

“Influence of knowledge hiding on innovation climate: The moderating role of artificial intelligence adoption”

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INFLUENCE OF KNOWLEDGE HIDING ON INNOVATION CLIMATE: THE MODERATING ROLE OF ARTIFICIAL INTELLIGENCE ADOPTION

Abstract

In emerging digital economies, knowledge hiding can disrupt organizational knowledge flows that support innovation, yet empirical evidence on how artificial intelligence adoption shapes these effects remains limited. This study examines how knowledge hiding influences knowledge integration capability and innovation climate in digital firms and tests the moderating role of artificial intelligence adoption. Data were collected in May 2025 through a questionnaire survey of 145 firms operating in Thailand's New S-Curve digital sectors. Respondents included senior executives, middle managers, and knowledge management specialists involved in artificial intelligence implementation, knowledge management, and innovation activities. A total of 426 responses were obtained and aggregated to the firm level. The data were analyzed using partial least squares structural equation modeling. Results show that knowledge hiding significantly reduces knowledge integration capability ($\beta = -0.503, p < 0.001$) and innovation climate ($\beta = -0.339, p < 0.001$), while knowledge integration capability positively affects innovation climate ($\beta = 0.337, p < 0.001$). Artificial intelligence adoption weakens the negative effects of knowledge hiding on knowledge integration capability (interaction $\beta = 0.359, p < 0.001$) and innovation climate (interaction $\beta = 0.500, p < 0.001$), indicating a buffering mechanism through improved access to organizational knowledge. These findings suggest that digital firms should address knowledge hiding while strengthening knowledge integration practices and implementing artificial intelligence in ways that complement collaborative knowledge processes.

Keywords

knowledge integration, knowledge management, artificial intelligence, organizational innovation, Thailand

JEL Classification

O33, M15, M10

INTRODUCTION

Rapid technological advancement is reshaping how organizations operate in the digital economy. Within this context, knowledge has become one of the most critical strategic resources of organizations (Wang et al., 2018). The ability to create, integrate, and apply knowledge plays a central role in sustaining competitive advantage. Two important organizational capabilities reflect this process: knowledge integration capability and innovation climate. Both have been recognized as key conditions that support organizational learning and innovation development.

Despite the growing recognition of knowledge management, knowledge hiding remains a persistent challenge within organizations. Knowledge hiding refers to the intentional withholding or concealment of knowledge when it is requested by others. Such behavior can weaken organizational learning, reduce collaboration, and hinder innovation development. When knowledge hiding becomes widespread,



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it disrupts knowledge integration processes and undermines an organizational environment that supports innovation. This issue is particularly important in the digital economy, where organizations increasingly rely on knowledge-intensive activities. In developing countries such as Thailand, national policies promoting advanced technology industries under the New S-Curve strategy have accelerated this transition. Digital organizations in these sectors depend heavily on knowledge, technology, and innovation capabilities. As a result, employees' knowledge behaviors, including the sharing or withholding of knowledge, can significantly influence organizational performance.

In recent years, artificial intelligence adoption has begun to reshape knowledge management and organizational work processes. Artificial intelligence technologies can process large volumes of data, identify knowledge patterns, and improve access to organizational knowledge. Artificial intelligence-driven systems can also function as mechanisms for collecting, organizing, and distributing knowledge. This can make knowledge access more systematic and reduce the limitations of relying solely on interpersonal knowledge exchange. However, although artificial intelligence adoption has the potential to support organizational knowledge processes, its role in shaping employees' knowledge behaviors remains unclear. This issue becomes particularly important in digital organizations characterized by high innovation pressure and strong knowledge intensity. Despite the growing adoption of artificial intelligence technologies in organizations, the mechanisms through which knowledge hiding influences knowledge integration capability and innovation climate remain insufficiently understood.

1. LITERATURE REVIEW AND HYPOTHESES

In digital organizations, the ability to create value from knowledge has become a fundamental condition for sustaining competitive advantage (Grant, 1996). However, such an advantage does not arise from merely possessing knowledge. It depends on an organization's ability to connect, integrate, and apply knowledge from diverse sources in actual work processes. From this perspective, knowledge integration capability represents an organizational capability that transforms dispersed knowledge into decisions and practices that generate value. At the same time, innovation climate reflects a work environment that encourages creative thinking, experimentation with new ideas, and continuous innovation development. This study integrates perspectives from the knowledge-based view, conservation of resources theory, and technology adoption research to explain how knowledge behaviors and digital technologies jointly shape innovation-related outcomes.

From a process perspective, knowledge integration capability is commonly described as a systemic capability that involves knowledge acquisition, cross-unit knowledge exchange, and the application of knowledge through organizational routines (Zan et al., 2024; Acharya et al., 2022).

Effective knowledge integration often requires mechanisms that allow knowledge to move across functional and expertise boundaries (Zahra et al., 2020). At the team level, collaborative learning environments accelerate knowledge flow and facilitate the practical application of knowledge. These processes ultimately contribute to broader innovation outcomes within teams and across organizations (Li et al., 2023).

