on individual motivation toward research. This gap underscores the need for a more nuanced and empirical investigation into how KM infrastructure and processes shape academic staff's intrinsic motivation to engage in research activities.

In contemporary higher education, particularly in the post–COVID-19 era, the significance of intrinsic motivation among academic staff has received renewed attention. Studies indicate that faculty members with high levels of intrinsic motivation tend to be more creative, publish more prolifically, and demonstrate greater resilience in the face of external pressures [17]. Conversely, when lecturers are overwhelmed by bureaucratic demands, quantitative evaluation mechanisms, or insufficient academic support, extrinsic motivators may dominate, leading to academic burnout [18], [27]

Emerging literature also highlights the role of digital competence, particularly AI proficiency, as a potential mediator or moderator in the relationship between self-efficacy and research motivation. As academic tasks become increasingly digitized, the ability to use AI tools effectively may enhance an individual's confidence and willingness to engage in research. [20] found that AI proficiency is positively associated with both self-efficacy and motivation, whereas a lack of AI-related skills may result in feelings of helplessness, inefficacy, or even fear of being replaced. Thus, technological literacy, especially in the context of AI, is no longer optional but a critical competency shaping academic motivation and resilience in digitally mediated research environments.

Based on this theoretical and empirical foundation, the following hypotheses are proposed:

H1: KM infrastructure has a positive effect on faculty research motivation.

H2: KM processes have a positive effect on faculty research motivation.

2.3. The mediating role of research self-efficacy

Research Self-Efficacy is a psychological construct rooted in Social Cognitive Theory [12], and refers to an individual's belief in their ability to successfully perform research-related tasks [28]. These tasks range from problem formulation and methodological design to data collection, analysis, writing, and publication. According to Bandura, self-efficacy influences not only observable behavior but also cognitive processes, emotional reactions, and strategies for coping with challenges—making it a critical factor in sustaining long-term academic engagement and research persistence [29].

Within the context of higher education, RSE has been shown to directly predict research motivation, scholarly productivity, and resilience in the face of academic demands [16]. Faculty members who perceive themselves as competent in conducting research are more likely to initiate and persist in research activities, even when external incentives are limited or institutional constraints are present [8] . Moreover, RSE is influenced by organizational conditions such as access to knowledge infrastructure, opportunities for knowledge exchange, and supportive academic cultures—elements closely tied to effective knowledge management (KM) practices [5,23,26].

Given this dual function—being shaped by KM systems and in turn influencing research motivation—RSE is theoretically positioned as a key mediating variable that transmits the effects of KM infrastructure and KM processes onto individual-level research engagement. This mediating role is further supported by empirical findings showing that self-efficacy bridges the relationship between organizational support and academic outcomes [19], [30]. Thus, the following hypotheses are proposed:

H3: KM infrastructure positively influences research self-efficacy.

H4: KM processes positively influence research self-efficacy.

H5: Research self-efficacy positively influences faculty research motivation.

H6a: Research self-efficacy mediates the relationship between KM infrastructure and research motivation.

H6b: Research self-efficacy mediates the relationship between KM processes and research motivation.

2.4. The oderating role of AI proficiency

Large Language Models - LLMs (e.g., GPT-class models) increasingly mediate academic tasks such as literature mapping, methodological planning, and drafting. From a Task–Technology Fit view, LLMs enhance performance when their affordances match research tasks; from Self-Determination Theory, perceived mastery of LLMs may bolster competence and autonomy, thus amplifying motivation. This paper therefore conceptualize LLM literacy as a salient sub-dimension of AI proficiency relevant to research self-efficacy effects.

In the era of digital transformation and Higher education 4.0, the rapid proliferation of artificial intelligence (AI) tools has fundamentally reshaped how academic research is conducted [31,32. Platforms such as ChatGPT, Elicit, Scite, Perplexity AI, and other citation management, text analysis, or data extraction tools have increasingly become default components of research toolkits across universities worldwide [10]. However, the actual impact of AI on research behavior depends not merely on technological availability, but on the user's proficiency—that is, their level of AI Proficiency.

AI Proficiency is defined as the ability to understand, utilize, and integrate AI tools into the research process in an effective, ethical, and reflective manner [33]. It encompasses not only technical competence, but also evaluative judgment, critical thinking regarding reliability, and the ability to align AI output with one's disciplinary expertise.

From a theoretical standpoint, AI Proficiency can be conceptualized as a moderating variable, drawing on Task–Technology Fit Theory (TTF) [34] and Self-Determination Theory (SDT) . TTF posits that technology enhances performance only when it aligns with both the user's capabilities and the task's requirements [35]. A faculty member with high research self-efficacy (RSE) but poor AI skills may be unable to fully leverage their potential. In contrast, SDT suggests that a sense of technological mastery (AI literacy) reinforces autonomy, which in turn fosters intrinsic motivation.

Recent empirical studies support this logic. A study by [20], found that AI Proficiency significantly moderates the relationship between Research Self-Efficacy and Research Engagement—that is, self-efficacy translates into active research motivation only when accompanied by sufficient AI-related competence. Similarly, [36] reported that lecturers with high AI proficiency demonstrated higher research productivity than those with limited AI use, despite both groups having comparable levels of self-efficacy.

However, evidence also cautions against over-reliance on AI. When AI use exceeds an individual's cognitive capacity or lacks alignment with academic foundations, it can undermine one's sense of autonomy and perceived competence—a phenomenon referred to as cognitive offloading [37]. This suggests that AI does not universally enhance the relationship between self-efficacy and motivation; rather, its moderating effect depends on the quality and depth of AI usage.Based on this theoretical and empirical foundation, this study proposes that:

H7: AI Proficiency has a positive effect on Research Self-Efficacy.

H8: AI Proficiency has a positive effect on Faculty Research Motivation.

H9: AI Proficiency moderates the relationship between Research Self-Efficacy and Research Motivation, such that the relationship is stronger when AI Proficiency is high.

Figure 1 shows the research model of this study.

