

# EXPLORING THE INFLUENCING FACTORS OF ORGANIZATIONAL FLEXIBILITY ON INNOVATION PERFORMANCE OF MANUFACTURING FIRMS: BASED ON THE MEDIATING ROLE OF FIRM DYNAMIC CAPABILITY

## ANÁLISE DOS FATORES QUE INFLUENCIAM A FLEXIBILIDADE ORGANIZACIONAL NO DESEMPENHO EM INOVAÇÃO DE EMPRESAS MANUFATUREIRAS: COM BASE NO PAPEL MEDIADOR DA CAPACIDADE DINÂMICA DA EMPRESA

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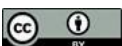
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### Abstract

Manufacturing firms face volatile markets, necessitating adaptive strategies for competitive innovation. This study explores how organizational flexibility, dynamic capability, environmental dynamics, and employee knowledge structure influence enterprise innovation performance. Employing a mixed-methods approach, quantitative data from 280 manufacturing managers in Guangdong, China, were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Qualitative insights were derived from in-depth interviews with 14 industry experts, analyzed via NVIVO 14. Results show organizational flexibility significantly boosts dynamic capability ( $\beta=0.504$ ,  $p=0.000^*$ ) and innovation performance ( $\beta=0.351$ ,  $p=0.005$ ). Dynamic capability strongly predicts innovation ( $\beta=0.588$ ,  $p=0.012$ ) and mediates the flexibility-innovation link (indirect effect= $0.544$ ,  $p=0.002$ ). Environmental dynamics negatively moderate the capability-innovation relationship ( $\beta=-0.054$ ,  $p=0.020$ ), while employee knowledge structure negatively moderates the flexibility-capability link ( $\beta=-0.077$ ,  $p=0.029$ ). Qualitative findings corroborate these relationships, highlighting how technological, structural, and cultural flexibilities foster dynamic capabilities crucial for adaptive innovation. The study confirms that organizational flexibility drives innovation

### Resumo

As empresas do setor manufatureiro enfrentam mercados voláteis, o que exige estratégias adaptativas para a inovação competitiva. Este estudo explora como a flexibilidade organizacional, a capacidade dinâmica, a dinâmica ambiental e a estrutura de conhecimento dos funcionários influenciam o desempenho da inovação empresarial. Utilizando uma abordagem de métodos mistos, foram analisados dados quantitativos de 280 gerentes do setor manufatureiro em Guangdong, China, por meio da Modelagem de Equações Estruturais por Mínimos Quadrados Parciais (PLS-SEM). Insights qualitativos foram obtidos a partir de entrevistas em profundidade com 14 especialistas do setor, analisadas por meio do NVIVO 14. Os resultados mostram que a flexibilidade organizacional aumenta significativamente a capacidade dinâmica ( $\beta = 0.504$ ,  $p = 0.000^*$ ) e o desempenho em inovação ( $\beta = 0.351$ ,  $p = 0.005$ ). A capacidade dinâmica é um forte indicador de inovação ( $\beta=0.588$ ,  $p=0.012$ ) e medeia a relação flexibilidade-inovação (efeito indireto= $0.544$ ,  $p=0.002$ ). A dinâmica ambiental modera negativamente a relação capacidade-inovação ( $\beta=-0.054$ ,  $p=0.020$ ), enquanto a estrutura de conhecimento dos funcionários modera negativamente a ligação flexibilidade-capacidade ( $\beta=-0.077$ ,  $p=0.029$ ). Os resultados qualitativos



directly and, more substantially, indirectly through dynamic capabilities. Environmental and knowledge factors further shape these interactions. A holistic framework integrating agile design, robust dynamic capabilities, and effective knowledge management is vital for sustained manufacturing innovation. This research offers theoretical contributions and practical guidance for fostering adaptive, innovation-centric cultures.