Regarding innovation climate, prior studies emphasize that it reflects employees' shared perceptions of managerial support for innovation. Such support may include access to resources, trust, autonomy in decision-making, and appropriate reward systems (Alblooshi et al., 2023). A socio-cognitive perspective suggests that when employees perceive their work environment as supportive of experimentation and idea generation, innovative behavior is more likely to emerge through intrinsic motivation and constructive interpretations of risk (Jiang et al., 2023; Newman et al., 2020). Innovation climate is also closely related to collective learning and knowledge sharing, which help transform ideas into practical innovations (Ding et al., 2022). In some contexts, innovation climate is further associated with psychological conditions that encourage team creativity and innovative work behavior (Nong et al., 2025; Du & Chang, 2023).

Despite these supportive structures, knowledge processes may still be disrupted by individual behavior. One significant barrier is knowledge hiding, defined as the intentional concealment or withholding of requested knowledge. This behavior differs from situations where knowledge is not shared simply because individuals do not possess the information (Connelly et al., 2012). Although knowledge hiding may occasionally arise from positive intentions, such as protecting confidentiality or avoiding interpersonal harm (Fauzi, 2023), it often creates hidden costs in knowledge-intensive organizations. By restricting knowledge flow, knowledge hiding weakens collaboration and slows collective learning processes (Chen et al., 2023).

Theoretical perspectives provide further explanations for knowledge hiding. According to the conservation of resources theory, employees seek to protect valuable personal resources such as expertise, job security, and career opportunities. When these resources are perceived as threatened, individuals may adopt knowledge hiding as a defensive strategy (Liu et al., 2025). Similarly, social exchange theory proposes that when individuals perceive an imbalance in reciprocal relationships or lack trust in others' intentions, they may limit knowledge disclosure to reduce personal risk (Blau, 2017). Empirical studies indicate that knowledge hiding is associated with reduced creativity and lower innovative behavior at the team level (Bashir et al., 2023). It may also undermine knowledge integration capability by disrupting knowledge flow and application and weaken innovation climate by reducing trust and psychological safety within the organization (Shen et al., 2025; Guo et al., 2022). From a managerial perspective, previous research suggests that mitigating knowledge hiding requires clear communication, supportive leadership, and psychologically safe work environments (Iram et al., 2026). In addition, organizational systems that reduce perceived threats to employees' resources may further help alleviate knowledge hiding behavior (Liu et al., 2025).

With ongoing digital transformation, artificial intelligence adoption has emerged as a critical factor influencing both knowledge management and knowledge-related behaviors. Research on technology adoption often explains artificial intelligence adoption using the Unified Theory of

Acceptance and Use of Technology framework, which highlights perceived usefulness, ease of use, social influence, and facilitating conditions (Venkatesh et al., 2003). However, more recent studies suggest that artificial intelligence adoption at the organizational level reflects broader system readiness. It arises from the interaction of individual, organizational, and environmental factors rather than from individual attitudes alone (Khanfar et al., 2026). At the individual level, relevant factors include information and communication technology or artificial intelligence knowledge, trust in technology, and concerns about job displacement (Merhi & Harfouche, 2024). At the organizational and environmental levels, artificial intelligence adoption depends on managerial support, technological infrastructure, competitive pressure, and support from external providers (Horani et al., 2025; Chatterjee et al., 2021).

When linked to knowledge dynamics, artificial intelligence technologies can significantly improve the systematic accessibility of organizational knowledge (Yu et al., 2023). Artificial intelligence systems are capable of processing large volumes of data and extracting explicit knowledge from tacit experience (Chen et al., 2022). They also facilitate broader knowledge access through searchable knowledge bases, thereby reducing reliance on direct interpersonal knowledge exchange (Hossain et al., 2022). Under this logic, artificial intelligence may reduce knowledge monopolies within organizations by making knowledge more widely available (Kohtamäki et al., 2022). Artificial intelligence-driven systems can further function as intermediaries that collect, organize, and distribute knowledge continuously across the organization (Sjodin et al., 2021).

Nevertheless, the relationship between artificial intelligence adoption and knowledge hiding is not necessarily linear. During the early stages of artificial intelligence adoption, employees may perceive artificial intelligence as a threat to job security and career advancement. Such perceptions may increase motivations to hide knowledge to maintain personal advantages (Arias-Pérez & Vélez-Jaramillo, 2022). Moreover, when algorithmic systems increasingly guide work processes, some employees may experience a loss of control and respond by "controlling through knowledge,"

for example, by concealing or avoiding knowledge sharing (Liu et al., 2025). However, as artificial intelligence becomes embedded as a practical support tool within organizations, it may reduce dependence on individual knowledge holders and make knowledge more systematically accessible. This development can decrease incentives for knowledge hiding (Chen et al., 2022; Arias-Pérez & Vélez-Jaramillo, 2022). Consequently, artificial intelligence adoption may function as a moderating condition that weakens the negative effects of knowledge hiding on both knowledge integration capability and innovation climate, particularly in digital organizations characterized by high innovation pressure and strong knowledge intensity.

