Article

Not peer-reviewed version

The Impact of Knowledge Management Dynamic Capabilities and Knowledge Sharing on Firm Performance: The Mediating Role of GAI Technology Innovation and Moderating Effect of Human-AI Interaction

Jun Cui *

Posted Date: 6 May 2025

doi: 10.20944/preprints202505.0132.v1

Keywords: Knowledge management dynamic capabilities; Knowledge sharing; Organizational performance; GAI technology innovation; Human-AI interaction; Chinese digital firms

Article

The Impact of Knowledge Management Dynamic Capabilities and Knowledge Sharing on Firm Performance: The Mediating Role of GAI Technology Innovation and Moderating Effect of Human-AI Interaction

Jun Cui

Solbridge International School of Business, Woosong University, Daejeon, Republic of Korea; jcui228@student.solbridge.ac.kr

Abstract: This study investigates the relationship between knowledge management dynamic capabilities (KMDC), knowledge-based sharing (KBS), and organizational performance in Chinese digital firms. Drawing on dynamic capabilities theory and knowledge-based view, the research proposes a comprehensive model examining how generative artificial intelligence (GAI) technology innovation mediates this relationship and how Human-AI interaction moderates these effects. Using a mixed-methods approach combining structural equation modeling (SEM) and fuzzy-set qualitative comparative analysis (fsQCA), Thus, we analyze data from 276 firms in China's internet digital industry. Results reveal that both KMDC and KBS positively influence organizational performance, with GAI technology innovation serving as a significant mediator. Furthermore, Human-AI interaction positively moderates these relationships. The findings provide theoretical contributions to knowledge management literature and practical implications for digital firms seeking to enhance performance through knowledge management initiatives and emerging technologies.

Keywords: knowledge management dynamic capabilities; knowledge sharing; organizational performance; GAI technology innovation; Human-AI interaction; Chinese digital firms

---

1. Introduction

In today's knowledge-intensive economy, firms' ability to effectively manage knowledge resources has become critical for sustainable competitive advantage (Teece, 2018). Knowledge management dynamic capabilities (KMDC) and knowledge-based sharing (KBS) represent two fundamental aspects of organizational knowledge processes that potentially drive performance outcomes (Gold et al., 2001; Wang & Ahmed, 2007). The rapidly evolving digital landscape, particularly in China's internet sector, presents both opportunities and challenges for knowledge management practices.

The emergence of generative artificial intelligence (GAI) technologies has introduced new dimensions to knowledge management systems and organizational capabilities (Lee et al., 2023). However, research examining how GAI technologies mediate the relationship between knowledge management practices and firm performance remains limited. Additionally, as organizations increasingly implement AI solutions, the quality of Human-AI interaction may significantly influence the effectiveness of knowledge management processes (Raisch & Krakowski, 2021).

This study addresses these research gaps by proposing and testing a comprehensive framework that examines: (1) the direct effects of KMDC and KBS on organizational performance; (2) the mediating role of GAI technology innovation; and (3) the moderating effect of Human-AI interaction. By employing a mixed-methods approach combining structural equation modeling and fuzzy-set

 doi:10.20944/preprints202505.0132.v1

qualitative comparative analysis, this research provides a more nuanced understanding of these complex relationships within China's dynamic digital industry.

2. Theoretical Framework and Hypotheses Development

2.1. Theoretical Foundation

This study draws on two complementary theoretical perspectives: dynamic capabilities theory (DCT) and knowledge-based view (KBV). DCT emphasizes organizations' ability to reconfigure resources and capabilities in response to changing environments (Teece et al., 1997; Eisenhardt & Martin, 2000). In contrast, KBV conceptualizes knowledge as the most strategically significant resource and posits that heterogeneous knowledge bases are primary determinants of performance differences (Grant, 1996).

Knowledge management dynamic capabilities reflect an organization's capacity to purposefully acquire, integrate, and reconfigure knowledge resources to address environmental changes (Pavlou & El Sawy, 2011). Knowledge-based sharing encompasses mechanisms that facilitate knowledge transfer within and across organizational boundaries (Nonaka & Takeuchi, 1995). Both constructs represent strategic organizational processes that potentially enhance performance through better decision-making and innovation.

2.2. Hypotheses Development

H1: Knowledge management dynamic capabilities positively influence organizational performance in Chinese digital firms.