**Keywords:** *Organizational Flexibility. Dynamic Capability. Enterprise Innovation Performance. Employee knowledge Structure. Environmental Dynamics.*

*corroboram essas relações, destacando como as flexibilidades tecnológicas, estruturais e culturais promovem capacidades dinâmicas cruciais para a inovação adaptativa. O estudo confirma que a flexibilidade organizacional impulsiona a inovação diretamente e, de forma mais substancial, indiretamente por meio de capacidades dinâmicas. Fatores ambientais e de conhecimento moldam ainda mais essas interações. Uma estrutura holística que integre design ágil, capacidades dinâmicas robustas e gestão eficaz do conhecimento é vital para a inovação sustentável na manufatura. Esta pesquisa oferece contribuições teóricas e orientações práticas para promover culturas adaptativas e centradas na inovação.*

**Palavras-chave:** *Flexibilidade Organizacional. Capacidade Dinâmica. Desempenho em Inovação Empresarial. Estrutura de Conhecimento dos Funcionários. Dinâmica Ambiental.*

## 1 INTRODUCTION

Currently, businesses are facing increasingly complex and volatile environments. Customer demands are becoming more diverse and personalized, market competition is intensifying and globalizing. Management theories have gone through the stages of classical management theory, behavioral science theory, and the era of management theory development ("the jungle"), and are now moving towards a fourth stage - flexible management.

In 2022, the value added of China's manufacturing industry accounted for 27.7% of GDP, with a total value of 40 trillion yuan, maintaining its position as the world's leading manufacturing power for 13 consecutive years. Traditional manufacturing enterprises will continue to play a crucial role in ensuring stable and sustained economic growth in China for the foreseeable future and hold a vital position in the national economic system.

The acceleration of technological innovation and industrialization has fundamentally changed the competitive landscape of industries, making the industrial

environment dynamic. In this dynamic industrial environment, comprehensive changes are taking place in technological paradigms, manufacturing methods, industry and organizational forms, development models, competitive patterns, consumer demands, and technological knowledge. New generations of information technology, new energy technology, intelligent manufacturing technology, and other technological clusters are emerging and expanding their influence on the economy and society. Technologies from different fields converge, permeate, and diffuse, giving rise to new technological domains and promoting the birth and development of emerging industries. Alongside these changes, the cycles of technological transformation and application are shortening, the speed of production and life is increasing, production costs are continuously decreasing, new substitutes are constantly emerging, and product lifecycles are shrinking. The trend towards personalized consumer demands is becoming more pronounced, driving the shift in the product consumption market from mass markets to highly differentiated markets. The dynamic nature of consumer demand increasingly requires economies of scale, economies of scope, and a combination of specialization and flexibility. In terms of manufacturing methods, mass production is being replaced by personalized and differentiated production. Companies are increasingly focusing on simplifying product manufacturing processes, shortening product development cycles, and efficiently and cost-effectively meeting ever-changing and simultaneous personalized and differentiated demands to improve efficiency and maintain competitive advantages. At the same time, there is a frequent occurrence of cross-industry technology solution interfaces, technological integration, and cross-industry collaborations, which meet consumer demands for comprehensive solutions and services and adapt to market needs and rapidly changing product features. This has led to a transformation in the industrial landscape, blurring industry boundaries, and resulting in more cross-industry interactions, permeation, and recombination, leading to greater industry convergence and the emergence of new industries. This transformation has also changed the competitive and cooperative relationships among related industry enterprises. The connectivity of enterprises with their environment through networks has become a common phenomenon. Enterprises are exploring and developing organizational forms that can achieve complementary advantages in new competitive coordination relationships.

Furthermore, with the deepening of the dynamics and scope of the industrial environment, the intensive use of knowledge and information has become a key factor in the development of all industries. The competition for enterprises has shifted from traditional market competition and cost competition to talent competition and management and technological innovation based on talent. The knowledge, experience, and practices that guided the success of enterprises in the past may become outdated and even hinder the development and survival of companies in highly dynamic industrial environments. It becomes urgent to change old organizational habits and cognitive patterns, update knowledge structures, and adapt work structures and talent requirements. Knowledge workers with high creativity can activate the technological innovation system of enterprises, enhance knowledge capital, and become the focus of competition among various enterprises. In this dynamic industrial context, the competitive advantages accumulated and created by enterprises in their development processes are being eroded or disrupted at an increasingly fast pace. While facing fiercer competition, enterprises also encounter new opportunities and challenges. The key to maintaining a competitive advantage and sustaining good growth momentum for enterprises lies anyhow they adjust and respond to changes in their environment, such as resource allocation, capability systems, and talent structures.