Overall, the literature indicates that knowledge integration capability enables organizations to integrate and apply knowledge effectively, while innovation climate provides an environment that supports creativity and innovation development. In contrast, knowledge hiding disrupts knowledge flows and weakens trust within organizations, thereby undermining both knowledge integration capability and innovation climate. At the same time, artificial intelligence adoption represents a contemporary factor that may reshape these dynamics. Despite these insights, several important gaps remain. First, many studies examine antecedents or outcomes of knowledge hiding separately, but limited research tests the effects of knowledge hiding on both knowledge integration capability and innovation climate within a single analytical framework. Second, studies on artificial intelligence adoption largely focus on technology adoption or organizational readiness, while the manner in which artificial intelligence adoption reshapes the relationship between employee knowledge, behaviors, and innovation outcomes remains insufficiently understood. Third, prior research on reducing knowledge hiding mainly emphasizes social and managerial mechanisms, with less attention to the role of technology as a potential buffer that mitigates the negative consequences of knowledge hiding, particularly in digital organizations in developing countries.

Therefore, this study aims to examine the effects of knowledge hiding on both knowledge integration capability and innovation climate and to test the moderating role of artificial intelligence adoption

in digital organizations. The following hypotheses are proposed:

- H1: Knowledge integration capability has a positive effect on innovation climate.*
- H2: Knowledge hiding has a negative effect on knowledge integration capability.*
- H3: Knowledge hiding has a negative effect on innovation climate.*
- H4: Artificial intelligence adoption positively moderates the relationship between knowledge hiding and knowledge integration capability.*
- H5: Artificial intelligence adoption positively moderates the relationship between knowledge hiding and innovation climate.*

2. METHODOLOGY

This empirical study examined digital firms in Thailand operating within New S-Curve industries promoted under the Thailand 4.0 policy, which are characterized by emerging technologies and substantial growth prospects. Thailand represents an emerging digital economy in which the government actively advances these industries as part of its national development strategy. These industries form a rapidly evolving digital ecosystem in which knowledge, technological capability, and artificial intelligence play a critical role in shaping firm competitiveness, making them an appropriate context for examining the key variables of this study.

The minimum sample size was determined using G*Power version 3.1. The calculation assumed a medium effect size ($f^2 = 0.15$), a significance level of 0.05, statistical power of 0.95, and three predictors. The analysis indicated that a minimum sample of 119 firms was required (Faul et al., 2009; Hair et al., 2022). The sampling process followed a two-phase procedure. First, firms were selected through computerized simple random sampling using the Digital Economy Promotion Agency registry (data as of April 20, 2025) as the sampling frame, with the organization serving as the unit of analysis. Second, purposive sampling was applied to identify three

key informants per firm – senior executives, middle managers, and knowledge management specialists. These respondents were selected because they are directly involved in artificial intelligence implementation, knowledge management, and innovation activities within their organizations, allowing them to provide informed assessments while reducing single-source bias.

To ensure adequate exposure to artificial intelligence practices, the questionnaire included a screening question asking respondents how long artificial intelligence had been implemented in their organizations. Responses indicating no artificial intelligence use or an implementation period of less than six months were excluded from the final dataset, thereby ensuring sufficient exposure to artificial intelligence adoption practices. Data were collected in May 2025 through questionnaire distribution to 300 targeted firms via postal and electronic channels, with two follow-up reminders at two-week intervals. A total of 184 responses were returned, of which 39 were excluded because the firms did not meet the eligibility criteria. Consequently, 145 firms were retained for analysis, representing a response rate of 48.33% and exceeding the minimum required sample size of 119 firms, thereby ensuring sufficient statistical power. These firms were represented by 426 respondents (Table 1). Temporal wave analysis was conducted by dividing responses into three chronological groups for comparison. The results revealed no significant differences among the groups, suggest-

ing that non-response bias is unlikely to be a major concern in this study (Armstrong & Overton, 1977). Common method bias was assessed using the full collinearity variance inflation factor approach recommended by Kock (2015). All variance inflation factor values were below the conservative threshold of 5.0, suggesting that common method bias is unlikely to substantially influence the study findings.

The research instrument consisted of a structured questionnaire validated through expert review by three specialists in business development, knowledge management, and information technology fields. The instrument demonstrated acceptable content validity (Index of Item-Objective Congruence > 0.50) and strong reliability (Cronbach’s alpha ranging from 0.82 to 0.89), based on a pilot test conducted with 30 executives from information technology firms. The questionnaire contained six sections, with the first two sections capturing demographic and firm characteristics, and the remaining sections measuring the key constructs. A five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) was used. The measurement items were developed based on conceptual foundations established in prior studies, including Yu et al. (2023) for artificial intelligence adoption, Connelly et al. (2012) for knowledge hiding, Acharya et al. (2022) for knowledge integration capability, and Du and Chang (2023) for innovation climate. These studies provided the conceptual basis for developing

Table 1. Sample characteristics

| Characteristics | Details | Frequencies | Percent |
|----------------------------------|----------------------------|-------------|---------|
| Firms (n = 145) | | | |
| Size | Micro (20-50 employees) | 62 | 42.76 |
| | Small (50-100 employees) | 46 | 31.72 |
| | Medium (100-200 employees) | 24 | 16.55 |
| | Large (> 200 employees) | 13 | 8.97 |
| | Total | 145 | 100.00 |
| Respondents (426 persons) | | | |
| Job position | Management | 76 | 17.84 |
| | Information Technology | 109 | 25.59 |
| | Research and Development | 197 | 46.24 |
| | Others | 44 | 10.33 |
| Work experience | < 5 years | 121 | 28.40 |
| | 6-10 years | 198 | 46.48 |
| | 11-15 years | 66 | 15.49 |
| | > 15 years | 41 | 9.62 |
| | Total | 426 | 100.00 |

the questionnaire items in the context of digital firms. The questionnaire items are presented in Appendix A.