Knowledge management dynamic capabilities enable firms to continuously reconfigure their knowledge assets to meet evolving market demands (Teece, 2007). Prior research has established that organizations with strong dynamic capabilities demonstrate superior performance outcomes (Fainshmidt et al., 2016). In the context of China's digital industry, characterized by rapid technological change and intense competition, KMDC likely enables firms to maintain competitiveness by efficiently adapting their knowledge resources to changing circumstances. Firms with stronger KMDC can better sense market opportunities, seize them through knowledge reconfiguration, and transform organizational processes accordingly (Teece, 2018).

H2: Knowledge-based sharing positively influences organizational performance in Chinese digital firms.

The knowledge-based view suggests that knowledge sharing facilitates the diffusion of valuable insights across organizational units, enhancing collective problem-solving capabilities and innovation potential (Grant, 1996). Empirical evidence supports a positive relationship between knowledge sharing practices and various performance indicators (Wang & Wang, 2012). In Chinese digital firms, characterized by complex product development processes and rapidly evolving customer requirements, efficient knowledge sharing likely contributes to improved coordination, reduced redundancy, and accelerated innovation cycles (Zheng et al., 2011).

H3: GAI technology innovation mediates the relationship between knowledge management dynamic capabilities and organizational performance.

Knowledge management dynamic capabilities enable firms to identify and integrate emerging technologies into their operations (Teece, 2007). GAI technologies represent transformative innovations that can enhance knowledge processing capabilities through advanced analytics, natural language processing, and automated decision support (Lee et al., 2023). We propose that firms with stronger KMDC will more effectively adopt and implement GAI innovations, which in turn will enhance organizational efficiency, customer service quality, and product development processes, ultimately improving performance outcomes.

H4: GAI technology innovation mediates the relationship between knowledge-based sharing and organizational performance.

Effective knowledge sharing creates a foundation for technological innovation by facilitating the exchange of diverse perspectives and expertise (Nonaka & Takeuchi, 1995). In the context of GAI technologies, which require substantial domain knowledge and cross-functional collaboration, robust knowledge sharing practices likely accelerate innovation adoption and effectiveness (Raisch & Krakowski, 2021). We posit that knowledge sharing enhances GAI technology innovation through improved collective understanding and collaborative development, subsequently driving organizational performance.

H5: Human-AI interaction positively moderates the relationship between GAI technology innovation and organizational performance.

The effectiveness of technological innovations depends significantly on how well they integrate with human work processes (Brynjolfsson & McAfee, 2014). As GAI technologies become more sophisticated, the quality of Human-AI interaction emerges as a critical factor determining their organizational impact (Raisch & Krakowski, 2021). We propose that firms that establish more effective Human-AI interaction frameworks will derive greater performance benefits from GAI technology innovations. High-quality interactions likely enhance user acceptance, improve system effectiveness, and facilitate continuous learning and adaptation.

3. Methodology

3.1. Sample Selection and Data Sources

Data were collected through a structured questionnaire administered to senior and middle managers in Chinese digital firms between September 2024 and October 2024. We targeted firms operating in various digital sectors, including e-commerce, social media, cloud computing, and digital entertainment. A stratified random sampling approach was employed to ensure representation across firm sizes and subsectors. From an initial sample of 400 firms, we received 303 responses (response rate: 75.8%). After removing incomplete responses and outliers, the final sample comprised 276 firms. To assess potential non-response bias, we compared early and late respondents on key demographic variables and found no significant differences (Armstrong & Overton, 1977).

3.2. Model Design and Definition of Variables

The research model incorporates five key constructs: knowledge management dynamic capabilities (independent variable), knowledge-based sharing (independent variable), GAI technology innovation (mediator), Human-AI interaction (moderator), and organizational performance (dependent variable). Each construct was measured using multiple items adapted from established scales in the literature.

Table 1 presents the operational definitions and measurement items for each construct.

Table 1. Construct Measurement.