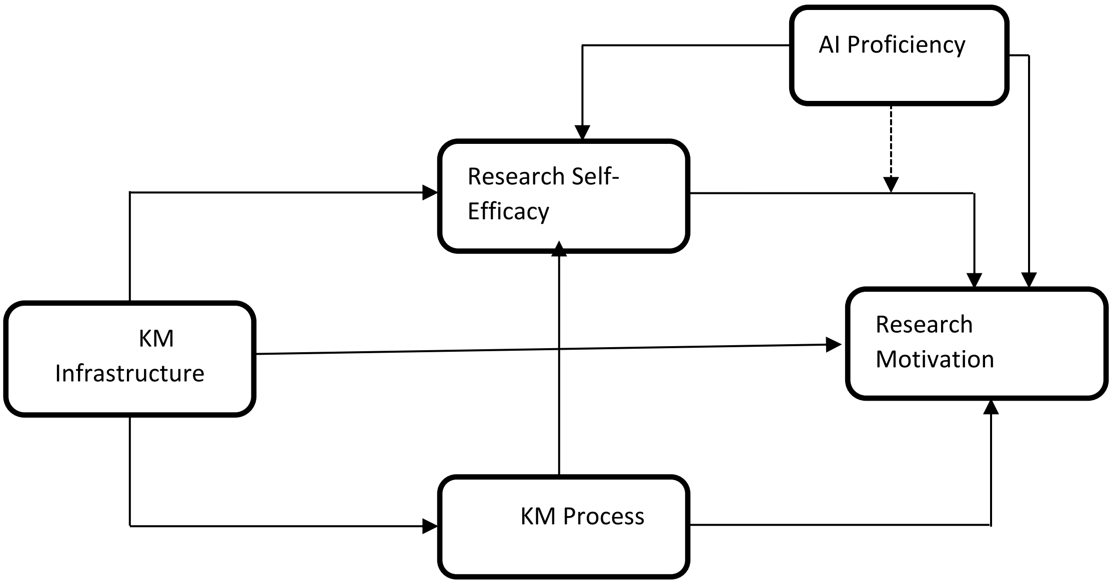

Figure 1. Research framework.

3. Research methodology

3.1. Research design

This study adopts a quantitative research approach using a survey design to examine the relationships among key constructs: components of knowledge management (infrastructure and processes), research self-efficacy, research motivation, and the moderating role of AI proficiency. The proposed research model is tested using Partial Least Squares Structural Equation Modeling (PLS-SEM)—a statistical technique well-suited for models that involve both mediation and moderation effects, as well as for handling small to medium sample sizes without requiring data to meet the assumptions of normal distribution [38]

3.2. Measurement instruments developed

To ensure content validity and theoretical alignment, all constructs in the proposed research model were measured using items adapted from established studies. The survey instrument included five latent constructs: KM Infrastructure, KM Process, Research Self-Efficacy, AI Proficiency, and Research Motivation. Measurement items were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Items for KMI were drawn from [24,25] capturing the technological and structural readiness of the institution to support knowledge sharing. The KMP construct was based on previous studies by [16] and extended to reflect knowledge acquisition, application, and dissemination in academic settings.

RSE was measured using items rooted in [12] theoretical framework and adapted for academic contexts from [39], emphasizing confidence in conducting various stages of the research process. AIP items were developed based on [33], with contextual adjustments to reflect practical integration of AI tools (e.g., ChatGPT, Elicit) in academic research.

Finally, Research Motivation was assessed using items adapted from prior motivational studies in higher education [8,26,40], focusing on intrinsic interest, initiative, and long-term commitment to research activities.

A summary of constructs, measurement codes, items, and their respective sources is provided in **Table 1**

Table 1. Measurement items for construct operationalization.

Construct	Code	Measurement Item	Source
KM Infrastructure	KMI1	The university has a well-established ICT infrastructure to support academic work.	[24]
	KMI 2	There is a strong culture of knowledge sharing among faculty members.	[25]
	KMI 3	Organizational structure facilitates knowledge management and retrieval.	
KM Process	KMP1	The university effectively acquires and disseminates academic knowledge.	[16]
	KMP2	Faculty frequently share research knowledge and experience with peers.	
	KMP3	Knowledge is systematically stored and easily retrievable when needed.	
	KMP4	I regularly apply acquired knowledge in my research activities.	
Research Self-Efficacy	RSE1	I am confident in identifying a suitable research topic in my field.	[12]
	RSE2	I believe I can independently design and carry out a research project.	[39]
	RSE3	I am capable of analyzing and interpreting research data effectively.	
AI Proficiency	AIP1	I can use AI tools (e.g., ChatGPT, Elicit) to support research idea generation.	[33]
	AIP2	I regularly use AI to search for and summarize academic literature.	
	AIP3	I am comfortable integrating AI into my research process.	Adapted for academic context
Research Motivation	RM1	I enjoy conducting academic research.	[8], [26], [40]
	RM2	I actively seek opportunities to initiate new research.	
	RM3	Research is a central part of my long-term career goals.	

The questionnaire was developed using a back-translation procedure, in which the original English version was translated into Vietnamese and then retranslated into English to ensure semantic equivalence. The content was reviewed through expert interviews and pilot-tested with 30 university lecturers prior to formal data collection. Results from the reliability analysis indicated that all constructs achieved Cronbach's alpha values above 0.70, confirming internal consistency reliability in accordance with recommended thresholds [41].

Data were collected from academic staff at both public and private universities in Vietnam who were engaged in teaching and/or research during the 2024–2025 academic year. A purposive-convenience sampling method was employed, with eligibility criteria requiring respondents to have at least one year of teaching experience or a minimum of one completed research project.

The survey was administered through a combination of online distribution via Google Forms and paper-based collection at academic conferences. After removing incomplete or irregular responses, a total of 295 valid questionnaires were retained for analysis.

3.3. Assessment of common method bias

Given that the data for this study were collected using self-reported questionnaires from a single source (university lecturers) at a single point in time, the potential for common method bias (CMB) was carefully considered. To assess the extent of CMB, Harman's single-factor test was employed—a widely used diagnostic technique in behavioral research [42]. Specifically, all observed variables in the model were subjected to an unrotated exploratory factor analysis (EFA) using SPSS. According to the test, if a single factor accounts for more than 50% of the total variance extracted, this may indicate the presence of substantial CMB. However, the results showed that the first factor accounted for only 37.3% of the total variance, which is well below the critical threshold of 50%. These findings suggest that common method variance is not a serious concern in this study, and that the measured relationships among constructs are unlikely to be artifacts of measurement bias.

3.4. Data analysise

The data were analyzed using SmartPLS 3.0, following a two-step analytical approach. Step 1: Measurement Model Evaluation. The reliability and validity of the constructs were assessed through the following criteria: Internal consistency reliability, using Cronbach's Alpha and Composite Reliability (CR); Convergent validity, assessed via Average Variance Extracted (AVE); Discriminant validity, evaluated using both the Fornell–Larcker criterion and the Heterotrait-Monotrait ratio (HTMT). Step 2: Structural Model Evaluation. The structural relationships among latent variables were examined through: Estimation of path coefficients to test direct effects; Mediation analysis using bootstrapping procedures to assess indirect effects; Moderation analysis through the creation of interaction terms and evaluation of moderation coefficients; Calculation of model fit and explanatory power metrics, including R^2 (coefficient of determination), f^2 (effect size), and Q^2 (predictive relevance). This two-stage process ensured that both the measurement properties and structural relationships in the proposed research model were robust and met the accepted standards for partial least squares structural equation modeling (PLS-SEM).