Data were analyzed using partial least squares structural equation modeling with SmartPLS version 4.1.1.6. Based on the theoretical meaning and content of the questionnaire items, the residual variances of the indicators were deemed likely to contain meaningful information beyond mere measurement error (Guenther et al., 2023). Accordingly, variance-based structural equation modeling was considered appropriate for this study. Preliminary analysis examined missing data patterns and confirmed that they were consistent with the missing completely at random assumption. Two incomplete respondent cases were therefore removed using listwise deletion. Organizational-level analysis was conducted by aggregating responses from multiple respondents within each firm using mean values because the organization served as the unit of analysis in this study. The analytical procedure followed two stages (Hair et al., 2019). First, the reflective measurement model was evaluated by examining indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Second, the structural model was assessed, and hypotheses were tested using bootstrapping with 10,000 subsamples. Moderating effects were estimated using the two-stage approach in partial least squares structural equation modeling. In the first stage, the main effects model was estimated to obtain latent variable scores. In the second stage, interaction terms were created by multiplying the latent variable scores of the predictor and moderator constructs. These interaction terms were then included in the structural model, and moderation effects were assessed based on the significance of the interaction paths (Hair et al., 2022).

This study received ethical approval from the Human Research Ethics Committee of Sirindhorn College of Public Health, Yala (No. SCPHYLIRB-2568/348). Participation was voluntary, and informed consent was obtained from all respondents. Consent forms were stored separately from survey responses to ensure anonymity and prevent the identification of individual participants. All data were treated confidentially and used solely for academic purposes. Research

materials will be securely stored for three years after study completion before being permanently destroyed. All potentially identifiable organizational information was removed, and results were reported only in aggregated form to ensure that no participating firm could be identified.

3. RESULTS

The evaluation of reflective measurement models (Table 2) began with examining outer loadings, which revealed that all indicators had values above 0.708. Second, construct reliability was assessed through Cronbach's alpha and composite reliability (ρ_c and ρ_A), showing that all constructs exceeded the threshold of 0.7. Third, convergent validity was evaluated using average variance extracted, demonstrating that all constructs had values greater than 0.5. Finally, discriminant validity was examined through heterotrait-monotrait ratios, indicating that each pair of constructs had values below 0.85 (Guenther et al., 2023). These results confirm the reliability and validity of the reflective measurement model. To ensure correct model specification, confirmatory tetrad analyses were applied (Hair et al., 2022), and the results supported the reflective measurement specification of all constructs.

The examination of variance inflation factor values revealed that most indicators had values below 5, indicating no multicollinearity issues that would affect the accuracy of regression analysis results (Guenther et al., 2023). Subsequently, in-sample explanatory power was assessed using R^2 . The results indicated that knowledge integration capability exhibited weak-to-moderate explanatory power ($R^2 = 0.390$), whereas innovation climate exhibited moderate explanatory power ($R^2 = 0.673$). Finally, out-of-sample predictive power was evaluated through PLSpredict, revealing that both knowledge integration capability and innovation climate were at high levels. Therefore, it can be concluded that the structural model demonstrates acceptable explanatory and predictive performance. Although the in-sample explanatory power of knowledge integration capability was relatively low, the high out-of-sample predictive power for both variables indicates strong predictive relevance for real-world settings, which pro-

