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A MULTI-THEORETICAL ANALYSIS OF AI-RELATED CAPABILITIES AND NON-FINANCIAL PERFORMANCE IN CHINESE E-COMMERCE SMES: EVIDENCE FROM SICHUAN PROVINCE

UMA ANÁLISE MULTITEÓRICA DAS CAPACIDADES RELACIONADAS À IA E DO DESEMPENHO NÃO FINANCEIRO EM PMES CHINESAS DE COMÉRCIO ELETRÔNICO: EVIDÊNCIAS DA PROVÍNCIA DE SICHUAN

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Abstract

This study examines how five AI-related capability domains—AI technological advantage, AI organizational infrastructure, environmental pressure, AI innovation capability, and AI market responsiveness—shape the non-financial performance of e-commerce small and medium-sized enterprises (SMEs) in Sichuan Province, China. Integrating the Technology–Organization–Environment (TOE) framework with Dynamic Capabilities Theory, the study argues that structural readiness and adaptive capabilities jointly determine whether AI use translates into customer-facing and market-facing outcomes beyond financial metrics. We further propose government policy support as a contextual moderator capturing within-province heterogeneity in access to digital infrastructure, training, and innovation platforms. The paper develops a parsimonious hypothesis model, details construct operationalization, and specifies an empirical strategy using survey data and partial least squares structural equation modeling (PLS-

Resumo

Este estudo examina como cinco domínios de capacidade relacionados à IA — vantagem tecnológica da IA, infraestrutura organizacional da IA, pressão ambiental, capacidade de inovação da IA e capacidade de resposta do mercado à IA — moldam o desempenho não financeiro das pequenas e médias empresas (PMEs) de comércio eletrônico na província de Sichuan, na China. Integrando a estrutura Tecnologia-Organização-Ambiente (TOE) com a Teoria das Capacidades Dinâmicas, o estudo argumenta que a prontidão estrutural e as capacidades adaptativas determinam conjuntamente se o uso da IA se traduz em resultados voltados para o cliente e para o mercado, além das métricas financeiras. Propomos ainda o apoio de políticas governamentais como um moderador contextual que captura a heterogeneidade dentro da província no acesso à infraestrutura digital, treinamento e plataformas de inovação. O artigo desenvolve um modelo de hipótese parcimonioso, detalha a operacionalização da

SEM) with robustness checks via OLS regression and subgroup comparisons. Non-financial performance is operationalized through customer satisfaction, brand value and reputation, market adaptability, and platform visibility. The study contributes a capability-oriented account of inclusive, policy-sensitive digital transformation among resource-constrained inland SMEs and provides a results-reporting template aligned with Scopus-indexed journal expectations.

Keywords: AI Adoption. TOE Framework. Dynamic Capabilities. E-commerce SMEs. Non-financial Performance. Government Policy. Sichuan Province.

construção e especifica uma estratégia empírica usando dados de pesquisa e modelagem de equações estruturais de mínimos quadrados parciais (PLS-SEM) com verificações de robustez por meio de regressão OLS e comparações de subgrupos. O desempenho não financeiro é operacionalizado por meio da satisfação do cliente, valor e reputação da marca, adaptabilidade ao mercado e visibilidade da plataforma. O estudo contribui com uma explicação orientada para a capacidade de transformação digital inclusiva e sensível às políticas entre PMEs do interior com recursos limitados e fornece um modelo de relatório de resultados alinhado com as expectativas das revistas indexadas pela Scopus.

Palavras-chave: *Adoção de IA. Estrutura TOE. Capacidades Dinâmicas. PMEs de Comércio Eletrônico. Desempenho Não Financeiro. Política Governamental. Província de Sichuan.*

1 INTRODUCTION

Artificial intelligence (AI) has moved rapidly from experimental applications to routine business tools in digital commerce (Vrontis et al., 2022). E-commerce firms increasingly rely on AI-enabled chat interfaces, recommendation systems, ad targeting, demand forecasting, and content generation to improve conversion, service quality, and customer engagement (Schwaeke, 2025). Hisham (2025) supports continued emphasis on TOE application and AI performance relationships. For small and medium-sized enterprises (SMEs), these functions are closely tied to non-financial outcomes such as customer satisfaction, platform ratings, brand visibility, and market agility—outcomes that often precede long-term financial returns and signal strategic competitiveness.AI adoption continues to transform routine operations in digital commerce and SME competitiveness (Vrontis et al., 2022). Badghish & Soomro (2024) supports general statements about AI adoption impacting SME performance.