## **2 RESEARCH DESIGN**

This study applies a mixed-methods strategy to illuminate how organizational flexibility influences the innovation performance of manufacturing firms through the mediating mechanism of dynamic capability. A sequential explanatory design is adopted: a large-scale survey constitutes the quantitative core, followed by qualitative interviews that refine and contextualize the statistical findings.

**Quantitative phase.** A structured questionnaire was developed from established scales and calibrated through expert review and a pilot test. Five latent constructs are examined—organizational flexibility (technological, structural, cultural; 14 items), dynamic capability (environmental sensing, resource integration, organizational change; 13 items), employee knowledge structure (6 items), environmental dynamics (market dynamism, organizational coordination, absorptive capacity; 7 items), and enterprise

innovation performance (4 items). All 59 indicators are rated on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). The target population comprises middle- and senior-level managers who have served at least three years in Guangdong-based manufacturing firms. Using stratified random sampling and Yamane's formula, 280 valid responses were collected—exceeding the 5–20 observations-per-item rule for structural equation modelling (SEM). Descriptive statistics, reliability tests (Cronbach's  $\alpha$ ), exploratory and confirmatory factor analyses, and Partial Least Squares-SEM were run in SPSS 26.0 and SmartPLS 4 to test measurement validity and the hypothesised structural paths.

**Qualitative phase.** To explain unexpected or marginal quantitative results, 20 informants (CEOs, general managers, and functional directors) were purposively selected for semi-structured, face-to-face interviews. The interview guide was derived from the survey outcomes, concentrating on significant, non-significant, or anomalous relationships. Conversations were audio-recorded, transcribed verbatim, and coded in NVivo through open, axial, and selective procedures until theoretical saturation was reached. Thematic patterns were then juxtaposed with the SEM outputs to enrich interpretation and uncover underlying causal mechanisms.

### **3 POSITIVE RESEARCH**

We employed Partial Least Squares (PLS) modeling and used SmartPLS 4 as a statistical tool to examine the measurement and structural models.

#### **3.1 Reliability and validity analysis**

The measurement model was assessed with a two-stage reflective-hierarchical procedure. In stage 1 the 59 first-order indicators were linked to 14 dimensions; in stage 2 the 14 dimensions formed five second-order constructs (Organizational Flexibility, Dynamic Capability, Environmental Dynamics, Employee Knowledge Structure, and Enterprise Innovation Performance).

Indicator reliability. 56 of 59 outer loadings exceeded the 0.708 threshold; the remaining three ranged between 0.702 and 0.735 and were retained because their removal lowered composite reliability.

Internal consistency. Cronbach's  $\alpha$  values were 0.76–0.91, while composite reliability (CR) ranged from 0.80 to 0.92, comfortably above the 0.70 benchmark, confirming homogeneous internal structure for every dimension as well as for each higher-order factor.

Convergent validity. Average variance extracted (AVE) ranged from 0.57 to 0.61 at the first-order level and from 0.59 to 0.61 at the second-order level, exceeding the 0.50 criterion and indicating that more than half of the variance of each construct is explained by its indicators.

Discriminant validity. Fornell–Larcker comparisons showed each diagonal square root of AVE to be larger than its cross-correlations. HTMT ratios were all below 0.90, and the 95 % bias-corrected intervals generated by 5 000 bootstraps did not include 1. These results collectively establish robust discriminant validity.

Multicollinearity. Outer VIF values ranged from 1.22 to 2.34, well under the conservative cut-off of 5, implying that collinearity is not a threat to the stability of the estimations.