Table 2. Measurement model and structural model assessment

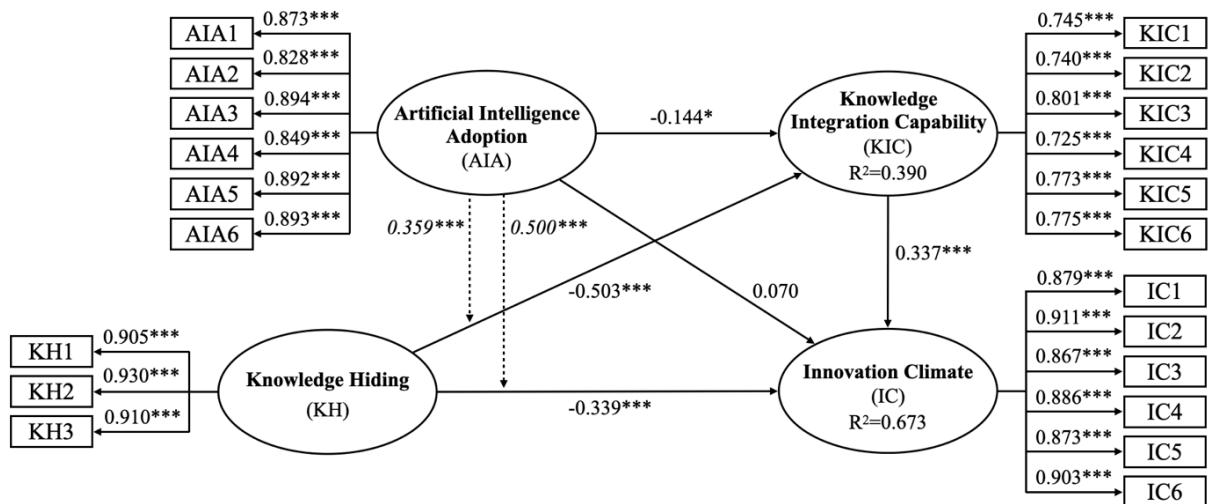
| Construct | Outer loading | VIF | Model type | HTMT | R ² | R ² adjusted | PLSpredict |
|---|---------------|-------|------------|---|---------------------------|---------------------------|-----------------------|
| Knowledge Hiding (KH) (AVE = 0.837, α = 0.903, rho_c = 0.939, rho_A = 0.903) | | | | | | | |
| KH1 | 0.905 | 2.693 | Reflective | KH-AIA = 0.073 KH-KIC = 0.550 KH-IC = 0.493 | - | - | - |
| KH2 | 0.930 | 3.306 | | | | | |
| KH3 | 0.910 | 2.782 | | | | | |
| Artificial Intelligence Adoption (AIA) (AVE = 0.760, α = 0.938, rho_c = 0.950, rho_A = 0.988) | | | | | | | |
| AIA1 | 0.873 | 2.889 | Reflective | AIA-KIC = 0.193 AIA-IC = 0.056 | - | - | - |
| AIA2 | 0.828 | 2.689 | | | | | |
| AIA3 | 0.894 | 3.792 | | | | | |
| AIA4 | 0.849 | 2.837 | | | | | |
| AIA5 | 0.892 | 4.172 | | | | | |
| AIA6 | 0.893 | 3.193 | | | | | |
| Knowledge Integration Capability (KIC) (AVE = 0.578, α = 0.854, rho_c = 0.891, rho_A = 0.856) | | | | | | | |
| KIC1 | 0.745 | 1.647 | Reflective | KIC-IC = 0.726 | 0.390 weak-to-moderate | 0.377 weak-to-moderate | High predictive power |
| KIC2 | 0.740 | 1.692 | | | | | |
| KIC3 | 0.801 | 1.971 | | | | | |
| KIC4 | 0.725 | 1.661 | | | | | |
| KIC5 | 0.773 | 1.760 | | | | | |
| KIC6 | 0.775 | 1.910 | | | | | |
| Innovation Climate (IC) (AVE = 0.786, α = 0.946, rho_c = 0.957, rho_A = 0.947) | | | | | | | |
| IC1 | 0.879 | 3.193 | Reflective | - | 0.673 moderate | 0.664 moderate | High predictive power |
| IC2 | 0.911 | 4.163 | | | | | |
| IC3 | 0.867 | 2.935 | | | | | |
| IC4 | 0.886 | 3.346 | | | | | |
| IC5 | 0.873 | 3.142 | | | | | |
| IC6 | 0.903 | 3.989 | | | | | |

vides useful insight for practical application. The goodness-of-fit was assessed using the standardized root mean square residual. The obtained value of 0.054 was below the recommended threshold of 0.08, suggesting an acceptable approximate model fit in partial least squares structural equation modeling (Hair et al., 2022).

The structural model revealed that knowledge integration capability positively affected innovation climate ($\beta = 0.337, p < 0.001$), whereas knowledge hiding exerted significant negative effects on both knowledge integration capability ($\beta = -0.503, p < 0.001$) and innovation climate ($\beta = -0.339, p < 0.001$). Thus, *H1*, *H2*, and *H3* were supported.

Table 3. Predictor assessment

| H | Paths | Beta | Mean | S.D. | t-value | p-value | f ² | Support |
|---|--|--------|--------|-------|---------|---------|----------------|---------|
| 1 | Knowledge Integration Capability → Innovation Climate | 0.337 | 0.346 | 0.064 | 5.245 | 0.000 | 0.212 | Yes |
| 2 | Knowledge Hiding → Knowledge Integration Capability | -0.503 | -0.503 | 0.053 | 9.442 | 0.000 | 0.409 | Yes |
| 3 | Knowledge Hiding → Innovation Climate | -0.339 | -0.332 | 0.071 | 4.771 | 0.000 | 0.247 | Yes |
| - | Knowledge Hiding → Knowledge Integration Capability → Innovation Climate | -0.170 | -0.174 | 0.038 | 4.444 | 0.000 | - | - |
| - | Artificial Intelligence Adoption → Knowledge Integration Capability | -0.144 | -0.145 | 0.070 | 2.068 | 0.019 | 0.034 | - |
| - | Artificial Intelligence Adoption → Innovation Climate | 0.070 | 0.073 | 0.064 | 1.099 | 0.136 | 0.014 | - |
| 4 | Artificial Intelligence Adoption x Knowledge Hiding → Knowledge Integration Capability | 0.359 | 0.357 | 0.059 | 6.086 | 0.000 | 0.217 | Yes |
| 5 | Artificial Intelligence Adoption x Knowledge Hiding → Innovation Climate | 0.500 | 0.489 | 0.057 | 8.815 | 0.000 | 0.643 | Yes |



Note: * $p < 0.05$; *** $p < 0.001$ (one-tailed test). Dashed arrows indicate interaction effects estimated using the two-stage approach.

