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The Impact of Generative Artificial Intelligence Knowledge Integration on Virtual Team Innovation Performance: The Dual-Path Mechanism of Transactive Memory Systems and Knowledge Dependence

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Abstract: *Generative artificial intelligence is becoming deeply embedded in the knowledge workflows of virtual teams, yet how it affects team innovation performance through knowledge integration lacks direct team-level evidence. Drawing on the knowledge-based view, this study develops a dual-path model linking generative AI knowledge integration to virtual team innovation performance through transactive memory systems and knowledge dependence, with team virtuality as a boundary condition. Using survey data from 455 virtual team members, we find that generative AI knowledge integration significantly improves team innovation performance. Both transactive memory systems and knowledge dependence mediate this effect; contrary to the expectation that dependence constitutes a drain, the mediating effect of knowledge dependence is stronger than that of transactive memory systems. Team virtuality positively moderates the main effect and specifically strengthens the knowledge-dependence path. These findings reveal the dual mechanisms through which generative AI shapes team innovation and inform the deployment of AI in virtual team contexts.*

Keywords: *generative artificial intelligence, knowledge integration, virtual teams, transactive memory system, knowledge dependence*

1. Introduction

Virtual teams have become a normal form for knowledge-based organizations to carry out innovation activities. A systematic review by Martins et al. (2004)[1] shows that distributed collaboration mediated by information technology operates differently from traditional teams across the input–process–output stages. In parallel with the evolution of team forms, generative artificial intelligence (AI) is embedding the full chain of "knowledge retrieval–restructuring–deployment" into everyday team work: a field experiment with 776 employees at Procter & Gamble by Dell'Acqua et al. (2025)[2] found that individuals supported by generative AI reached the performance level of teams working without AI, and that AI broke down knowledge barriers between research and development (R&D) and commercial functions; from Google's "co-scientist" to the VirSci system developed by the Shanghai AI Laboratory, multi-agent AI systems are already reshaping how research teams collaborate (China Daily, 2025)[3]. In China, the national standard Cybersecurity Technology—Security Basic Requirements for Generative AI Services (GB/T 45654—2025) was issued in 2025, marking the entry of generative AI into a stage of regulated application [4]. As the technology diffuses and governance frameworks fall into place, scholars have begun to ask: when team members routinely use generative AI to acquire, restructure, and deploy knowledge, what happens to team-level innovation performance?

Existing research cannot yet answer this question fully. First, most empirical evidence on generative AI and innovation is at the individual level: Li and Xue (2026)[5] found that employees' orientation toward generative AI (heuristic or shortcut) moderates the path from AI use to idea generation and innovation performance; Zhang et al. (2026)[6] showed that cognitive and social usage orientations of generative AI improve employee innovation performance through different mechanisms; and the experiment by Noy and Zhang (2023)[7] showed that generative AI reduced the time required for writing tasks by 40%. Extrapolating from individual-level conclusions to the team level remains risky, however, because team innovation also depends on how knowledge is distributed, interacted with, and integrated among members. Second, the classic conclusions on knowledge integration in virtual teams

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were formed before the generative AI era. Alavi and Tiwana (2002)[8] identified four challenges facing virtual teams—constrained transactive memory, insufficient mutual understanding, loss of contextual knowledge, and rigid organizational ties—and predicted that knowledge management systems would be the remedy; using meta-analysis, Mesmer-Magnus et al. (2011)[9] found a curvilinear relationship between virtuality and information sharing, with low virtuality promoting open sharing while high virtuality obstructing it. Whether and how generative AI, as a new generation of knowledge infrastructure, changes these conditions remains to be tested. Finally, the paradox between enhanced individual creativity and converging collective output has not been explained consistently within team processes. The experiment by Doshi and Hauser (2024)[10] showed that generative AI improves the quality of individual ideas but makes AI-assisted proposals similar to one another, narrowing collective novelty; Reif and Cummings (2026)[11] proposed the "generative AI dilemma": proficient users shift knowledge-seeking behavior from teammates to AI, and the team's collaboration network consequently degrades. How the benefits and costs of knowledge dependence on generative AI unfold in team innovation processes is a new problem for knowledge management theory.