4. Results and discussion

4.1. Sample characteristics

A total of 400 structured questionnaires were distributed to lecturers at eight higher education institutions located in Hanoi, Vietnam, including five public universities and three private universities. The institutions were selected to reflect diversity in ownership, academic disciplines, and research orientation. The selection criteria ensured representation from both research-intensive and teaching-focused universities. Out of the 400 distributed surveys, 295 valid responses were retained for further analysis, yielding a valid response rate of 73.75%. Questionnaires with substantial missing data, patterned responses, or completion times below the minimum threshold were excluded to enhance data quality. The final sample was considered sufficient for conducting structural equation modeling using PLS-SEM, following the recommendations of [38] regarding minimum sample size. The demographic profile of the respondents is presented in **Table 2**, covering gender, age, academic qualification, years of experience, and academic discipline.

Table 2. Demographic characteristics of the respondents (N = 295).

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	157	53.2
	Female	138	46.8
Age	Under 30	76	25.8
	30–45	146	49.5
	Above 45	73	24.7
Academic qualification	Bachelor's degree	69	23.4
	Master's degree	108	36.6
	Doctoral degree	118	40.0
Years of experience	Less than 10 years	86	29.2
	10–15 years	115	39.0
	More than 15 years	94	31.9
Academic discipline	SSH (Social Sciences, Humanities & Education)	152	51.5
	STEM (Science, Technology, Engineering & Math)	143	48.5

The sample consisted of 295 university lecturers from various public and private institutions across Hanoi, Vietnam. In terms of gender distribution, male respondents accounted for 53.2%, while female respondents made up 46.8%, indicating a relatively balanced gender composition.

Regarding age, the majority of participants (49.5%) were between 30 and 45 years old, reflecting the typical career stage of early to mid-career researchers. Additionally, 25.8% were under 30, and 24.7% were above 45, suggesting a diverse age distribution that supports generalizability across generations of academics.

In terms of academic qualifications, 76.6% of respondents held postgraduate degrees (Master's or Doctoral), with 40.0% possessing a Ph.D. This indicates a highly educated sample, which aligns with the target population of research-active faculty.

When examining work experience, 39.0% had between 10 and 15 years of experience, while 31.9% had over 15 years, and 29.2% had less than 10 years. This suggests that the sample included both seasoned and relatively newer academics, providing a well-rounded perspective on knowledge management and research motivation.

Finally, with respect to academic disciplines, 51.5% of respondents came from the Social Sciences, Humanities, and Education (SSH), while 48.5% represented Science, Technology, Engineering, and Mathematics (STEM). This near-equal distribution ensures that the findings are not biased toward a specific academic domain and allows for meaningful comparison between SSH and STEM faculties in later analyses.

4.2. Assessment of measurement model

To evaluate the reliability and convergent validity of the measurement model, standard criteria including Cronbach's Alpha (α), Composite Reliability (CR), and Average Variance Extracted (AVE) were applied [38]. The results are summarized as **Table 3**.

Table 3. Measurement model summary.

Construct	Indicator	Outer Loading	Cronbach's Alpha	Composite Reliability	AVE
KM Infrastructure	KMI1	0.828	0.77	0.866	0.683
	KMI2	0.858			
	KMI3	0.793			
KM Process	KMP1	0.847	0.877	0.915	0.73
	KMP2	0.836			
	KMP3	0.869			
	KMP4	0.865			
AI Proficiency	RSE1	0.84	0.824	0.895	0.74
	RSE2	0.879			
	RSE3	0.862			
Research Self-Efficacy	AIP1	0.815	0.828	0.898	0.745
	AIP2	0.873			
	AIP3	0.9			
Research Motivation	RM1	0.864	0.848	0.908	0.767
	RM2	0.904			
	RM3	0.86			

Table 3 show that all constructs reported Cronbach's Alpha values above the recommended threshold of 0.70 , indicating satisfactory internal consistency. Composite Reliability (CR) values for all constructs exceed the cutoff of 0.70, ranging from 0.866 to 0.915, confirming strong construct reliability. All constructs demonstrate AVE values above the threshold of 0.50, indicating that each construct explains more than 50% of the variance of its indicators. Outer loadings of all items are above 0.70, with most exceeding 0.80. This provides strong evidence of indicator reliability. Based on the reported values, the measurement model exhibits adequate reliability and convergent validity across all constructs. The constructs are internally consistent, and their indicators load strongly on their respective latent variables, supporting the adequacy of the measurement instrument.

To evaluate discriminant validity, two established methods were employed: the Fornell–Larcker criterion [43] and the Heterotrait–Monotrait Ratio (HTMT) of correlations [44].

According to the Fornell–Larcker criterion, the square root of the AVE for each construct (shown on the diagonal) should be greater than its highest correlation with any other construct. As displayed in the correlation matrix, this condition is met for all constructs:

Table 4. Fornell-Larcker criterion.

	KMI	KMP	AIP	RSE	RM
KMI	0.827				
KMP	0.239	0.854			
AIP	0.119	0.350	0.860		
RSE	0.298	0.456	0.388	0.863	
RM	0.389	0.653	0.502	0.593	0.876

The **Table 4**'s results support discriminant validity, indicating that each construct is empirically distinct from the others.

The HTMT ratio provides a more stringent assessment of discriminant validity. Values below 0.90 are considered acceptable [44], with a more conservative threshold of 0.85 in some contexts.

Table 5. Heterotrait-Monotrait ratio (HTMT).

	KMI	KMP	AIP	RSE	RM
KMI					
KMP	0.284				
AIP	0.145	0.408			
RSE	0.372	0.532	0.468		
RM	0.475	0.755	0.600	0.705	

Table 5 show that all HTMT values are well below the critical value of 0.90, further confirming acceptable discriminant validity. The Fornell–Larcker criterion and HTMT results indicate strong discriminant validity among the constructs in the measurement model. This ensures that each latent variable captures a unique aspect of the theoretical model and justifies proceeding with structural model analysis.

4.3. Structure model analysis

After assessing the reliability and convergent/discriminant validity of the measurement model, the next step in the PLS-SEM procedure is to analyze the structural model in order to test the proposed hypotheses. Structural model analysis enables the examination of the relationships among latent variables, as well as the overall model fit using key indicators such as the coefficient of determination (R^2), path coefficients, statistical significance (p-values), and predictive relevance (Q^2).

To ensure the robustness of parameter estimates, a bootstrapping procedure with 5,000 resamples was employed to assess the significance and confidence of the path coefficients. The results of the structural model analysis are presented in the following tables and figures, providing a comprehensive overview of the explanatory power and empirical validity of the proposed research model.