Figure 1. Results of the structural model with moderation effects

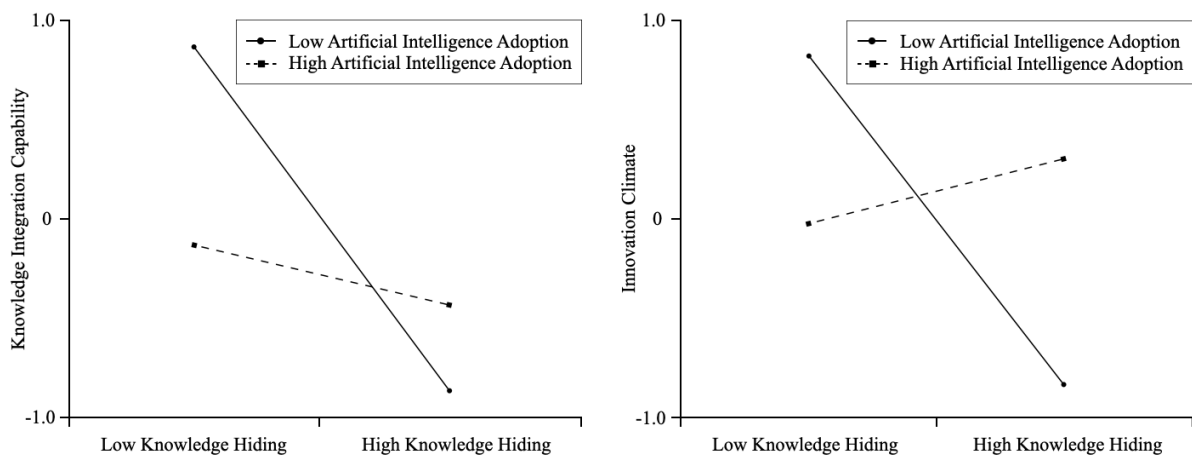


Figure 2. Moderating effect of artificial intelligence adoption

Knowledge integration capability also functions as a partial complementary mediator in the relationship between knowledge hiding and innovation climate, with a variance accounted for of 33.40%. Artificial intelligence adoption had a significant negative effect on knowledge integration capability ($\beta = -0.144$, $p = 0.019$), but its direct influence on innovation climate was nonsignificant ($\beta = 0.070$, $p = 0.136$), as shown in Table 3 and Figure 1.

The moderation effect was assessed using the two-stage approach (Hair et al., 2022). The R^2 value of knowledge integration capability increased from 0.258 in Stage 1 to 0.390 in Stage 2 ($\Delta R^2 = 0.132$), and the R^2 value of innovation climate increased

from 0.463 to 0.673 ($\Delta R^2 = 0.210$), indicating that the interaction term contributed additional explanatory power. The effect sizes ($f^2 = 0.22$ and 0.64) suggest medium and large moderating effects, respectively (Cohen, 1988). Therefore, the structural results reported correspond to the Stage 2 model, which incorporates the interaction effect.

The analysis of artificial intelligence adoption's moderating role in the relationships between knowledge hiding-knowledge integration capability and knowledge hiding-innovation climate (Figure 2) showed that when artificial intelligence adoption levels were low, knowledge hiding had a clear negative impact on both knowledge integration capability and innovation climate. However,

when artificial intelligence adoption levels were high, the slope of the relationship decreased noticeably, indicating that artificial intelligence adoption can effectively mitigate the negative effects of knowledge hiding. The study findings suggest that artificial intelligence adoption functions as a protective moderator that helps organizations alleviate the effects of knowledge hiding occurring within the organization. Thus, *H4* and *H5* were supported.

4. DISCUSSION

The findings indicate that knowledge hiding significantly undermines both knowledge integration capability and innovation climate in Thai digital firms. When employees intentionally withhold requested knowledge, knowledge exchange becomes fragmented. This limits the organization's ability to combine and apply knowledge across roles and units. This result is consistent with the conservation of resources theory, which explains knowledge hiding as a defensive response to perceived threats to valuable resources such as expertise, status, or job security. The finding also aligns with prior research showing that knowledge hiding disrupts knowledge integration by reducing knowledge sharing and weakening team relationships (Khan et al., 2024; Zamrudi, 2023). Similarly, knowledge hiding can hinder knowledge exchange, integration, and co-creation processes, leading to knowledge gaps that reduce collective efficiency (Donate et al., 2022). In Thai digital firms, critical know-how may be concentrated among specific experts or functional groups. This pattern may be particularly salient in contexts where organizations rely heavily on specialized expertise, consistent with the knowledge-based view that strategic knowledge is often embedded in individuals and specialized units (Grant, 1996). As a result, knowledge hiding may be particularly harmful because it restricts the cross-boundary knowledge recombination required for effective integration.