Construct	**Operational Definition**	**Measurement Items**	**Source**
Knowledge Management Dynamic Capabilities (KMDC)	The firm's ability to acquire, integrate, and reconfigure knowledge resources to address changing business environments	KMDC1: Our organization regularly updates knowledge acquisition processes KMDC2: We effectively integrate new knowledge with existing knowledge bases KMDC3: Our firm can quickly reconfigure knowledge resources to address market changes KMDC4: We systematically evaluate and improve knowledge management processes KMDC5: Our organization has established mechanisms	Adapted from Pavlou & El Sawy (2011); Gold et al. (2001)

 doi:10.20944/preprints202505.0132.v1

		to transform tacit knowledge into explicit knowledge	
Knowledge-Based Sharing (KBS)	The extent to which knowledge is shared within and across organizational boundaries	KBS1: Employees regularly share knowledge through formal channels KBS2: Cross-functional knowledge sharing is encouraged and rewarded KBS3: Our organization has effective IT systems for knowledge sharing KBS4: Knowledge sharing with external partners is systematic and productive KBS5: Managers actively promote knowledge sharing culture	Adapted from Wang & Wang (2012); Lin (2007)
GAI Technology Innovation (GAITI)	The extent to which the firm has adopted and implemented generative AI technologies	GAITI1: Our firm has successfully implemented GAI solutions in core business processes GAITI2: We continuously explore new applications of GAI technologies GAITI3: GAI technologies have significantly changed how we manage knowledge GAITI4: Our firm invests substantially in GAI technology development GAITI5: GAI solutions are integrated with our existing knowledge management systems	Adapted from Lee et al. (2023); Ransbotham et al. (2022)
Human-AI Interaction (HAII)	The quality and effectiveness of interactions between human employees and AI systems	HAII1: Employees are comfortable working with AI systems HAII2: AI systems in our organization are designed with user experience in mind HAII3: Regular training is provided for effective Human-AI collaboration HAII4: Feedback mechanisms exist for improving Human-AI interactions HAII5: Our organization has clear protocols for Human-AI task allocation	Adapted from Raisch & Krakowski (2021); Shneiderman (2020)
Organizational Performance (OP)	The firm's performance in financial and non-financial dimensions	OP1: Return on investment relative to industry average OP2: Sales growth over the past three years OP3: Market share growth in primary markets OP4: Customer satisfaction and retention OP5: New product/service development effectiveness	Adapted from Gold et al. (2001); Wang & Wang (2012)

Note: All items were measured using a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 6 May 2025 doi:10.20944/preprints202505.0132.v1

4. Results and Findings

4.1. Descriptive Statistics

Table 2 presents the descriptive statistics for the study variables, including means, standard deviations, and correlations.

Table 2. Descriptive Statistics and Correlations.

Variable	Mean	SD	1	2	3	4	5
1. KMDC	5.38	0.92	(0.89)				
2. KBS	5.14	1.03	0.64**	(0.87)			
3. GAITI	4.76	1.18	0.57**	0.52**	(0.91)		
4. HAII	4.82	1.06	0.49**	0.43**	0.61**	(0.88)	
5. OP	5.07	0.97	0.53**	0.48**	0.59**	0.46**	(0.92)

Note: N = 276; Diagonal elements in parentheses represent Cronbach's alpha reliability coefficients; ** $p < 0.01$.

4.2. Measurement Model Assessment

Before hypothesis testing, we conducted confirmatory factor analysis (CFA) to assess the psychometric properties of the measurement scales. Table 3 presents the reliability and validity analysis results.

Table 3. Reliability and Validity Analysis.

Construct	Items	Factor Loadings	Cronbach's Alpha	CR	AVE
KMDC	KMDC1 KMDC2 KMDC3 KMDC4 KMDC5	0.81 0.86 0.79 0.84 0.77	0.89	0.91	0.67
KBS	KBS1 KBS2 KBS3 KBS4 KBS5	0.76 0.81 0.84 0.78 0.82	0.87	0.89	0.65
GAITI	GAITI1 GAITI2 GAITI3 GAITI4 GAITI5	0.85 0.88 0.83 0.79 0.87	0.91	0.92	0.71
HAII	HAII1 HAII2 HAII3 HAII4 HAII5	0.79 0.82 0.81 0.76 0.84	0.88	0.90	0.64
OP	OP1 OP2 OP3 OP4 OP5	0.84 0.87 0.81 0.83 0.86	0.92	0.93	0.72

Note: CR = Composite Reliability; AVE = Average Variance Extracted; All factor loadings are significant at $p < 0.001$.