Table 6. Structural model evaluation.

Coefficient evaluation	Variables	Testing values			Reference values
R^2		R^2		R^2 Adjusted	>=0.75: considerable =<0.5: Moderate =< 0.25: Weak [38]
	KMP	0.057		0.054	
	RSE	0.302		0.294	
	RM	0.619		0.612	
Effect Size(f^2)		KMP	RSE	RM	0.35=> Large effect 0.15 => Medium 0.02=> Small effect [38]
	KMI	0.061	0.049	0.094	
	KKP		0.124	0.327	
	AIP		0.081	0.138	
	RSE			0.08	
Collinearity(Inner VIF)	KMI	1.000	1.062	1.157	VIF<5.0 [38]
	KKP		1.193	1.342	
	AIP		1.141	1.385	

Coefficient evaluation	Variables	Testing values		Reference values
	RSE		1.631	
	Q^2			
Predictive Relevance(Q^2)	KMP	0.041		Q^2 >0: Predictive relevance [45]
	RSE	0.463		
	RM	0.219		

Table 6. (*Continued*)

The R² values reflect the proportion of variance explained by the exogenous variables for each endogenous construct. As shown in **Table 6**, RM demonstrates a high level of explanatory power ($R^2 = 0.619$), indicating a substantial effect. RSE has a moderate R^2 value (0.302), while KMP exhibits a weak explanatory power ($R^2 = 0.057$). These results suggest that the model performs well in explaining RM but leaves room for improvement in explaining KMP.

To evaluate the impact of individual predictors on dependent constructs, [46]'s criteria were applied, wherein f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively. The most notable effect was observed from KMP to RM ($f^2 = 0.327$), approaching a large effect size. In contrast, most other relationships, such as INF → SE ($f^2 = 0.049$), KMI → KMP ($f^2 = 0.061$), and RSE → RM ($f^2 = 0.080$), exhibited small effects. These findings emphasize the central role of Knowledge Process in influencing.

All inner VIF values ranged from 1.000 to 1.631, well below the critical threshold of 5.0, suggesting that multicollinearity is not a concern in the model. This confirms the stability and interpretability of the path coefficients.

The Q^2 values, obtained through blindfolding procedures, were all greater than zero, indicating acceptable predictive relevance for all endogenous constructs [47]. Notably, SE achieved the highest predictive relevance ($Q^2 = 0.463$), followed by RM ($Q^2 = 0.219$) and KMP ($Q^2 = 0.041$). This demonstrates that the model possesses adequate out-of-sample predictive power, especially for RSE and RM.

Overall, the structural model demonstrates satisfactory explanatory and predictive capabilities. The strongest predictive pathway was from KMP to RM, both in terms of effect size and explained variance. While the model performs strongly in predicting RM and RSE, its low R^2 for KMP suggests the need to consider additional antecedents in future model refinements.

The structural model results, presented in both the path diagram and the corresponding statistical summary, confirm that all hypothesized relationships are statistically supported at the 0.05 significance level. **Table 7** summarizes the standardized path coefficients (β), t-values, and p-values for each hypothesized path.

Table 7. Direct path coefficients and moderating effects of AI proficiency.

Path	Beta (β)	T – values	P -Values	Results
KMI-> KMP	0.239	3.972	0.000	Supported
KMI -> RSE	0.191	3.338	0.001	Supported
KMP -> RM	0.204	5.474	0.000	Supported
KMP -> RSE	0.321	6.600	0.000	Supported
KMP -> RM	0.409	11.340	0.000	Supported
AIP -> RSE	0.253	5.783	0.000	Supported
AIP -> RM	0.270	6.817	0.000	Supported

Path	Beta (β)	T – values	P -Values	Results
RSE -> RM	0.223	4.071	0.000	Supported
RSE*AIP -> RM	0.089	2.901	0.004	Supported

Table 7. (*Continued*)

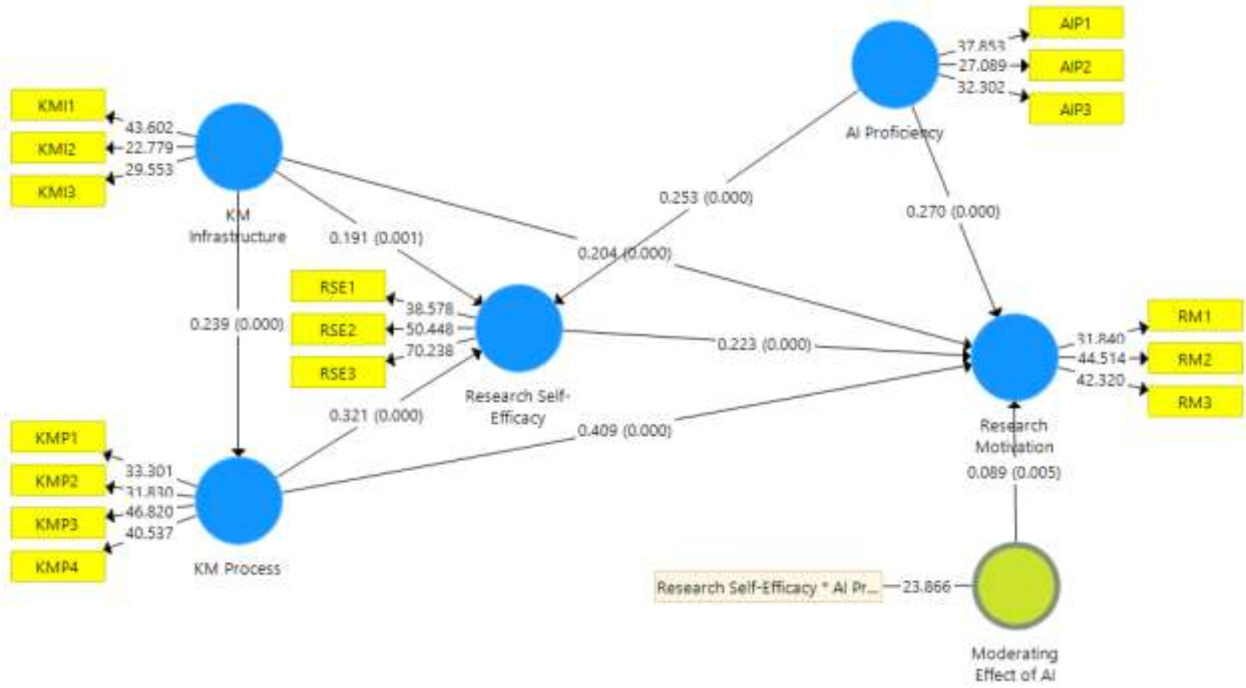

Figure 2. Structural model results with path coefficients and moderating effect of AI proficiency.