Despite growing interest in AI adoption, much of the existing evidence remains skewed toward large firms, technology-intensive industries, or coastal innovation hubs. Inland regions in China are underrepresented in theory testing, even though they host a large share of SMEs and face distinct constraints related to infrastructure, talent, and institutional support (Boonmee, 2025; Cohen et al., 2021).This imbalance limits the external validity of prevailing AI adoption findings and weakens the policy relevance of recommendations for regions where inclusive digitalization is most challenging. Rresearch directions in AI adoption within SMEs have been rapidly expanding (Kraus et al., 2021).

Sichuan Province provides an analytically meaningful setting because it contains both relatively high-support digital ecosystems (e.g., Chengdu and Mianyang) and areas where SMEs face weaker access to public digital services and AI-related resources. Many Sichuan e-commerce SMEs operate across agricultural products, consumer goods, and lifestyle brands, often depending on platform ecosystems and short-video commerce. In these ecosystems, performance is increasingly AI-mediated: recommendation algorithms, ranking rules, and automated advertising mechanisms determine visibility and engagement, while customer experience is shaped by real-time service quality and content relevance. These conditions make non-financial outcomes central to understanding AI value creation.

This study addresses empirically the following research questions: (1) Which AI-related capabilities most strongly predict the non-financial performance of Sichuan e-commerce SMEs? (2) Does government policy support strengthen the capability–performance relationships? To answer these questions, the paper integrates the Technology–Organization–Environment (TOE) framework with Dynamic Capabilities Theory to develop a capability-oriented model that is both theoretically grounded and managerially actionable.

The paper contributes by (i) moving beyond generic “AI adoption” toward five actionable capability domains; (ii) foregrounding non-financial performance outcomes that capture customer-facing and market-facing value; and (iii) conceptualizing government policy support as a moderator that conditions capability effectiveness within a single inland province.

2 LITERATURE REVIEW AND HYPOTHESES

2.1 Theoretical foundations

The TOE framework explains technology adoption through technological attributes, organizational readiness, and environmental conditions (Tornatzky & Fleischer, 1990; Maroufkhani et al., 2020; Badghish & Soomro, 2024). It is well suited for examining AI in SMEs because adoption depends not only on the technical properties of AI tools (e.g., integration difficulty, reliability, and perceived advantage) but also on organizational preparedness (e.g., leadership support, skills, and IT resources) and on external pressures (e.g., competitive intensity and platform requirements). Adam (2025) relevant for technological readiness and employee skills within the TOE framework.

Dynamic Capabilities Theory complements TOE by explaining why similarly "ready" firms may still achieve different outcomes (Teece et al., 1997; Teece, 2018). In fast-moving e-commerce contexts, firms must sense market signals (platform rule changes, keyword trends, competitor actions, and customer sentiment) and transform routines and resources to seize opportunities quickly(Eisenhardt & Martin, 2000).. AI can accelerate sensing and enable faster transforming, but value creation depends on whether firms build innovation routines and responsiveness mechanisms rather than treating AI as a one-time tool purchase.

Integrating the two theories enables a clear separation between (i) conditions that enable AI use (readiness and pressure) and (ii) capabilities that convert AI use into market-facing outcomes (innovation capability and market responsiveness). This separation helps avoid overly broad constructs and supports a parsimonious, testable model appropriate for SME research and policy evaluation.

2.2 AI technological advantage

AI technological advantage refers to SMEs' perceptions that AI tools provide superior functionality, compatibility, scalability, and usability compared with existing methods. For e-commerce SMEs, perceived advantage often depends on plug-and-play integration with online storefronts, customer relationship management systems, and content pipelines. When AI tools are reliable and easy to integrate, SMEs tends to reduce service friction, provide more consistent customer interactions, and sustain higher platform ratings and repeat purchases (Badghish & Soomro, 2024; Yesuf, 2025).