To address these gaps, this study takes the virtual team as the unit of analysis and, drawing on the knowledge-based view, develops a dual-path model: generative AI knowledge integration enhances innovation performance through transactive memory systems and affects it through deepened knowledge dependence, with team virtuality introduced as a boundary condition. Using survey data from 455 virtual team members, the study seeks to contribute in three respects: first, it provides direct team-level evidence for the "generative AI–knowledge integration–innovation performance" chain; second, it integrates the augmentation and substitution debates through a dual-path framework of gain versus substitution; third, it identifies the boundary role of virtuality, responding to the era limitations of pre-generative-AI virtual team theory.

2. Theoretical foundation and research hypotheses

2.1 Core concepts and theoretical foundation

2.1.1 Generative AI knowledge integration

The knowledge-based view treats the firm as a knowledge integration mechanism. Grant (1996)[12] identified four integration mechanisms—rules and directives, sequencing, routines, and group problem solving and decision making—and argued that knowledge integration is the key step through which specialized knowledge is transformed into products and services. The experiment by Okhuysen and Eisenhardt (2002)[13] further identified three formal interventions—information sharing, questioning others, and time management—that improve group knowledge integration by creating "windows of opportunity." Davenport and Prusak (1998)[14] deconstructed knowledge work into four types of activities—acquiring, generating, embedding, and transferring—providing an analytical tool for understanding knowledge flows in organizations. Extending this line of work to the generative AI context, we define generative AI knowledge integration as the level at which virtual team members use generative AI to acquire external knowledge, restructure its meaning, and deploy it in innovation tasks. It comprises three dimensions: knowledge acquisition (searching for and aggregating cross-domain, cross-cultural, and multi-format information), knowledge restructuring (iterative questioning, causal inquiry, experiential comparison, and structured synthesis), and knowledge deployment (task-oriented retrieval and combination of knowledge). Alavi and Tiwana's account of the four challenges of knowledge integration in virtual teams [8] provides a reference for understanding what is distinctive about this construct in virtual contexts: with immediate responses and unlimited patience, generative AI partially addresses the problems of constrained transactive memory and loss of contextual knowledge.

2.1.2 Virtual teams and innovation performance

Martins et al. (2004)[1] defined virtual teams in terms of virtuality, emphasizing the degree to which members are dispersed geographically, organizationally, and culturally and their dependence on electronic communication technologies. The meta-analysis by Mesmer-Magnus et al. (2011)[9] reveals that virtuality is a double-edged sword: it increases the sharing of unique information but hinders open sharing, and its overall relationship with information sharing is inverted U-shaped. Innovation performance refers to a team's comprehensive outcomes in product and service improvement, function expansion, experience extraction, technology diffusion, new product invention, and new technology adoption.

ISSN 2616-5902 Vol. 8, Issue 10: 24-32, DOI: 10.25236/AJBM.2026.081004

2.1.3 Transactive memory systems and knowledge dependence

A transactive memory system (TMS) is the shared directory of "who knows what and who knows how" among team members, comprising three components: specialization, credibility, and coordination. The analysis of 477 managers by Belbaly et al. (2022)[15] showed that TMS components positively affect knowledge sharing and team creativity. Knowledge dependence refers to the state in which team members increasingly place generative AI above teammates and their own knowledge networks, making it the default knowledge source for acquisition, problem solving, and decision making. A distinction is needed here: knowledge dependence is a behavioral and cognitive orientation, whereas awareness of smart technology replacement (STARA) is an individual's perceived threat of being replaced by technology [16]; the former concerns being unable to do without, the latter fearing replacement. The two are related but conceptually distinct. The theoretical roots of knowledge dependence lie in the "generative AI dilemma" of Reif and Cummings [11] and the automation–augmentation paradox proposed by Raisch and Krakowski (2021)[17]: automation (machines taking over) and augmentation (human–machine collaboration) are interdependent in management contexts, and overemphasizing either triggers negative cycles.