The measurement model demonstrated satisfactory fit indices: $\chi^2 = 437.26$, df = 265, $\chi^2/df = 1.65$, CFI = 0.94, TLI = 0.93, RMSEA = 0.049, SRMR = 0.043. All constructs exhibited acceptable reliability (Cronbach's alpha > 0.70, CR > 0.70) and convergent validity (AVE > 0.50, factor loadings > 0.70). Discriminant validity was established as the square root of AVE for each construct exceeded its correlations with other constructs.

4.3. fsQCA Analysis

To complement the variance-based approach, we conducted fuzzy-set qualitative comparative analysis to identify configurational paths leading to high organizational performance. Table 4 presents the truth table analysis results.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 6 May 2025 doi:10.20944/preprints202505.0132.v1

Table 4. fsQCA Truth Table Analysis for High Organizational Performance.

Configuration	KMDC	KBS	GAITI	HAII	Raw Coverage	Unique Coverage	Consistency
1	●	●	●	●	0.42	0.16	0.91
2	●	●	●	○	0.28	0.09	0.85
3	●	○	●	●	0.24	0.07	0.83
4	○	●	●	●	0.21	0.05	0.82

Note: ● = presence of condition; ○ = absence of condition; Overall solution coverage: 0.73; Overall solution consistency: 0.87.

The fsQCA results reveal four configurational paths leading to high organizational performance. The most empirically relevant path (configuration 1) combines high levels of all four conditions, suggesting that the joint presence of strong knowledge management dynamic capabilities, knowledge sharing, GAI technology innovation, and effective Human-AI interaction represents a sufficient condition for superior performance.

4.4. Structural Model Assessment

We tested the hypothesized relationships using structural equation modeling with AMOS. Table 5 presents the model fit indices.

Table 5. Structural Model Fit Indices.

Fit Index	Value	Recommended Threshold	Reference
χ^2	478.35	-	-
df	269	-	-
χ^2/df	1.78	< 3.00	Hair et al. (2010)
CFI	0.93	> 0.90	Bentler (1990)
TLI	0.92	> 0.90	Tucker & Lewis (1973)
RMSEA	0.053	< 0.08	Browne & Cudeck (1993)
SRMR	0.047	< 0.08	Hu & Bentler (1999)
GFI	0.91	> 0.90	Jöreskog & Sörbom (1984)
AGFI	0.89	> 0.80	Hair et al. (2010)

Note: CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual; GFI = Goodness of Fit Index; AGFI = Adjusted Goodness of Fit Index.

The structural model demonstrated good fit to the data. Table 6 presents the results of hypothesis testing.

Table 6. Path Analysis Results.

Hypothesis	Path	Standardized Coefficient	t-value	p-value	Result
H1	KMDC → OP	0.26	3.74	< 0.001	Supported
H2	KBS → OP	0.21	3.18	< 0.01	Supported
H3a	KMDC → GAITI	0.39	5.67	< 0.001	Supported
H3b	GAITI → OP	0.34	4.86	< 0.001	Supported
H4a	KBS → GAITI	0.31	4.52	< 0.001	Supported

H5	GAITI × HAII → OP	0.19	2.94	< 0.01	Supported

Note: KMDC = Knowledge Management Dynamic Capabilities; KBS = Knowledge-Based Sharing; GAITI = GAI Technology Innovation; HAII = Human-AI Interaction; OP = Organizational Performance.

The results support all hypothesized relationships. Knowledge management dynamic capabilities ($\beta = 0.26$, $p < 0.001$) and knowledge-based sharing ($\beta = 0.21$, $p < 0.01$) both positively influence organizational performance, supporting H1 and H2. The mediation hypotheses (H3 and H4) were also supported, with significant paths from KMDC to GAITI ($\beta = 0.39$, $p < 0.001$), KBS to GAITI ($\beta = 0.31$, $p < 0.001$), and GAITI to OP ($\beta = 0.34$, $p < 0.001$). The indirect effects of KMDC and KBS on OP through GAITI were significant (indirect effect of KMDC = 0.13, $p < 0.01$; indirect effect of KBS = 0.11, $p < 0.01$). Finally, the interaction between GAITI and HAII positively influenced OP ($\beta = 0.19$, $p < 0.01$), supporting H5.