H1: AI technological advantage is positively associated with SMEs' non-financial performance.

2.3 AI organizational infrastructure

AI organizational infrastructure captures internal readiness for AI deployment, including top management commitment, employee skills, IT resources, data availability, and cross-functional coordination. Because SMEs often operate with limited specialist staff, infrastructure also includes organizational routines that make AI use repeatable (e.g., standard operating procedures for customer-service escalation, content review, and campaign optimization). Strong infrastructure supports more effective use of AI in daily operations, strengthening brand reputation, service quality, and adaptive capacity.

H2: AI organizational infrastructure is positively associated with SMEs' non-financial performance.

2.4 Environmental pressure

Environmental pressure reflects competitive intensity, platform standards, regulatory expectations, and customer demand volatility. In platform-mediated markets, SMEs face continuous pressure to maintain responsiveness, improve content relevance, and meet service expectations. Such pressure can motivate firms to invest in AI-enabled tools for personalization and compliance, thereby improving reputation and perceived professionalism. However, pressure may also expose capability gaps, making it important to test whether it functions as a net driver of performance improvements in resource-constrained inland SMEs.

H3: Environmental pressure is positively associated with SMEs' non-financial performance.

2.5 AI innovation capability

AI innovation capability refers to the firm's capacity to experiment with and implement new AI-enabled products, services, content formats, and marketing campaigns. In e-commerce, innovation can involve iterative improvement of product presentation, rapid testing of promotional messages, and development of new customer engagement formats. AI tends to reduce the time and cost of experimentation, but performance gains depend on whether firms institutionalize experimentation and learning rather than relying on ad hoc efforts (Zahra et al., 2022; Yesuf, 2025).

H4: AI innovation capability is positively associated with SMEs' non-financial performance.

2.6 AI market responsiveness

AI market responsiveness captures the speed and precision with which firms detect market signals and adjust actions through AI analytics. Responsiveness includes rapid pricing and promotion adjustments, timely inventory and assortment changes, and quick customer communication based on real-time feedback. In highly dynamic platform environments, responsiveness is directly linked to visibility and customer retention, making it a central mechanism through which AI contributes to non-financial performance (Rialti et al., 2019; Badghish & Soomro, 2024).

H5: AI market responsiveness is positively associated with SMEs' non-financial performance.

2.7 Moderating role of government policy support

Government policy support tends to reduce SME resource constraints through training programs, subsidies, public digital service platforms, and support for collaboration with universities and technology providers (Helmi & Mughal, 2025; Boonmee, 2025). In inland regions, such support may function as a multiplier by lowering adoption costs and enabling more advanced AI use. Policy support is theorized to strengthen the performance returns of AI-related capabilities by improving access to infrastructure and by legitimizing AI-related investments. At the same time, heterogeneous policy implementation within provinces suggests that support levels may vary across cities and counties, making moderation testing substantively meaningful.

H6a–H6e: Government policy support positively moderates the relationships between each AI-related capability (technological advantage, organizational infrastructure, environmental pressure, innovation capability, and market responsiveness) and non-financial performance, such that the relationships are stronger under higher policy support.

3 METHODOLOGY

3.1 Research design and sampling

The study adopts a quantitative explanatory research design. The unit of analysis is the firm. The target population is e-commerce SMEs operating in Sichuan Province. SMEs are defined as firms with fewer than 300 employees and at least two years of operation, with online channels constituting a primary sales and marketing route. A stratified sampling strategy was used to ensure representation across high-support (Chengdu, Mianyang) and low-support (e.g., Zigong, Leshan) areas, as well as across major sectors such as agri-products, consumer goods, apparel, and electronics (3C).

Data collection was conducted via an online questionnaire distributed through SME registries, industry associations, and entrepreneurial networks. To reduce non-response bias, follow-up contacts (email and phone) and collaboration with local chambers of commerce were implemented. A pilot test with 32 SMEs was conducted to refine item clarity and assess preliminary reliability, resulting in minor adjustments to 4 measurement items (e.g., rephrasing “AI tools are scalable” to “AI tools can be expanded to support business growth”).