As shown in **Figure 2** and **Table 7** all hypothesized relationships were statistically significant, 2providing strong empirical support for the proposed model. Specifically, KMI positively influenced both KMP ($\beta = 0.239$, $p < 0.001$), RSE ($\beta = 0.191$, $p = 0.001$), and RM ($\beta = 0.204$, $p < 0.001$), indicating that a robust infrastructure for knowledge management enhances research-related capabilities and intentions. Similarly, KMP exerted significant effects on RSE ($\beta = 0.321$, $p < 0.001$) and RM ($\beta = 0.409$, $p < 0.001$), highlighting the critical role of operationalized knowledge flows in facilitating researcher development.

In addition, AIP was found to significantly affect both RSE ($\beta = 0.253$, $p < 0.001$) and RM ($\beta = 0.270$, $p < 0.001$), suggesting that individuals with higher digital competence are more confident and intrinsically motivated toward research activities. Furthermore, RSE significantly predicted RM ($\beta = 0.223$, $p < 0.001$), aligning with the core tenets of Social Cognitive Theory.

Notably, the interaction effect between RSE and AIP on RM was also significant ($\beta = 0.089$, $p = 0.004$), confirming a moderating effect. This finding implies that the positive influence of self-efficacy on motivation is amplified when individuals possess higher levels of AI proficiency, thus revealing a synergistic relationship between psychological readiness and technological competency.

Overall, the model demonstrates strong explanatory and predictive validity, supporting the integration of knowledge management and AI readiness as key drivers of research motivation.

To complement the analysis of direct relationships, this study further investigated the indirect effects among constructs to explore the underlying mechanisms through which exogenous variables influence the endogenous outcome — RM. In particular, RSE was examined as a mediating variable in several causal paths. The bootstrapping technique with 5,000 subsamples was employed to estimate the significance of indirect effects, utilizing the path coefficient (β), t-value, p-value, and 95% bias-corrected confidence intervals [48]. An indirect effect is considered significant if the confidence interval does not include zero. Additionally, the type of mediation (full or partial) was assessed by comparing the significance of direct and indirect paths. The results of the indirect effects analysis are summarized in **Table 8**.

Table 8. Indirect effects via research self-efficacy.

Path	β	t-value	95% CI	P Values	Results
KMI -> RSE -> RM	0.042	2.735	[0.015, 0.075]	0.006	Supported
KMP-> RSE -> RM	0.072	3.160	[0.029, 0.119]	0.002	Supported
AIP -> RSE -> RM	0.056	3.115	[0.024, 0.094]	0.002	Supported

Table 8 presents the results of the bootstrapped indirect effects analysis, focusing on the mediating role of RSE in the relationship between the exogenous variables (KMI, KMP, AIP) and the endogenous outcome Research Motivation (RM). All three indirect paths were found to be statistically significant, as indicated by: t-values greater than 1.96, p-values less than 0.01, and 95% bias-corrected confidence intervals that do not contain zero, thereby confirming the presence of meaningful mediation effects.

The path KMI -> RSE -> RM yielded a standardized indirect effect of β = 0.042 (t = 2.735, p = 0.006), suggesting that KM Infrastructure exerts a significant but relatively small influence on Research Motivation through the enhancement of Self-Efficacy. The strongest indirect effect was observed for KMP-> RSE -> RM (β = 0.072, t = 3.160, p = 0.002), indicating that the Knowledge Process indirectly boosts Research Motivation by strengthening researchers' confidence in their capabilities. Likewise, AIP -> RSE -> RM showed a significant mediating effect (β = 0.056, t = 3.115, p = 0.002), highlighting the important role of AI Proficiency in enhancing motivation via improved self-efficacy.

These results underscore the central mediating role of Research Self-Efficacy in translating knowledge management and technological competencies into research-related motivational outcomes. The findings align with Social Cognitive Theory [12], which posits that beliefs in one's capabilities are a critical driver of motivation and behavior.

As an extension of the structural results, we conducted an Importance–Performance Map Analysis (IPMA) with Research Motivation (RM) as the target construct.

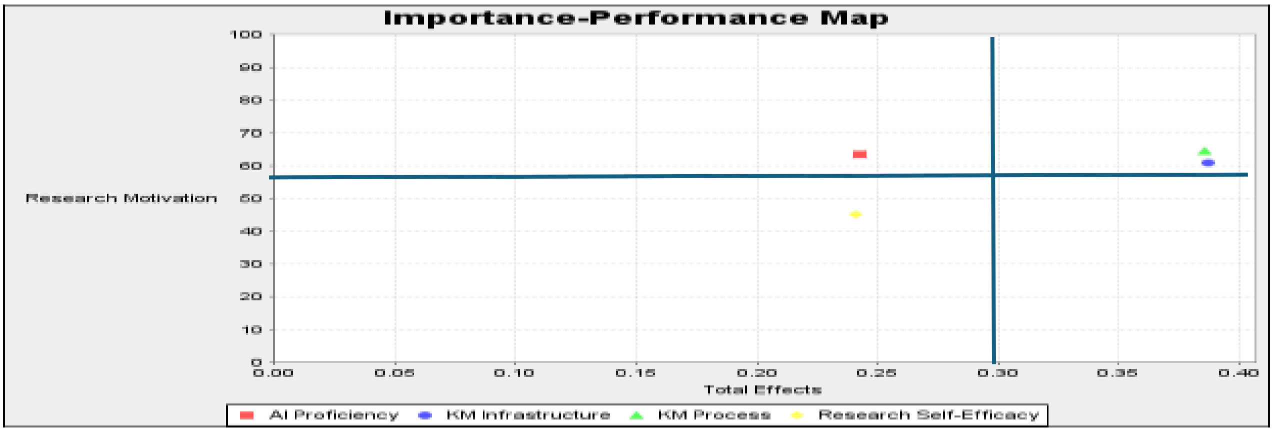

Figure 3. Importance–Performance Map (Target: Research motivation).

The map indicates that KM Process exhibits the highest importance for RM (total effect in the upper-0.3 range) while also achieving high performance (mid-60s on a 0–100 scale), suggesting it is a "maintain and leverage" driver. KM Infrastructure likewise shows high importance and solid—though slightly lower—performance (around 60), implying that selective upgrades to digital platforms, knowledge repositories, and incentive mechanisms could yield additional gains. AI Proficiency presents moderate importance with relatively high performance (mid-60s), calling for a quality-focused strategy (e.g., LLM literacy, fact-checking, and ethical use) rather than broad expansion. By contrast, Research Self-Efficacy displays moderate importance but the lowest performance (mid-40s), marking it as the clearest improvement lever through targeted mentoring, method workshops, and AI-assisted research coaching. Notably, because IPMA is based on total effects, it does not fully capture moderation, so the conditional value of AI proficiency in strengthening the RSE → RM pathway may be understated. Overall, the IPMA prioritizes (1) sustaining KM Process, (2) selective enhancement of KM Infrastructure, and (3) capability building to lift Research Self-Efficacy, with AI proficiency development used to amplify these gains.