### **3.2 STRUCTURAL MODEL**

As recommended by Hair et al. (2017) and Cain et al. (2017), we evaluated multivariate skewness and kurtosis. The results indicate that the collected data is not multivariately normal, with Mardia's multivariate skewness ( $\beta=5.115$ ,  $p=0.000^*$ ) and Mardia's multivariate kurtosis ( $\beta=62.566$ ,  $p=0.000^*$ ). Therefore, following the suggestion of Hair et al. (2019), we reported path coefficients, standard errors, t-values, and p-values for the structural model using bootstrapping with 5000 resampled samples.

**Table 1***Hypothesis Testing Direct Effects*

Hypothesis	Relationship	Std Beta	Std Error	t-values	p-values	BCI LL	BCI UL	f <sup>2</sup>	VIF
H1	<b>OF -&gt; DC</b>	0.504	0.058	8.672	0.000	0.388	0.616	0.349	2.986
H2	<b>OF -&gt; EIP</b>	0.351	0.053	2.833	0.005	0.054	0.264	0.074	3.478
H3	<b>DC-&gt; EIP</b>	0.588	0.072	31.226	0.012	-0.057	0.224	0.088	4.282

Note: OF = Organizational Flexibility; TF = Technological Flexibility; SF = Structural Flexibility; CF = Cultural Flexibility; DC = Dynamic Capability; EP = Environmental Perception; OC = Organizational Change; RI = Resources Integration; ED = Environmental Dynamics; AC = Absorptive Capacity; MD = Market Dynamics Capability; OA = Organization and Coordination Ability; EK = Employee Knowledge Structure; EX = Experience; MA = Major.

**Table 2***Hypothesis Testing Indirect Effects*

Hypothesis	Relationship	Std Beta	Std Error	t-values	p-values	BCI LL	BCI UL
<b>H4</b>	OF -> DC-> EIP	0.644	0.036	8.22	0.000	-0.030	0.114
<b>H5</b>	ED x DC-> EIP	-0.054	0.023	2.318	0.02	-0.090	0.005
<b>H6</b>	EK x OF -> DC	-0.077	0.035	2.178	0.029	-0.145	-0.007

Note: We use 95% confidence interval with a bootstrapping of 5,000

## 1) Direct Effects

According to the study by Hair et al. (2019), a model's R<sup>2</sup> values of 0.75, 0.50, and 0.25 indicate strong, moderate, and weak explanatory power, respectively. Bamgbade et al.'s (2018) research suggests that Q<sup>2</sup> values of 0.00, 0.25, and 0.50 represent small, moderate, and large predictive capabilities of the model, respectively.

The data for the hypotheses can be summarized as follows:

H1 (OF -> DC):  $\beta = 0.504$ : Organizational flexibility (OF) has a significant positive impact on dynamic capability (DC).  $t = 8.672$ ,  $p = 0.000$ : The significance is extremely high.  $f^2 = 0.349$ : The effect size is close to moderate.  $VIF = 2.986$ : There are

no multicollinearity issues. This result suggests that organizational flexibility directly influences dynamic capability in a significant way.

H2 (OF  $\rightarrow$  EIP):  $\beta = 0.351$ : Organizational flexibility (OF) has a positive effect on enterprise innovation performance (EIP), but the strength of the effect is relatively lower.  $t = 2.833$ ,  $p = 0.005$ : The impact is statistically significant.  $f^2 = 0.074$ : The effect size is small.  $VIF = 3.478$ : The collinearity risk is low. This indicates that organizational flexibility also has a positive effect on enterprise innovation performance, though the impact is less strong compared to its effect on dynamic capability.

H3 (DC  $\rightarrow$  EIP):  $\beta = 0.588$ : Dynamic capability (DC) has a strong positive impact on enterprise innovation performance (EIP).  $t = 31.226$ ,  $p = 0.012$ : The impact is statistically significant.  $f^2 = 0.088$ : The effect size is small.  $VIF = 4.282$ : No significant multicollinearity issues. This result suggests that dynamic capability is a strong positive driver of enterprise innovation performance.