2.2 Main effect: Generative AI knowledge integration and virtual team innovation performance (H1)

Generative AI knowledge integration improves virtual team innovation performance through three channels. First, it expands knowledge boundaries. Generative AI enables teams to access cross-disciplinary, cross-cultural, and multi-format knowledge at low cost; the experiment by Dell'Acqua et al. [2] showed that AI broke down knowledge barriers between R&D and commercial functions, bringing AI-supported individuals up to the level of traditional teams. Second, it lowers the cost of cross-functional knowledge flow. The survey of 268 new product development teams in Chinese manufacturing firms by Kong et al. (2026)[18] found that augmented human–AI interaction promotes team innovation behavior; the experiment by Wei et al. (2025)[19] showed that embedding generative AI in collaborative tasks significantly improves collaborative problem solving and team creativity performance. Third, it supplies immediate cognitive support. Generative AI provides real-time feedback throughout idea divergence, convergence, and formation, reducing the cognitive cost of team trial and error. Evidence from the Chinese context supports this direction: Liu et al. (2024)[20] found that AI developmental feedback improves employee innovation performance through learning goal orientation. We therefore propose:

H1: Generative AI knowledge integration positively affects virtual team innovation performance.

2.3 Mediating mechanism 1: Transactive memory system (H2)

The transactive memory system is the organizational outcome of team knowledge integration. Generative AI knowledge integration strengthens the TMS by cataloguing and externalizing "who knows what": team members use AI to quickly locate the distribution of internal knowledge, while knowledge gained through interaction with AI is codified into reusable team assets, reinforcing the components of specialization, credibility, and coordination. The evidence of Belbaly et al. [15] shows that TMS components improve team creativity through knowledge sharing; the team experiment by Li et al. (2025)[21] found that the "human–generative AI dual brokerage" model improves team innovation performance more than human-only knowledge brokerage, with the TMS playing a mediating role. We therefore propose:

H2: The transactive memory system plays a positive mediating role between generative AI knowledge integration and virtual team innovation performance.

The "generative AI dilemma" of Reif and Cummings [11] suggests the opposite possibility: when knowledge seeking shifts from teammates to AI, transactive memory among teammates may be weakened. This tension shares its theoretical root with H3 below: the shift of knowledge seeking toward AI may both dilute transactive memory among teammates and translate into deep dependence on AI. The two are two sides of the same transfer process, and their relative strength is left to the data.

2.4 Mediating mechanism 2: Knowledge dependence (H3)

The convenience and immediacy of generative AI induce members to set it as their default knowledge source, and knowledge dependence thus forms. If the negative effects of dependence dominate, innovation performance will suffer through four channels. First, knowledge exchange among

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teammates degrades. Reif and Cummings [11] noted that after proficient users shift knowledge seeking from teammates to AI, the collaboration network degrades and performance gains are offset by missing collaboration and declining satisfaction. Second, outputs converge. Homogeneous use of the same AI source causes team outputs to converge; the experiment by Doshi and Hauser [10] showed that AI-assisted proposals resemble one another and collective novelty narrows. Third, exploration depth suffers. Zheng et al. (2025)[22] found that generative AI teammates trigger cognitive fixation during the idea divergence stage, suppressing team idea generation. Fourth, opportunity costs arise. The crowdsourcing challenge of Boussioux et al. (2024)[23] showed that solutions conceived independently by humans are more novel than AI-assisted ones, and the advantage of human–AI collaboration depends on differentiated search strategies. In addition, deepening dependence may be accompanied by rising replacement awareness, further suppressing innovation behavior: the experiment by Yin et al. (2024)[16] found that highly intelligent AI assistants suppress employee innovation behavior through the STARA pathway. We therefore propose:

H3: Knowledge dependence plays a negative mediating role between generative AI knowledge integration and virtual team innovation performance.

H2 and H3 run in opposite directions, forming a dual-path competition of augmentation versus substitution—a concrete instantiation of the automation–augmentation paradox in the context of team knowledge integration [17].