4.4. Discussion

The structural model analysis confirms the positive relationships among KM components (infrastructure and processes), RSE, and faculty research motivation. These findings are generally consistent with prior studies while also offering novel insights that enrich both theoretical understanding and practical implications in the context of higher education in Vietnam. The moderated effect suggests that institutions should complement KM systems with LLM-oriented capacity building. When LLM literacy is high, the self-efficacy → motivation pathway is amplified, aligning with competence/autonomy mechanisms (SDT) and task–technology alignment (TTF). Conversely, low LLM proficiency may blunt psychological gains, underscoring the need for targeted training and governance for trustworthy use.

Specifically, support for Hypotheses H1 and H2 affirms that both KM infrastructure and KM processes exert significant positive effects on faculty research motivation. These results align with earlier research by [22,25,18] which emphasize that effective KM systems enhance knowledge accessibility, foster academic collaboration, and ultimately stimulate intrinsic motivation for research. In the Vietnamese context—where universities are striving to digitize academic resources and foster knowledge-sharing cultures—these findings are particularly relevant and timely.

Hypotheses H3 to H5, which examine the mediating role of research self-efficacy, are also supported. RSE is confirmed as a critical bridge between KM and research motivation, echoing findings from [49,39,19] These results reinforce Social Cognitive Theory, which posits that self-efficacy shapes how individuals interpret challenges, sustain effort, and translate available organizational resources into active engagement. Importantly, the mediating mechanism of RSE offers a clearer explanation of how KM indirectly fosters research motivation by enhancing faculty members' belief in their own research capabilities.

A key contribution of this study lies in its examination of AI Proficiency as both an independent and moderating variable. The confirmation of Hypotheses H7 and H8 indicates that AI Proficiency positively influences both RSE and research motivation, complementing recent empirical findings by [20], [36]. Mastery of AI tools not only enhances research productivity but also reinforces autonomy and creativity—core elements of intrinsic motivation as outlined in Self-Determination Theory (SDT).

Notably, the validation of Hypothesis H9 confirms that AI Proficiency moderates the relationship between RSE and research motivation, such that the relationship is stronger among those with higher AI proficiency. This suggests that even faculty members with strong self-belief may experience diminished motivation if they lack the technological capabilities to actualize their potential. This finding is consistent with the Task–Technology Fit (TTF) framework [34] and further supports concerns regarding cognitive offloading raised by [37]—In which overreliance on AI without adequate user competence may erode perceived control and competence.

Overall, this study not only validates existing theoretical frameworks linking KM, RSE, and research motivation but also advances the literature by introducing and empirically testing AI Proficiency as a novel moderating construct. This contribution is particularly salient in the context of ongoing digital transformation in higher education, where the integration of AI into academic workflows is becoming increasingly prevalent.

This section may be divided by subheadings. It should provide a concise and pre-cise description of the experimental results, their interpretation, as well as the experi-mental conclusions that can be drawn.

5. Conclusion

This study provides a comprehensive examination of how knowledge management (KM) infrastructure and processes affect faculty members' research motivation, highlighting the mediating role of research self-efficacy (RSE) and the moderating role of AI proficiency. Drawing on Social Cognitive Theory, Task–Technology Fit Theory, and Self-Determination Theory, the proposed model was empirically tested using PLS-SEM with data collected from 312 faculty members across public and private universities in Vietnam.

The findings confirm that KM infrastructure and KM processes have significant direct effects on faculty research motivation, and these effects are partially mediated by research self-efficacy. This underscores the importance of creating supportive knowledge environments that not only provide access to resources but also build individuals' belief in their research capabilities. Furthermore, AI proficiency emerged as a critical factor—both as a direct predictor of RSE and motivation and as a moderator that strengthens the relationship between self-efficacy and motivation. These results suggest that technological competence, especially the ability to integrate AI tools effectively, is now an essential component of academic productivity and engagement.

By integrating KM, psychological, and technological perspectives, this study contributes to a more holistic understanding of faculty research engagement in the era of digital transformation. The research model offers a theoretically grounded and practically relevant framework for university leaders aiming to foster a high-performing academic culture.

5.1. Theoretical contributions

This study contributes to the growing body of literature on knowledge management (KM) and academic motivation by offering several key theoretical advancements.

First, the study extends existing KM frameworks by empirically validating a dual-path model in which both KM infrastructure and KM processes exert not only direct effects on research motivation but also indirect effects through research self-efficacy (RSE). While prior studies [22], [25] acknowledged KM's impact on general employee motivation, this research advances the conversation by identifying RSE as a critical psychological conduit that links KM practices to academic engagement. This reinforces Social Cognitive Theory [12] in the context of higher education.

Second, this research integrates the concept of AI proficiency as a moderating construct, drawing on Task–Technology Fit Theory [34] and Self-Determination Theory [35]. By doing so, the study introduces a novel theoretical lens for understanding how digital competence—particularly the ability to effectively harness AI tools—can shape the motivational outcomes of self-efficacy. This contributes to the emerging discourse on AI in academia, moving beyond debates on ethics or performance to highlight its role in psychological and behavioral dynamics.

Third, the proposed model offers a multi-level explanatory framework that integrates structural, psychological, and technological variables. In doing so, it provides a more holistic account of faculty research motivation and bridges three previously distinct streams of literature: knowledge management, self-efficacy theory, and AI-enabled academic practice.

Finally, the study enriches the discussion around research motivation in developing country contexts—an area often overlooked in KM and AI scholarship. By empirically testing the model within the Vietnamese higher education system, this work offers context-specific insights while laying the groundwork for comparative studies across other emerging academic systems.

5.2. Practical implications

The findings of this study offer several actionable insights for academic institutions and policymakers aiming to enhance research motivation among faculty members. First, investing in robust knowledge management infrastructure—such as open-access databases, internal knowledge-sharing platforms, and academic support units—can create an enabling environment that fosters intellectual engagement. However, infrastructure alone is insufficient; universities must also develop systematic KM processes that promote knowledge acquisition, application, and peer collaboration.

Second, research self-efficacy is a key psychological mechanism that translates structural and procedural supports into motivational outcomes. As such, institutions should implement training programs that not only enhance methodological and publication skills but also reinforce faculty members' confidence in their research capabilities.