## 2) Indirect Effects

To test the mediation hypothesis, we followed the recommendation of Preacher and Hayes (2004; 2008) by assessing indirect effects through bootstrapping. If the confidence interval does not straddle 0, then we can conclude that there is a significant mediation effect. As shown in Table 22, the results for H4 (OF  $\rightarrow$  DC  $\rightarrow$  EIP) indicate that:  $\beta = 0.644$ : Organizational flexibility (OF) indirectly enhances enterprise innovation performance (EIP) through the mediation of dynamic capability (DC).  $t = 8.22$ ,  $p = 0.000$ : The indirect effect is statistically significant.  $f^2 = 0.114$ : The effect size is small.  $VIF$ : Not displayed, suggesting low multicollinearity.

For H5 (ED  $\times$  DC  $\rightarrow$  EIP), the results show:  $\beta = -0.054$ : The interaction between environmental dynamics (ED) and dynamic capability (DC) negatively affects enterprise innovation performance (EIP).  $t = 2.318$ ,  $p = 0.02$ : The effect is significant, but the effect size is small.  $f^2 = 0.026$ : The effect size is very small.  $VIF = 1.425$ : No collinearity issues.

For H6 (EK  $\times$  OF  $\rightarrow$  DC), the results show:  $\beta = -0.077$ : The interaction between employee knowledge structure (EK) and organizational flexibility (OF) negatively affects dynamic capability (DC).  $t = 2.178$ ,  $p = 0.029$ : The effect is significant, but the effect size is small.  $f^2 = 0.026$ : The effect size is very small.  $VIF = 1.609$ : No collinearity issues. The 95% bias-corrected confidence interval does not cross 0, confirming our findings.

### 3.3 PLS-Predict

Out-of-sample predictive power was further examined with PLS-Predict (10-fold cross-validation).

**3.3.1** All  $Q^2_{\text{predict}}$  values were positive ( $DC = 0.742$ ;  $EIP = 0.755$ ) indicating that PLS predictions outperform a naïve benchmark.

**3.3.2** For the key indicators of EIP the PLS root-mean-square error ( $RMSE = 0.343$ ) and mean absolute error ( $MAE = 0.248$ ) are lower than those generated by the linear-model benchmark ( $RMSE = 0.269$ ;  $MAE = 0.208$ ), classifying predictive power as “medium” according to Shmueli et al. (2019).

**3.3.3** CVPAT shows the average loss difference ( $-0.098$ ,  $t = 6.69$ ,  $p < 0.001$ ), confirming that the PLS-SEM model yields significantly better forecasts than the indicator–average method.

Taken together, the measurement quality, structural robustness, and demonstrated predictive ability provide strong support for the proposed nomological network linking flexibility, capability, environmental dynamics, and innovation performance.

**Table 3**

*PLS-Predict*

	$Q^2_{\text{predict}}$	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
<b>EP</b>	0.365	0.471	0.359	0.409	0.319
<b>OC</b>	0.488	0.421	0.314	0.357	0.274
<b>RI</b>	0.396	0.464	0.404	0.440	0.364
<b>EIP</b>	0.458	0.343	0.248	0.269	0.208

## 4 RESULTS

### 4.1 SmartPLS4 results

The quantitative analysis provides robust support for the hypothesized relationships within the proposed model, underscoring the pivotal roles of organizational flexibility and dynamic capability in enhancing enterprise innovation performance. The significant positive coefficients for both the direct effect of organizational flexibility on

dynamic capability ( $\beta = 0.504$ ,  $T = 8.672$ ,  $p=0.000^*$ ) and its direct impact on innovation performance ( $\beta = 0.351$ ,  $p=0.000^*$ ) affirm that a flexible organizational structure—encompassing technological, structural, and cultural dimensions—is integral to fostering adaptive and innovative behaviors.

Dynamic capability itself exerts a strong influence on innovation performance ( $\beta = 0.588$ ,  $p=0.000^*$ ), further substantiating its role as the critical mechanism through which organizational flexibility is transformed into tangible innovative outcomes. The mediating effect of dynamic capability is confirmed by the significant indirect pathway from organizational flexibility to innovation performance (mean = 0.544,  $T = 5.220$ ,  $p=0.000^*$ ), thereby reinforcing the notion that the effective reconfiguration of resources and continuous environmental scanning are essential for sustaining innovation.