2.5 Moderating mechanism: Team virtuality (H4a, H4b)

Team virtuality determines the conditions under which the value of generative AI is realized. At the level of the main effect, the higher the virtuality, the more salient the barriers of geographic dispersion and communication asynchrony, and the greater the compensatory value of generative AI for constrained transactive memory—Alavi and Tiwana [8] predicted that knowledge management systems would be key to addressing the integration challenges of virtual teams, and generative AI is the technological realization of that prediction. We therefore expect virtuality to positively moderate the main effect (H4a). At the level of the dependence path, two competing possibilities exist. On the one hand, under high virtuality, AI is the lowest-cost channel for knowledge acquisition, making dependence easier to form and harder to offset through offline interaction. On the other hand, the higher the virtuality, the more likely teams are to establish norms for AI use to hedge dependence risks. This study does not presuppose a direction and leaves the question to the data (H4b).

2.6 Conceptual model

Synthesizing the above reasoning, the conceptual model of this study holds that generative AI knowledge integration influences virtual team innovation performance through two mediators—the transactive memory system (the augmentation path) and knowledge dependence (the substitution path)—with team virtuality moderating both the main effect and the dependence path. This model differs from the "human–AI dual brokerage" research of Li et al. [21], which focuses on the knowledge brokerage mode of human–AI collaboration, in that it takes the level of knowledge integration as the core independent variable and explicitly incorporates the drain risks of dependence. The empirical reference for the virtuality moderation comes from the finding of Kong et al. [18] on the differentiated effects of forms of human–AI interaction, while the inverted U-shaped relationship between virtuality and information sharing revealed by Mesmer-Magnus et al. [9] also suggests that team knowledge processes are nonlinear, providing indirect support for the existence of moderation.

3. Research design

3.1 Research subjects and data collection

This study surveys virtual teams, operationally defined as teams of three or more members that are geographically dispersed, collaborate mainly through electronic communication tools, and have jointly completed at least one full work project in the past three months. Data were collected anonymously through a questionnaire platform, using a combination of snowball and community distribution, from April 1 to 7, 2026. After excluding questionnaires with excessively short response times or obviously patterned answers, 455 valid responses were obtained. The sample is distributed across gender, age group, education level, team size, team tenure, and industry type, with team size concentrated in the

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small-to-medium categories, consistent with the surveyed teams' reliance on online collaboration tools. All items were measured on a 6-point Likert scale (1 = strongly disagree, 6 = strongly agree; the virtuality items used 1 = strongly not dependent, 6 = strongly dependent), and the data contain no missing values.

3.2 Variable measurement

All variables were measured with established scales adapted to the context of this study. Generative AI knowledge integration: Drawing on Grant's classification of knowledge integration mechanisms [12] and the formal intervention framework of Okhuysen and Eisenhardt [13], and referring to the measurement approach of Kong et al. for human–AI interaction [18], we developed 8 items across the three dimensions of knowledge acquisition, knowledge restructuring, and knowledge deployment, such as “The team uses generative AI to acquire interdisciplinary and cross-domain knowledge” and “The team uses generative AI to connect fragmented knowledge points into structured, in-depth systems or frameworks.” Transactive memory system: Referring to the measurement of TMS components by Belbaly et al. [15], 6 items were designed covering specialization, credibility, and coordination. Knowledge dependence: Based on the theoretical definition of Reif and Cummings [11] and drawing on the measurement tradition for technology-related cognitive orientations of Yin et al. [16], 4 items were adapted to measure the “irreplaceability” dimension, such as “Without knowledge support generated by generative AI, the team's innovation work cannot proceed effectively.” Innovation performance: Drawing on the basic dimensions of established domestic and international scales and adapting them to the team context, 8 items were designed covering product improvement, function expansion, experience extraction, technology diffusion, new product invention, and new technology adoption. Team virtuality: Referring to the virtuality definition of Martins et al. [1], 4 items measured dependence on email, video conferencing, collaborative office software, and electronic communication tools overall. Control variables: gender, age group, education, team size, team tenure, and industry type, all entered into the models as dummy variables.

3.3 Control of common method bias

Since the data were self-reported by team members, this study combined procedural controls with statistical tests. Procedurally, the questionnaire was answered anonymously, some items were reverse-scored, and the items for independent and dependent variables were placed in separate sections of the questionnaire. Statistically, Harman's single-factor test and a single-factor confirmatory factor analysis were used to assess the severity of common method bias.