Third, AI proficiency has emerged as a strategic academic competency. Rather than treating AI tools as optional add-ons, universities should integrate AI literacy into faculty development programs. Providing targeted workshops on using tools like ChatGPT, Elicit, and Scite for research design, literature review, and data analysis can empower faculty to work more efficiently and confidently.

Finally, the moderating role of AI proficiency suggests that personalized support—tailored to each faculty member's technological skill level—may be more effective than generic digital transformation policies. Administrators should consider differentiated strategies based on faculty members' self-efficacy and digital readiness when designing research incentives or evaluating performance.

5.3. Limitations and future research

Despite its contributions, this study has several limitations that should be addressed in future research. First, the dataset is confined to Hanoi (five public and three private universities) and gathered via controlled convenience sampling, limiting external validity. Although N = 295 satisfies PLS-SEM guidelines, it may be underpowered for fine-grained multi-group or multilevel analyses. The cross-sectional, single-source self-report design precludes causal inference and risks method bias despite our procedural and statistical remedies. Key constructs (AI/LLM proficiency, research motivation) are perceptual measures without triangulation to objective indicators (usage logs, publications, grants). Future research should employ multi-site, multi-wave, and multi-source datasets, test measurement invariance (e.g., SSH vs. STEM; public vs. private), and integrate behavioral/administrative data.

Second, the sample was drawn exclusively from Vietnamese higher education institutions, which may limit the generalizability of the findings to other national or cultural contexts. Future research could replicate this model in diverse settings to validate its applicability across different academic systems.

Third, AI proficiency was measured as a self-reported construct, which may be subject to social desirability bias or overestimation. Subsequent studies could incorporate objective measures of AI use or performance-based assessments to strengthen validity.

Finally, while this study focuses on KM and AI as structural and technological enablers, future models could include additional organizational and psychological variables, such as institutional trust, academic identity, or digital burnout, to further unpack the complex dynamics of faculty research engagement.

Author contributions

Conceptualization, Quang Vinh Nguyen and Thi Lua Mai; methodology, Quang Vinh Nguyen; software, Manh Hien Luc; validation, Quang Vinh Nguyen, Thi Lua Mai, and Manh Hien Luc; formal analysis, Quang Vinh Nguyen; investigation, Thi Lua Mai; resources, Thi Lua Mai; data curation, Manh Hien Luc; writing—original draft preparation, Thi Lua Mai; writing—review and editing, Quang Vinh Nguyen; visualization, Manh Hien Luc; supervision, Quang Vinh Nguyen; project administration, Quang Vinh Nguyen;, Quang Vinh Nguyen. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest

References

1. M. D. Santoro and P. E. Bierly, "Facilitators of knowledge transfer in university-industry collaborations: A knowledge-based perspective," IEEE Trans Eng Manag, vol. 53, no. 4, pp. 495–507, 2006.
2. N. Salo, "Knowledge management in education in Indonesia: An Overview," Global Journal of human social science, vol. 11, no. 1, 2011.
3. S. S. Abu-Naser, M. J. Al Shobaki, and Y. M. Abu Amuna, "Knowledge Management Maturity in Universities and its Impact on Performance Excellence" Comparative study"," 2016.
4. Đ. Đ. Anh and Đ. Lê Anh, "Quản trị tri thức của sinh viên trong các trường đại học trong bối cảnh kinh tế số," Tạp chí Kinh tế và Phát triển, no. 301, pp. 83–92, 2022.
5. N. Ngoc-Tan and A. Gregar, "Knowledge management and its impacts on organisational performance: An empirical research in public higher education institutions of Vietnam," Journal of Information & Knowledge Management, vol. 18, no. 02, p. 1950015, 2019.
6. N. M. Ngoc and N. H. Tien, "Quality of scientific research and world ranking of public and private universities in Vietnam," International journal of public sector performance management, vol. 10, no. 1, pp. 1–15, 2023.
7. H. T. L. Nguyen, "A review of university research development in Vietnam from 1986 to 2019," Higher education in market-oriented socialist Vietnam: New players, discourses, and practices, pp. 63–86, 2020.
8. M. Franco and H. Haase, "University–industry cooperation: Researchers' motivations and interaction channels," Journal of Engineering and technology Management, vol. 36, pp. 41–51, 2015.
9. J. McGurk and A. Baron, "Knowledge management–time to focus on purpose and motivation," Strategic HR Review, vol. 11, no. 6, pp. 316–321, 2012.
10. M. M. Paladhi and V. Maruthaveeran, "Evaluating AI literacy proficiency among LIS researchers in ASEAN," Library hi tech news, vol. 41, no. 4, pp. 6–8, 2024.
11. D. Zhao, "The impact of AI-enhanced natural language processing tools on writing proficiency: An analysis of language precision, content summarization, and creative writing facilitation," Educ Inf Technol (Dordr), pp. 1–32, 2024.
12. A. Bandura, "Social cognitive theory of personality," Handbook of personality, vol. 2, no. 1, pp. 154–196, 1999.
13. L. Nonaka, H. Takeuchi, and K. Umemoto, "A theory of organizational knowledge creation," International journal of technology Management, vol. 11, no. 7–8, pp. 833–845, 1996.
14. A. D. Smith, "Knowledge management strategies: A multi-case study," Journal of knowledge management, vol. 8, no. 3, pp. 6–16, 2004.
15. D. L. Miltiadis and P. Athanasia, "Project management as a knowledge management primer: the learning infrastructure in knowledge-intensive organizations: projects as knowledge transformations and beyond," The Learning Organisation, vol. 10, no. 4, pp. 237–250, 2003.