Knowledge hiding also shows a significant negative relationship with innovation climate. This suggests that knowledge concealment is not only an information barrier but also a social signal that weakens the conditions necessary for innovation. Prior studies similarly report that knowledge hid-

ing reduces trust, cooperation, and psychological safety, which are essential elements of an innovation-supportive climate (Bashir et al., 2023). Other studies further indicate that self-protective behaviors arising from relational tension can suppress creativity and weaken team climate dynamics (Wei & Zheng, 2025). Low psychological safety may also encourage silence and reduce collaboration, ultimately weakening innovation-related climate conditions (Lei, 2024). In Thai organizations, where knowledge management systems are still developing, employees often rely heavily on interpersonal knowledge exchange. Under these conditions, the negative climate effects of knowledge hiding may become stronger because employees have fewer alternative channels to access knowledge.

The results also confirm that knowledge integration capability positively influences innovation climate. Organizations that effectively integrate dispersed knowledge are more likely to create a work environment that supports experimentation and innovation. This finding is consistent with the knowledge-based view, which views knowledge integration as a mechanism that transforms knowledge into coordinated action and value creation. It also aligns with socio-cognitive explanations, suggesting that integrated knowledge processes strengthen shared understanding and reduce uncertainty. These conditions can support a climate that encourages innovation. Empirical evidence also shows that a stronger knowledge integration capability is associated with better innovation outcomes (Li et al., 2023). In addition, prior research emphasizes that knowledge integration depends on knowledge exchange and collaboration (Lu et al., 2024). These processes provide a mechanism through which knowledge integration capability can foster an innovation climate. In Thai digital firms, practices such as cross-functional meetings, training, and workshops may help operationalize knowledge integration. These activities can also encourage idea exchange and experimentation, thereby reinforcing an innovation climate even under resource constraints.

The mediation results further show that knowledge hiding weakens innovation climate partly through its negative effect on knowledge integration capability. This finding suggests a dual mech-

anism. Knowledge hiding directly reduces innovation climate, and it also indirectly reduces innovation climate by weakening knowledge integration capability. When knowledge hiding restricts knowledge exchange, organizations lose important integrative routines and cross-boundary learning processes. These processes are essential for building shared understanding and coordinated experimentation. As a result, the organization's ability to sustain an innovation-supportive climate is weakened. This finding highlights knowledge integration capability as a key mechanism that links employee-level knowledge concealment to broader climate-level outcomes.

Finally, the results show that artificial intelligence adoption moderates the relationships between knowledge hiding and both knowledge integration capability and innovation climate. Specifically, artificial intelligence adoption reduces the negative effects of knowledge hiding on these outcomes. The positive interaction terms indicate that the negative relationships of knowledge hiding with knowledge integration capability and innovation climate become weaker as artificial intelligence adoption increases. This suggests that artificial intelligence-enabled knowledge processes can partially buffer the damage caused by knowledge concealment. Artificial intelligence systems improve systematic access to organizational knowledge and reduce exclusive reliance on specific knowledge holders. This interpretation is consistent with technology adoption research, including arguments associated with the Unified Theory of Acceptance and Use of Technology perspective. When artificial intelligence tools are accessible and supported, employees may rely more on system-mediated knowledge retrieval rather than solely on interpersonal knowledge exchange. Although prior studies rarely test this exact moderating mechanism, existing research supports the underlying logic. Knowledge hiding disrupts knowledge flows needed for integration, whereas artificial intelligence-enabled

systems can centralize and retrieve explicit knowledge through digital platforms (Alateeg & Al-Ayed, 2024). As artificial intelligence becomes embedded in work processes, organizational knowledge can be increasingly codified, stored, and retrieved through digital systems, making it more accessible across the organization (Jarrahi et al., 2023). Consequently, the practical benefits of knowledge hiding may decline, reducing the impact of knowledge hiding on both knowledge integration and organizational climate.

An additional finding is that artificial intelligence adoption shows a negative direct effect on knowledge integration capability, while its direct effect on innovation climate is not statistically significant. This suggests that although artificial intelligence can mitigate the harmful effects of knowledge hiding, extensive reliance on artificial intelligence may also reduce face-to-face interactions that support deep knowledge integration (Leonardi, 2014). Such interactions are often necessary for dialogue, sensemaking, and tacit knowledge exchange (Rezaei, 2025). Therefore, digital firms should combine artificial intelligence-enabled knowledge access with intentional knowledge management practices that maintain collaborative interaction. Examples include cross-functional communities of practice, structured knowledge-sharing routines, and facilitated reflection sessions. Furthermore, the non-significant relationship between artificial intelligence adoption and innovation climate suggests that technology adoption alone may not be sufficient to create an innovation-supportive climate. Additional organizational factors – such as trust, teamwork, and risk tolerance – are likely to play critical roles. This interpretation is consistent with research suggesting that organizational climate depends on broader social and managerial signals, even though some studies indicate that supportive climates may also encourage openness to technology adoption (Bin-Nashwan & Li, 2025).