3.4 Data analysis strategy

The data analysis proceeded in three steps. First, the measurement model was tested: confirmatory factor analysis was used to evaluate the fit of the five-factor structure, reporting standardized loadings, composite reliability (CR), and average variance extracted (AVE), with discriminant validity tested by the Fornell-Larcker criterion and HTMT ratios. Second, hierarchical regression was used to test the hypotheses: Model 1 included the control variables and team virtuality, Model 2 added generative AI knowledge integration, Model 3 added the two mediators, and Model 4 added the interaction term. Mediating effects were tested with Bootstrap 5,000 resamples using percentile confidence intervals, and moderation effects were reported with simple slopes and conditional indirect effects. All continuous variables were standardized before entering the regressions, and the significance level was set at $\alpha = 0.05$.

4. Empirical results

4.1 Descriptive statistics and correlation analysis

Table 1 reports the means, standard deviations, and correlations of the variables. The means of generative AI knowledge integration, transactive memory system, knowledge dependence, innovation performance, and virtuality were 4.262, 4.256, 4.106, 4.210, and 4.230, respectively, all above the midpoint of the 6-point scale, indicating that the generative AI use and innovation performance reported by sample members were at a moderately high level. Correlation analysis showed that generative AI knowledge integration was significantly and positively correlated with innovation

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performance ($r = 0.539$, $p < 0.001$), and also with the transactive memory system ($r = 0.445$, $p < 0.001$) and knowledge dependence ($r = 0.493$, $p < 0.001$), providing preliminary support for hypothesis testing.

Table 1. Descriptive statistics and correlation matrix (N = 455)

Variable	M	SD	1	2	3	4	5
1 Generative AI knowledge integration	4.262	0.828	(0.850)				
2 Transactive memory system	4.256	0.988	0.445***	(0.907)			
3 Knowledge dependence	4.106	1.080	0.493***	0.411***	(0.876)		
4 Innovation performance	4.210	0.858	0.539***	0.462***	0.518***	(0.853)	
5 Virtuality	4.230	1.059	0.409***	0.364***	0.367***	0.443***	(0.884)

Note: Cronbach's α coefficients are shown in parentheses on the diagonal; *** $p < 0.001$.

4.2 Measurement model testing

Confirmatory factor analysis showed that the five-factor model fit well: $\chi^2(395) = 770.076$ ($p < 0.001$), CFI = 0.980, TLI = 0.978, RMSEA = 0.046, GFI = 0.960, AGFI = 0.956, NFI = 0.960. The standardized loadings of items on their respective factors ranged from 0.561 to 0.833, all above 0.5; the composite reliability of the five scales ranged from 0.836 to 0.906, all above 0.8; except for generative AI knowledge integration (AVE = 0.389) and innovation performance (AVE = 0.391), which were slightly below 0.5, the AVEs of the other scales were all above 0.5. For the two scales with slightly low AVEs, both the Fornell-Larcker criterion and the HTMT test supported their discriminant validity: the square root of each latent variable's AVE was greater than its correlations with the other variables (for example, the square root of innovation performance's AVE was 0.625, greater than its correlations with generative AI knowledge integration, 0.406, and with knowledge dependence, 0.552); all HTMT ratios ranged from 0.407 to 0.633, below the strict threshold of 0.85. Overall, the measurement model showed good reliability and discriminant validity.

4.3 Common method bias testing

Harman's single-factor test showed that the first unrotated principal component explained 33.57% of the variance, below the 40% critical threshold, and seven factors had eigenvalues greater than 1, with no single factor explaining the majority of the variance. Combined with the procedural controls, common method bias was judged not to pose a serious threat.

4.4 Hypothesis testing

Main effect and mediating effects. The hierarchical regression results are shown in Table 2. In Model 1, the control variables and virtuality explained 23.5% of the variance in innovation performance, with virtuality the strongest predictor ($\beta = 0.429$, $p < 0.001$); in Model 2, after adding generative AI knowledge integration, R^2 rose to 0.388, with a regression coefficient of $\beta = 0.440$ ($p < 0.001$) and $\Delta R^2 = 0.152$, supporting H1. In Model 3, after adding the two mediators, the coefficient of generative AI knowledge integration dropped from 0.440 to 0.274 ($p < 0.001$), and both the transactive memory system ($\beta = 0.176$, $p < 0.001$) and knowledge dependence ($\beta = 0.237$, $p < 0.001$) were significant, indicating that both paths are partially mediating.