16. N. T. Pham et al., "Research on knowledge management models at universities using fuzzy analytic hierarchy process (FAHP)," Sustainability (Switzerland), vol. 13, no. 2, 2021, doi: 10.3390/su13020809.
17. M. Lashkary, E. K. Matin, B. H. Kashani, and K. Kasraei, "Investigating the knowledge management implementation in distance education system in Iran," in Information and Knowledge Management, 2012, pp. 61–69.
18. A. Alzghoul and K. M. Aboalganam, "Investigating the effect of knowledge management systems on university performance: The interplay of intellectual and human capital," Knowledge and Performance Management, vol. 9, no. 1, p. 93, 2025.
19. L. D. Basileo, B. Otto, M. Lyons, N. Vannini, and M. D. Toth, "The role of self-efficacy, motivation, and perceived support of students' basic psychological needs in academic achievement," in Frontiers in Education, Frontiers Media SA, 2024, p. 1385442.
20. S. Bećirović, E. Polz, and I. Tinkel, "Exploring students' AI literacy and its effects on their AI output quality, self-efficacy, and academic performance," Smart Learning Environments, vol. 12, no. 1, p. 29, 2025.
21. H. Wu and H. Wang, "Is being intrinsically motivated a mixed blessing? The differential effects of daily intrinsic motivation on employee functioning," Tour Manag, vol. 107, p. 105073, 2025.
22. A. Kianto, M. Vanhala, and P. Heilmann, "The impact of knowledge management on job satisfaction," Journal of knowledge management, 2016.
23. S. P. Singh and H. K. Sharma, "Impact of work motivation on job satisfaction of teachers in professional education," The International Journal of Research Publication's. Research Journal of social science and management, vol. 6, no. 05, pp. 90–96, 2016.
24. B. Stensaker, P. Maassen, M. Borgan, M. Oftebro, and B. Karseth, "Use, updating and integration of ICT in higher education: Linking purpose, people and pedagogy," High Educ (Dordr), vol. 54, pp. 417–433, 2007, doi: 10.1007/s10734-006-9006-3.
25. C. N. L. Tan, "Enhancing knowledge sharing and research collaboration among academics: the role of knowledge management," High Educ (Dordr), vol. 71, pp. 525–556, 2016, doi: 10.1007/s10734-015-9922-6.
26. M. Nili, A. N. Isfahani, and M. H. Tanhaei, "Knowledge sharing and its impact on employees' motivation," International Journal of Academic Research in Progressive Education and Development, vol. 2, no. 3, pp. 142–152, 2013.
27. K. Levecque, F. Anseel, A. De Beuckelaer, J. Van der Heyden, and L. Gisle, "Work organization and mental health problems in PhD students," Res Policy, vol. 46, no. 4, pp. 868–879, 2017.
28. Y. Owusu-Agyeman, O. Larbi-Siaw, B. Brenya, and A. Anyidoho, "An embedded fuzzy analytic hierarchy process for evaluating lecturers' conceptions of teaching and learning," Studies in Educational Evaluation, vol. 55, pp. 46–57, 2017.
29. B. Hemmings and R. Kay, "Journal ratings and the publications of Australian academics," Issues in Educational Research, vol. 20, no. 3, pp. 234–243, 2010.
30. R. Fullwood, J. Rowley, and J. McLean, "Exploring the factors that influence knowledge sharing between academics," J Furth High Educ, vol. 43, no. 8, pp. 1051–1063, 2019.
31. B. D. Lund, T. Wang, N. R. Mannuru, B. Nie, S. Shimray, and Z. Wang, "ChatGPT and a new academic reality: Artificial Intelligence-written research papers and the ethics of the large language models in scholarly publishing," J Assoc Inf Sci Technol, vol. 74, no. 5, pp. 570–581, 2023.
32. S. Nah, J. McNealy, J. H. Kim, and J. Joo, "Communicating artificial intelligence (AI): Theory, research, and practice," 2020, Taylor & Francis.
33. Y. K. Dwivedi, A. Sharma, N. P. Rana, M. Giannakis, P. Goel, and V. Dutot, "Evolution of artificial intelligence research in Technological Forecasting and Social Change: Research topics, trends, and future directions," Technol Forecast Soc Change, vol. 192, p. 122579, 2023.
34. D. L. Goodhue and R. L. Thompson, "Task-technology fit and individual performance," MIS quarterly, pp. 213–236, 1995.
35. R. M. Ryan and E. L. Deci, "Intrinsic and extrinsic motivations: Classic definitions and new directions," Contemp Educ Psychol, vol. 25, no. 1, pp. 54–67, 2000, doi: 10.1006/ceps.1999.1020.
36. A. Fiedler and J. Döpke, "Do humans identify AI-generated text better than machines? Evidence based on excerpts from German theses," International Review of Economics Education, vol. 49, p. 100321, 2025, doi: 10.1016/j.iree.2024.100321.
37. Y. H. Yeo et al., "Assessing the performance of ChatGPT in answering questions regarding cirrhosis and hepatocellular carcinoma," Clin Mol Hepatol, vol. 29, no. 3, p. 721, 2023, doi: 10.3350/cmh.2023.0098.
38. J. F. Hair Jr, G. T. M. Hult, C. M. Ringle, and M. Sarstedt, A primer on partial least squares structural equation modeling (PLS-SEM). Sage publications, 2021.
39. B. Hemmings and R. Kay, "Research self-efficacy, publication output, and early career development," International Journal of Educational Management, vol. 24, no. 7, pp. 562–574, 2010, doi: 10.1108/09513541011080028.

40. M. Jofreh, A. Yasini, H. F. Dehsorkhi, and A. Hayat, “The relationship between EFL teachers’ quality of work life and job motivation,” Middle East J Sci Res, vol. 13, no. 3, pp. 338–346, 2013, doi: 10.5829/idosi.mejsr.2013.13.3.1748.
41. J. C. Nunnally and I. H. Bernstein, Psychometric Theory, 3rd ed. New York, NY: McGraw-Hill, Inc., 1994.
42. P. M. Podsakoff, S. B. MacKenzie, J.-Y. Lee, and N. P. Podsakoff, “Common method biases in behavioral research: a critical review of the literature and recommended remedies.,” Journal of applied psychology, vol. 88, no. 5, p. 879, 2003.
43. C. Fornell and D. F. Larcker, “Evaluating structural equation models with unobservable variables and measurement error,” Journal of Marketing Research, vol. 18, no. 1, pp. 39–50, 1981.
44. J. Henseler, C. M. Ringle, M. Sarstedt, and R. C. M. & S. M. Henseler J., “A new criterion for assessing discriminant validity in variance-based structural equation modeling,” J Acad Mark Sci, vol. 43, no. 1, pp. 115–135, 2015.
45. O. Götz, K. Liehr-Gobbers, and M. Krafft, “Evaluation of structural equation models using the partial least squares (PLS) approach,” in Handbook of partial least squares: Concepts, methods and applications, Springer, 2009, pp. 691–711.
46. J. Cohen, “1988: Statistical power analysis for the behavioral sciences. Hillsdale, NJ: Erlbaum,” 1988.
47. W. W. Chin, “Bootstrap cross-validation indices for PLS path model assessment,” in Handbook of partial least squares, Springer, 2010, pp. 83–97.
48. J. F. Hair Jr, G. Tomas. M. Hult, C. M. Ringle, M. Sarstedt, N. P. Danks, and S. Ray, Partial least squares structural equation modeling (PLS-SEM) using R: A workbook. 2021.
49. M. Carvache-Franco, O. Regalado-Pezúa, O. Carvache-Franco, and W. Carvache-Franco, “Sociodemographic aspects, satisfaction, loyalty, and motivations in religious tourism,” Cogent Soc Sci, vol. 10, no. 1, p. 2401145, 2024.