The final sample included 286 valid responses (response rate = 34.2%). Sample demographics: sector distribution (agri-products: 27.3%, consumer goods: 35.7%, apparel: 21.3%, electronics: 15.7%); firm age (2–5 years: 42.3%, 6–10 years: 38.8%, >10 years: 18.9%); platform scope (single platform: 58.4%, multi-platform: 41.6%); digital investment intensity (IT spending as % of revenue: <5%: 45.1%, 5–10%: 37.8%, >10%: 17.1%).

3.2 Measures and operationalization

All constructs are modeled as reflective latent variables measured with multi-item Likert scales (1 = strongly disagree; 5 = strongly agree). Measurement items were adapted from prior literature (e.g., Pavlou & El Sawy, 2006; Teece et al., 1997) and customized for e-commerce SMEs in inland China.

Table 1

Construct and Measurement Items

Construct	Items	Code
AI technological advantage	Our AI tools integrate smoothly with our existing e-commerce systems.	TA1
AI technological advantage	AI tools improve service quality compared with prior methods.	TA2
AI technological advantage	AI tools are scalable to support our business growth.	TA3
AI technological advantage	AI tools are easy to use for our team.	TA4
AI organizational infrastructure	Top management actively supports AI-related initiatives.	OI1
AI organizational infrastructure	Employees receive sufficient training to use AI tools effectively.	OI2
AI organizational infrastructure	Our firm has sufficient IT resources to support AI deployment.	OI3
AI organizational infrastructure	We have reliable data sources to power AI applications.	OI4
AI organizational infrastructure	Departments collaborate effectively to implement AI tools.	OI5
Environmental pressure	Competitors’ digital capabilities pressure us to upgrade AI practices.	EP1
Environmental pressure	Platform rules and algorithm changes require frequent adaptation.	EP2
Environmental pressure	Customers expect personalized experiences that AI can provide.	EP3
Environmental pressure	Regulatory requirements push us to adopt AI for compliance (e.g., data security).	EP4
AI innovation capability	We frequently experiment with new AI-enabled marketing content or formats.	IC1

Construct	Items	Code
AI innovation capability	We can translate data insights into new offerings or campaigns quickly.	IC2
AI innovation capability	We regularly test AI-driven product recommendation strategies.	IC3
AI innovation capability	We adapt AI tools to develop unique customer engagement models.	IC4
AI market responsiveness	We adjust prices/promotions rapidly based on AI-supported analytics.	MR1
AI market responsiveness	We respond quickly to customer feedback using AI-supported tools.	MR2
AI market responsiveness	We update product assortments based on AI-predicted demand trends.	MR3
AI market responsiveness	We adjust content strategies in real time using AI analytics.	MR4
Government policy support	Local policies provide accessible support for SME AI adoption (e.g., training/subsidies).	GP1
Government policy support	Policy support is effective in reducing our AI adoption costs or barriers.	GP2
Government policy support	Public digital service platforms help us access AI resources.	GP3
Government policy support	Collaboration programs with universities/tech firms (supported by policies) benefit our AI use.	GP4
Non-financial performance	Customer satisfaction with our online service is high.	NFP1
Non-financial performance	Our brand reputation on platforms has improved in the past 12 months.	NFP2
Non-financial performance	We adapt quickly to market changes compared with key competitors.	NFP3
Non-financial performance	Our platform visibility (traffic/exposure) has improved in the past 12 months.	NFP4
Non-financial performance	We receive positive customer reviews at a higher rate than industry peers.	NFP5

Control variables include firm age (categorical: 1=2–5 years, 2=6–10 years, 3=>10 years), sector (dummy variables: agri-products as reference), platform scope (0=single platform, 1=multi-platform), and digital investment intensity (categorical: 1=<5%, 2=5–10%, 3=>10%). These controls reduce alternative explanations linked to organizational maturity and baseline digital readiness.

3.3 Common method bias and endogeneity considerations

Because the study relies on survey self-reports, procedural and statistical steps were implemented to reduce common method bias (Kock, 2015; Jalil et al., 2024). Procedural remedies included anonymity assurance, careful item wording (avoiding leading questions), and separation of predictor (AI capabilities, environmental pressure, policy support) and criterion (non-financial performance) items in the questionnaire layout (split into two sections with a transition statement).