Table 2. Hierarchical regression results (dependent variable: innovation performance)

Variable	Model 1	Model 2	Model 3	Model 4
Control variables	Controlled	Controlled	Controlled	Controlled
Virtuality	0.429***	0.249***	0.170***	0.173***
Generative AI knowledge integration		0.440***	0.274***	0.271***
Transactive memory system			0.176***	0.173***
Knowledge dependence			0.237***	0.219***
Generative AI knowledge integration × Virtuality				0.109**
R^2	0.235	0.388	0.459	0.470
ΔR^2		0.152***	0.071***	0.010**

Note: Standardized regression coefficients are reported; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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Bootstrap tests confirmed both mediating paths: the indirect effect of the transactive memory system was 0.120, with a 95% confidence interval of [0.074, 0.169] excluding 0, supporting H2; the indirect effect of knowledge dependence was 0.156, with a 95% confidence interval of [0.107, 0.209] excluding 0, but positive in direction, contrary to the drain expectation of H3. Knowledge dependence thus emerged as the stronger augmentation path, and H3 was not supported, with the actual direction opposite to the hypothesis. This unexpected finding is discussed in detail in Section 5.

Moderating effects. In Model 4, the interaction term between generative AI knowledge integration and virtuality was significantly positive ($\beta = 0.109$, $p < 0.01$), with $\Delta R^2 = 0.010$, supporting H4a. The interaction term explained about 1% of additional variance; although the increment was limited, simple slope analysis showed that when virtuality was low (−1 SD), the main effect slope was 0.279 ($p < 0.001$); when virtuality was high (+1 SD), the slope rose to 0.569 ($p < 0.001$), nearly doubling, indicating that the boundary role of virtuality is practically meaningful. Tests of the two mediating paths found that neither the first stage ($a_3 = 0.043$, $p = 0.319$) nor the second stage of the transactive memory path was significantly moderated, with moderated mediation indices of 0.008 (95% CI [−0.010, 0.030]) and 0.022 (95% CI [−0.008, 0.055]), both confidence intervals including 0. In contrast, both stages of the knowledge dependence path were significantly moderated—the first-stage interaction was $a_3 = 0.130$ ($p < 0.01$), with a moderated mediation index of 0.030 (95% CI [0.010, 0.055]); the second-stage moderated mediation index was 0.041 (95% CI [0.005, 0.078]), supporting H4b. Conditional indirect effects showed that the indirect effect of the knowledge dependence path was 0.063 (95% CI [0.025, 0.109]) under low virtuality and rose to 0.123 (95% CI [0.070, 0.182]) under high virtuality, nearly doubling; the conditional indirect effects of the transactive memory path differed little between the low and high virtuality groups (0.060 vs. 0.076).

5. Discussion and conclusions

5.1 Summary of main findings

This study yields three core findings. First, generative AI knowledge integration has a robust positive effect on virtual team innovation performance; the effect remains significant after controlling for virtuality and other variables, explaining about 15.2% of the variance in innovation performance. Second, both the transactive memory system and knowledge dependence play mediating roles, and the mediating effect of knowledge dependence (0.156) is stronger than that of the transactive memory system (0.120). Generative AI both optimizes the team's internal directory of "who knows what" and deepens the team's embeddedness in external AI knowledge sources; the two channels jointly transmit the main effect. Third, team virtuality is a comprehensive boundary condition: it positively moderates the main effect and specifically strengthens the knowledge dependence path, while the moderating effect on the transactive memory path is not significant.