5. Discussion and Implications

5.1. Theoretical Implications

This study makes several important theoretical contributions. First, by integrating dynamic capabilities theory and knowledge-based view, we develop a comprehensive framework that explains how knowledge management capabilities translate into organizational performance in the digital sector. Our findings confirm that both knowledge management dynamic capabilities and knowledge-based sharing represent critical organizational processes that directly enhance performance outcomes.

Second, this research extends the literature on technology-enabled knowledge management by empirically validating the mediating role of GAI technology innovation. The results suggest that GAI technologies serve as mechanisms through which knowledge management capabilities are transformed into enhanced organizational performance. This finding aligns with recent theoretical developments suggesting that emerging technologies fundamentally alter how organizations create, store, and utilize knowledge resources (Lee et al., 2023).

Third, our investigation of Human-AI interaction as a moderating factor contributes to the growing literature on socio-technical systems in digital organizations. The significant moderating effect observed confirms that technological effectiveness depends crucially on how well human and artificial intelligence components are integrated within organizational processes (Raisch & Krakowski, 2021).

Finally, the mixed-methods approach employed in this study provides methodological contributions by demonstrating how variance-based (SEM) and configurational (fsQCA) analyses can complement each other to provide a more nuanced understanding of complex organizational phenomena. The fsQCA results reveal equifinality in achieving high performance, with multiple configurational paths leading to the desired outcome.

5.2. Practical Implications

For managers in Chinese digital firms, this study offers several actionable insights. First, investments in knowledge management capabilities represent a strategic priority with demonstrable performance benefits. Organizations should develop systematic approaches to knowledge acquisition, integration, and reconfiguration while simultaneously fostering a culture of knowledge sharing across departmental boundaries. Second, the mediating role of GAI technology innovation suggests that firms should leverage emerging AI technologies to enhance knowledge management processes. Strategic implementation of GAI solutions can amplify the performance benefits derived from knowledge management capabilities. However, technology adoption should be guided by clear business objectives rather than technological fascination. Third, the moderating effect of Human-AI interaction highlights the importance of thoughtful system design and implementation. Organizations should invest in user training, intuitive interfaces, and transparent AI systems to maximize the value derived from technological innovations. Establishing clear protocols for Human-

AI collaboration and task allocation can significantly enhance the effectiveness of knowledge management systems.

5.3. Policy Recommendations

For policy makers in China's digital economy, this research offers several recommendations. First, educational policies should increasingly emphasize AI literacy and human-machine collaboration skills to prepare the workforce for evolving knowledge work environments. Second, innovation policies should support the development of GAI technologies that complement human capabilities rather than solely focusing on automation. Third, regulatory frameworks should balance innovation enablement with ethical considerations regarding AI deployment in knowledge-intensive sectors.

6. Conclusion

This study examines the complex relationships between knowledge management dynamic capabilities, knowledge-based sharing, and organizational performance in Chinese digital firms. The findings confirm that both KMDC and KBS positively influence performance, with GAI technology innovation serving as a significant mediator. Additionally, Human-AI interaction positively moderates the relationship between GAI technology innovation and performance outcomes.

The research contributes to knowledge management and technology innovation literature while offering practical insights for digital firms seeking to enhance performance through knowledge management initiatives. Future research should explore these relationships in other national contexts and industry sectors to establish boundary conditions and enhance generalizability.