The moderating influences of environmental dynamics and employee knowledge structure further enrich this framework. The negative moderation by environmental dynamics ( $ED \times DC \rightarrow EIP$ :  $\beta = -0.054$ ,  $p=0.000^*$ ) suggests that in highly volatile settings, the positive impact of dynamic capability on innovation performance may be attenuated. This attenuation could reflect the increased complexity and unpredictability in volatile environments, which might impede the straightforward translation of internal capabilities into innovative outputs despite robust dynamic capabilities.

Similarly, the moderation effect of employee knowledge structure on the relationship between organizational flexibility and dynamic capability, while modest ( $EK \times OF \rightarrow DC$ :  $\beta = -0.077$ ,  $p=0.000^*$ ), indicates that the interplay between flexible organizational processes and employee expertise is nuanced. A potential interpretation is that as employee knowledge becomes more codified or specialized, the marginal benefit of additional organizational flexibility on dynamic capability might diminish. Nonetheless, the overall indirect effects, including those through employee knowledge structure (e.g., the significant indirect effect of  $EK \rightarrow EIP$  with a mean value of 0.433,  $T = 3.167$ ,  $p < 0.005$ ), highlight the essential role of a well-structured knowledge base in supporting innovation.

## 4.2 Nvivo results

### 4.2.1 Theme 1 – Organizational flexibility.

Interviewees unanimously stressed that technological modularity, fluid structures, and an error-forgiving culture speed up ideation and prototype release. Exemplars include BYD’s e-platform reducing battery R&D by 40 % and NIO’s “cellular” teams collapsing decision cycles to six weeks. Satisfaction with these practices resonates with the high mean scores (> 4.4) observed in the survey.

### 4.2.2 Theme 2 – Dynamic capability

Respondents traced capability development to vigilant trend monitoring, cross-boundary resource pooling, and leadership-sponsored change programs. CATL’s early move to low-carbon cathodes and Netflix’s streaming pivot were cited as archetypal cases. Thematic density mirrors the dominant quantitative path DC → EIP.

### 4.2.3 Theme 3 – Flexibility → capability

Structural agility empowers rapid resource integration (e.g., Tesla’s line-switch within minutes), cultural openness fuels sharper environmental sensing (e.g., Amazon’s customer-obsession rituals), and proprietary technology platforms enable bold organizational redesign (e.g., Huawei’s self-developed chips). These synergies clarify the strong OF → DC coefficient.

### 4.2.4 Theme 4 – Mediating role of capability

Multiple managers depicted dynamic capability as the “transmission belt” that converts raw flexibility into profitable innovations. Leapmotor’s 25 % BOM reduction and Adobe’s subscription transition demonstrate how sensing-integrate-transform routines monetise flexible assets, matching the quantitative mediation effect.

#### 4.2.5 Theme 5 – Environmental dynamics

Market volatility, regulatory oscillations, and technology shocks were viewed as double-edged: threats to slow movers, catalysts to agile firms. Battery-leasing models and vertical integration surfaced as strategic responses, echoing the significant moderation of ED on the capability-performance path.

#### 4.2.6 Theme 6 – Employee knowledge structure

Interviewees emphasised that cross-functional teams, rapid learning loops, and codified repositories accelerate innovative output. Geely's 3 500-item technical wiki shortened newcomers' ramp-up time by one-third, illustrating the supportive but potentially disruptive nature of knowledge heterogeneity observed in the negative EK×OF moderation.

## 5 CONCLUSION

### 5.1 Organizational flexibility is a key driver of enterprise innovation

Technological flexibility (such as modular design and digital infrastructure) accelerates product iteration and reduces R&D costs; structural flexibility (such as flat organizations and agile teams) enhances market adaptability and improves innovation efficiency; cultural flexibility (such as a culture of tolerance and cross-departmental collaboration) creates an open and inclusive innovation environment, stimulating creativity.