5.2 Theoretical contributions

The theoretical contributions of this study are threefold. First, it provides direct team-level evidence for the "generative AI–knowledge integration–innovation performance" chain. Existing research has largely remained at the individual level [5-7]; using survey data from 455 team members, this study demonstrates that knowledge integration is a key mechanism through which generative AI affects team innovation, responding to the call to advance from individual intelligence to collective intelligence. Second, it integrates the augmentation and substitution debates through the dual paths of gain and substitution. Reif and Cummings [11] predicted that shifting knowledge seeking from teammates to AI would trigger collaborative degradation, and Doshi and Hauser [10] warned of narrowing collective diversity; this study finds the net effect of the dependence path to be positive, suggesting that in virtual team contexts the gains of AI as a cross-geography knowledge infrastructure temporarily outweigh the substitution risks. This does not negate the dilemma itself; the conditions for its emergence are discussed below. In the data, knowledge dependence and the transactive memory system are positively correlated ($r = 0.411$). One possible theoretical explanation is that when an AI knowledge source is invoked jointly by the entire team, it effectively becomes a shared external transactive memory for the team: depending on AI and depending on teammates are therefore not zero-sum, and AI extends rather than replaces the boundaries of the team's transactive memory. Third, it identifies the boundary role of virtuality. The pre-generative-AI meta-analysis found that virtuality hinders open sharing [9], whereas this study shows that high virtuality amplifies the compensatory value of AI, particularly the transmission of the dependence path. In geographically dispersed teams, AI is not merely a tool but

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infrastructure for knowledge flow. This provides a correction for virtual team theory in the generative AI era.

5.3 Managerial implications

The findings have three practical implications. For organizations, generative AI deployment should be matched with knowledge management strategies: if a codification strategy is adopted, efforts should focus on building team-level AI knowledge bases and prompt norms to amplify the gains of the transactive memory path; if a personalization strategy is adopted, face-to-face or synchronous communication channels should be preserved to prevent over-concentration of dependence. For team managers, the double-edged nature of knowledge dependence must be acknowledged. Dependence itself is not a catastrophe; the data show that moderate dependence accompanies higher innovation performance. What truly needs to be prevented is the extreme pattern of "asking only AI, never teammates," which can be countered by designing cross-member knowledge verification mechanisms and conducting regular AI-free retrospectives to maintain the team's autonomous knowledge capacity. Yin et al. [16] found that organizational AI readiness moderates the two paths through which AI assistants affect innovation behavior, implying that organizations need capacity building and institutional design to amplify the constructive role of generative AI. In addition, the application of generative AI must be placed within a compliance framework: the requirements of GB/T 45654—2025 for training data security, model security, and safety measures [4] should serve as a basic reference for enterprises deploying AI tools; the practice of introducing "co-scientist" style multi-agent systems in research teams is also a reminder [3] that human oversight mechanisms must remain in place.

5.4 Limitations and future directions

This study has four limitations. First, cross-sectional self-reported data limit causal inference; the positive correlation between dependence and innovation performance may also stem from reverse causality (teams with higher innovation performance are more willing to use AI deeply) or common causes, and future research could adopt multi-wave designs or experiments to identify these effects. Second, H3 was not supported and ran opposite to the hypothesis, so the theorization of knowledge dependence needs refinement: this study measured embeddedness in the sense of "irreplaceability," whose positive effect may reflect the team's successful integration of AI knowledge sources; the collaborative degradation warned of by Reif and Cummings [11] may require a longer time span, or "full substitution" rather than "complementary" usage patterns, to emerge. The strengthening of the dependence path by virtuality suggests that in low-virtuality teams, teammate interaction can substitute for AI, and the boundary of the dilemma may lie precisely here. Third, the external validity of a single-culture sample is limited, and conclusions may differ under different digital infrastructures and levels of AI diffusion. Fourth, generative AI technology is evolving rapidly, so the scales and conclusions have a limited shelf life; future research could track generational changes in the technology and incorporate team process variables (such as conflict and psychological safety) for more fine-grained mechanism analysis.

5.5 Conclusion

Using survey data from 455 virtual team members, this study tested the dual-path mechanism through which generative AI knowledge integration affects innovation performance. The results show that knowledge integration significantly improves innovation performance; the transactive memory system and knowledge dependence constitute the augmentation and embeddedness paths, respectively; and team virtuality positively moderates the main effect and strengthens the dependence path. In an era when generative AI and virtual collaboration are deeply intertwined, the key to team innovation may lie not in whether AI is used, but in whether AI knowledge sources can be consciously integrated into the team's knowledge architecture while safeguarding the baseline of knowledge flow among teammates.

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