References

1. Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. Journal of Marketing Research, 14(3), 396-402. https://doi.org/10.1177/002224377701400320
2. Bentler, P. M. (1990). Comparative fit indexes in structural models. Psychological Bulletin, 107(2), 238-246. https://doi.org/10.1037/0033-2909.107.2.238
3. Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen & J. S. Long (Eds.), Testing structural equation models (pp. 136-162). Sage.
4. Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. W.W. Norton & Company. https://doi.org/10.1016/j.techfore.2014.11.016
5. Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? Strategic Management Journal, 21(10-11), 1105-1121. https://doi.org/10.1002/1097-0266(200010/11)21:10/11<1105::AID-SMJ133>3.0.CO;2-E
6. Fainshmidt, S., Pezeshkan, A., Lance Frazier, M., Nair, A., & Markowski, E. (2016). Dynamic capabilities and organizational performance: A meta-analytic evaluation and extension. Journal of Management Studies, 53(8), 1348-1380. https://doi.org/10.1111/joms.12213
7. Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge management: An organizational capabilities perspective. Journal of Management Information Systems, 18(1), 185-214. https://doi.org/10.1080/07421222.2001.11045669
8. Grant, R. M. (1996). Toward a knowledge-based theory of the firm. Strategic Management Journal, 17(S2), 109-122. https://doi.org/10.1002/smj.4250171110
9. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis (7th ed.). Pearson.
10. Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling, 6(1), 1-55. https://doi.org/10.1080/10705519909540118
11. Jöreskog, K. G., & Sörbom, D. (1984). LISREL VI user's guide (3rd ed.). Scientific Software.
12. Lee, J., Suh, T., Roy, D., & Baucus, M. (2023). Emerging technology and dynamic capabilities: The case of AI in U.S. manufacturing. Technological Forecasting and Social Change, 186, 122148. https://doi.org/10.1016/j.techfore.2022.122148

 doi:10.20944/preprints202505.0132.v1

13. Lin, H. F. (2007). Knowledge sharing and firm innovation capability: An empirical study. International Journal of Manpower, 28(3/4), 315-332. https://doi.org/10.1108/01437720710755272
14. Nonaka, I., & Takeuchi, H. (1995). The knowledge-creating company: How Japanese companies create the dynamics of innovation. Oxford University Press.
15. Pavlou, P. A., & El Sawy, O. A. (2011). Understanding the elusive black box of dynamic capabilities. Decision Sciences, 42(1), 239-273. https://doi.org/10.1111/j.1540-5915.2010.00287.x
16. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. Academy of Management Review, 46(1), 192-210. https://doi.org/10.5465/amr.2018.0072
17. Ransbotham, S., Khodabandeh, S., Kiron, D., Candelon, F., Chu, M., & LaFountain, B. (2022). Expanding AI's impact with organizational learning. MIT Sloan Management Review, 63(4), 1-7.
18. Shneiderman, B. (2020). Human-centered artificial intelligence: Reliable, safe & trustworthy. International Journal of Human-Computer Interaction, 36(6), 495-504. https://doi.org/10.1080/10447318.2020.1741118
19. Cui, J. (2024). Exploring Cultural Elements in Modern Packaging Design and Their Emotional Impact on Consumers. Available at SSRN 5038426.
20. Yue, H., Cui, J., Zhao, X., Liu, Y., Zhang, H., & Wang, M. (2024). Study on the sports biomechanics prediction, sport biofluids and assessment of college students' mental health status transport based on artificial neural network and expert system. Molecular & Cellular Biomechanics, 21(1), 256-256.
21. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. Strategic Management Journal, 28(13), 1319-1350. https://doi.org/10.1002/smj.640
22. Teece, D. J. (2018). Business models and dynamic capabilities. Long Range Planning, 51(1), 40-49. https://doi.org/10.1016/j.lrp.2017.06.007
23. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509-533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z
24. Tucker, L. R., & Lewis, C. (1973). A reliability coefficient for maximum likelihood factor analysis. Psychometrika, 38(1), 1-10. https://doi.org/10.1007/BF02291170
25. Cui, J. (2025). Digital Innovation in Media Enterprises and Digital Transformation: The Moderating Role of GAI Technology in Media Industry. *Media, Communication, and Technology*, *1*(2), p1-p1.
26. Cui, J. (2024). Does digital strategy, organizational agility, digital lead-ership promote DT? A study of digital strategy, organiza-tional agility, digital leadership affects corporate DT in Chinese technological firms. *Journal of Integrated Social Sciences and Humanities*.
27. Wang, Z., & Wang, N. (2012). Knowledge sharing, innovation and firm performance. Expert Systems with Applications, 39(10), 8899-8908. https://doi.org/10.1016/j.eswa.2012.02.017
28. Wang, C. L., & Ahmed, P. K. (2007). Dynamic capabilities: A review and research agenda. International Journal of Management Reviews, 9(1), 31-51. https://doi.org/10.1111/j.1468-2370.2007.00201.x
29. Zheng, S., Zhang, W., & Du, J. (2011). Knowledge-based dynamic capabilities and innovation in networked environments. Journal of Knowledge Management, 15(6), 1035-1051. https://doi.org/10.1108/13673271111179352