CONCLUSION

This study examined how knowledge hiding influences knowledge integration capability and innovation climate in Thai digital firms and whether artificial intelligence adoption moderates these relationships. The results show that knowledge hiding is negatively associated with both knowledge integration capability and innovation climate, while knowledge integration capability is positively associated with innovation climate.

The mediation results further show that knowledge hiding reduces innovation climate through knowledge integration capability, highlighting it as an important mechanism linking knowledge hiding to innovation-related outcomes. The moderation analysis indicates that higher artificial intelligence adoption weakens the negative associations between knowledge hiding and both outcomes, suggesting that artificial intelligence-enabled knowledge processes can partially buffer the consequences of knowledge hiding. In addition, artificial intelligence adoption has a negative direct effect on knowledge integration capability and no significant direct effect on innovation climate, suggesting that technology adoption alone may be insufficient without complementary organizational practices.

These results suggest several implications. First, knowledge hiding is not only an interpersonal behavior but also an organizational barrier that undermines integrative knowledge routines and an innovation-supportive climate. Second, strengthening knowledge integration capability appears central for sustaining an innovation climate because knowledge integration provides the shared understanding and coordinated learning needed for experimentation and innovation. Third, artificial intelligence adoption can reduce dependence on specific knowledge holders by improving systematic access to codified knowledge, thereby limiting the damage caused by knowledge hiding. At the same time, the negative direct association between artificial intelligence adoption and knowledge integration capability and the non-significant direct association with innovation climate indicate that technology adoption alone is insufficient; organizations still need deliberate practices that preserve dialogue, collaboration, and tacit knowledge exchange.

These findings contribute to the knowledge-based view and behavioral theories of knowledge management by clarifying how knowledge hiding can cascade into lower knowledge integration capability and innovation climate. In practice, digital firms should treat knowledge hiding as a risk to both knowledge integration capability and innovation climate, invest in routines that strengthen knowledge integration capability (e.g., cross-functional coordination and structured knowledge application), and implement artificial intelligence adoption in ways that complement rather than replace human interaction. Policymakers and industry actors can support these efforts through artificial intelligence capability development, digital infrastructure, and training that link artificial intelligence use with knowledge management and innovation practices.

Future research should examine these mechanisms over time using longitudinal designs, compare industries and countries, differentiate levels of artificial intelligence maturity, and employ mixed methods to better understand how artificial intelligence-enabled systems reshape interpersonal knowledge exchange and innovation-related climate dynamics in digital organizations.

AUTHOR CONTRIBUTIONS

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CONFLICT OF INTEREST

The author reported no conflict of interest.

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APPENDIX A

Table A1. Constructs and measurement items

| Construct | Code | Measurement Item | Conceptual Basis |
|--|------|---|------------------------|
| Artificial Intelligence Adoption (AIA) | AIA1 | Our organization has the technological infrastructure necessary to support artificial intelligence use. | Yu et al. (2023) |
| | AIA2 | Our organization provides training that enables employees to use artificial intelligence technologies in their work. | |
| | AIA3 | Employees in our organization actively use artificial intelligence technologies in their work tasks. | |
| | AIA4 | Artificial intelligence technologies are increasingly integrated into our work processes. | |
| | AIA5 | Our organization uses artificial intelligence to improve work efficiency. | |
| | AIA6 | Our organization uses artificial intelligence to enhance its competitiveness. | |
| Knowledge Hiding (KH) | KH1 | Employees in our organization provide incomplete or partial knowledge when colleagues request information. | Connelly et al. (2012) |
| | KH2 | Employees in our organization pretend not to know information even though they actually possess the knowledge. | |
| | KH3 | Employees in our organization justify not sharing knowledge by citing reasons such as confidentiality or organizational rules. | |
| Knowledge Integration Capability (KIC) | KIC1 | Our organization has clear processes for integrating knowledge from multiple sources to improve work practices. | Acharya et al. (2022) |
| | KIC2 | Our organization actively acquires knowledge from external sources (e.g., suppliers, customers, consultants) and combines it with internal knowledge to create new knowledge. | |
| | KIC3 | Employees in our organization are encouraged to connect knowledge from different disciplines and information sources to develop better solutions. | |
| | KIC4 | Our organization has systems or processes that facilitate the integration and use of knowledge across departments. | |
| | KIC5 | Our organization enables employees to exchange knowledge and collaborate to generate new knowledge. | |
| | KIC6 | Our organization can effectively apply integrated knowledge from multiple sources to improve problem-solving and work practices. | |
| Innovation Climate (IC) | IC1 | Our organization provides a work environment that supports brainstorming and the development of new ideas. | Du and Chang (2023) |
| | IC2 | Our organization encourages employees to trust one another, openly exchange ideas, and collaboratively develop new ideas. | |
| | IC3 | Our organization creates a safe atmosphere for proposing unconventional ideas and views failure as an opportunity for learning. | |
| | IC4 | Our organization has a culture that values creativity and innovation as core principles of work. | |
| | IC5 | Our organization has mechanisms that support new ideas, such as rewards or processes that help transform ideas into practice. | |
| | IC6 | Our organization encourages new ideas from employees at all levels and supports experimenting with alternative ways of working. | |