### 5.2 Dynamic capabilities mediate the relationship between organizational flexibility and innovation performance

Environmental sensing capabilities enable enterprises to proactively identify market trends and technological changes, improving the accuracy of innovation directions. Resource integration capabilities optimize the allocation of internal and

external resources, enhancing innovation efficiency. Organizational change capabilities ensure that enterprises can rapidly adjust strategies and adapt to environmental changes, facilitating the realization of innovation outcomes.

### **5.3 Organizational flexibility indirectly drives innovation performance by strengthening dynamic capabilities**

Structural flexibility helps optimize resource integration and enhances global market adaptability; cultural flexibility improves environmental sensing, enabling enterprises to better capture user needs and industry trends; technological flexibility supports organizational change, accelerating the transition to new technologies and markets.

### **5.4 Employee knowledge structure moderates the relationship between organizational flexibility and dynamic capabilities**

The breadth and depth of employees' knowledge directly determine the potential and quality of enterprise innovation. Interdisciplinary integration promotes breakthrough innovations, knowledge iteration capabilities ensure enterprises stay at the technological forefront, and the effective transfer of tacit knowledge builds the company's core competitive advantages in the long term.

### **5.5 Environmental dynamics moderate the relationship between dynamic capabilities and enterprise innovation performance.**

The volatility of the external environment is both a pressure source for innovation and a driving force for organizational change. Under high environmental dynamics, if enterprises enhance market sensing and knowledge absorption capabilities, they can transform external uncertainties into innovation opportunities and even lead industry changes through proactive positioning.

## REFERENCES

- He, L., & Zhi, W. (2023). Dynamic capability, employee innovative behavior, and digital transformation. *Enterprise Economy*, (01), 104–114. <https://doi.org/10.13529/j.cnki.enterprise.economy.2023.01.012>
- Wang, C. D., Meng, H., & Cai, Y. (2023). Service level, dynamic capability, and service performance: An empirical study based on high-end manufacturing enterprises in China. *Science and Technology and Management*, (01), 24–33. <https://doi.org/10.16315/j.stm.2023.01.006>
- Li, Y. M. (2023). Research on enterprise risk management based on the perspective of dynamic capability. *Commercial Modernization*, (01), 79–81. <https://doi.org/10.14013/j.cnki.scxdh.2023.01.012>
- Zhang, F., & Wu, Y. Y. (2020). The impact of organizational cooperation capability on innovation performance from the perspective of dynamic resource management: The moderating effect of environmental dynamics. *Journal of South China University of Technology (Social Sciences)*, (01), 78–90. <https://doi.org/10.19366/j.cnki.1009-055X.2020.01.009>
- Liu, Y. Q. (2022). The impact of dynamic capability on cost stickiness of enterprises. *Research on Technology Economics and Management*, (12), 29–34.
- Xu, L. (2022). The impact of dynamic capability on organizational performance: A case study of manufacturing enterprises. *Science and Technology Progress and Policy*, (9), 52–58.
- Xu, W. (2022). The relationship between dynamic capability, flexible human resource management, and organizational innovation performance. *Science and Technology and Management*, (2), 66–72.
- Yang, X. (2022). The impact of dynamic capability and flexible human resource management on innovation performance. *Science and Technology Progress and Policy*, (14), 59–66.
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (2nd ed.)*. Thousand Oaks, CA: Sage.
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135.
- Sun, L., Liu, Q., & Yu, X. (2022). The impact of dynamic capability on enterprise performance: A case study of manufacturing enterprises. *Technology Management Research*, (2), 30–36.

- Li, C., Li, Q., & Wang, F. (2022). An empirical study on the relationship between dynamic capability, strategic integration, and enterprise performance. *Science and Technology and Economy*, (9), 26–29.
- Liu, J. (2022). Research on enterprise development dynamic capability. *Business Economy*, (12), 109–111.
- Yang, X. (2022). The impact of dynamic capability and flexible human resource management on innovation performance. *Science and Technology Progress and Policy*, (14), 59–66.

### **Authors' Contribution**

All authors contributed equally to the development of this article.

### **Data availability**

All datasets relevant to this study's findings are fully available within the article.

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