Statistical checks included full collinearity assessment: variance inflation factor (VIF) values for all constructs ranged from 1.23 to 1.87 (well below the threshold of 3.3), indicating no severe common method bias (Kock, 2015). A marker-variable test (using "perceived industry growth rate" as an unrelated marker) showed that the average variance explained by the marker variable was 2.3% (vs. 42.8% for the focal constructs), confirming minimal bias.

To strengthen causal plausibility, robustness checks included OLS regression with controls and subgroup analyses (high vs. low policy support). Given data limitations, lagged measures were not feasible, but we controlled for firm age and digital investment intensity to account for temporal dynamics in capability development.

3.4 Data analysis strategy

Hypotheses were tested using PLS-SEM (SmartPLS 4.0) due to its suitability for prediction-oriented models with latent constructs, moderate sample sizes, and interaction terms (Ciampi et al., 2021; Jalil et al., 2024). The analysis proceeded as follows: (i) descriptive statistics and correlations; (ii) reliability and validity assessment (Cronbach's alpha, composite reliability [CR], average variance extracted [AVE], discriminant validity via HTMT ratio); (iii) structural model estimation with bootstrapped significance tests (5,000 resamples); (iv) moderation testing via interaction terms (product indicators approach) and multi-group analysis; and (v) robustness checks using OLS regression, multicollinearity diagnostics (VIF), and sensitivity analyses across sectors and platform scope.

4 RESULTS

4.1 Descriptive statistics and correlations

Table 2 presents descriptive statistics (mean, standard deviation) and bivariate correlations for all focal constructs. All constructs exhibit moderate to high mean values (range: 3.12–3.78 on a 5-point scale), indicating that Sichuan e-commerce SMEs perceive moderate levels of AI-related capabilities, environmental pressure, policy support, and non-financial performance. Correlations between focal constructs are positive and significant ($p<0.01$), providing preliminary support for the hypothesized relationships.

Table 2

*Descriptive statistics and correlations (n=286). Notes: **p<0.01 (two-tailed); SD=standard deviation.*

Construct	Mean	SD	1	2	3	4	5	6	7
1. AI Technological Advantage (TA)	3.56	0.72	1.00						
2. AI Organizational Infrastructure (OI)	3.41	0.68	0.63**	1.00					
3. Environmental Pressure (EP)	3.62	0.75	0.58**	0.51**	1.00				
4. AI Innovation Capability (IC)	3.28	0.81	0.67**	0.71**	0.54**	1.00			
5. AI Market Responsiveness (MR)	3.35	0.77	0.70**	0.73**	0.59**	0.78**	1.00		
6. Government Policy Support (GP)	3.12	0.84	0.42**	0.48**	0.39**	0.45**	0.43**	1.00	
7. Non-Financial Performance (NFP)	3.78	0.65	0.69**	0.72**	0.56**	0.76**	0.79**	0.46**	1.00

4.2 Reliability and validity

Table 3 reports reliability and validity metrics for all constructs. Cronbach's alpha values range from 0.82 to 0.91, exceeding the threshold of 0.70, indicating good internal consistency. Composite reliability (CR) values range from 0.87 to 0.93, above the recommended 0.80, confirming strong construct reliability. Average variance extracted (AVE) values range from 0.56 to 0.68, meeting the 0.50 criterion, demonstrating convergent validity (Fornell & Larcker, 1981).

Discriminant validity was assessed using the HTMT (heterotrait-monotrait) ratio. All HTMT values (max range: 0.71–0.83) are below the conservative threshold of 0.85 (Henseler et al., 2015), confirming that constructs are empirically distinct.

Table 3

Reliability and validity

Construct	Items	Alpha	CR	AVE	HTMT (max)
AI Technological Advantage (TA)	4	0.85	0.89	0.58	0.78 (vs. MR)
AI Organizational Infrastructure (OI)	5	0.88	0.91	0.62	0.81 (vs. MR)
Environmental Pressure (EP)	4	0.82	0.87	0.56	0.73 (vs. TA)
AI Innovation Capability (IC)	4	0.89	0.92	0.65	0.83 (vs. MR)
AI Market Responsiveness (MR)	4	0.90	0.93	0.68	0.83 (vs. IC)
Government Policy Support (GP)	4	0.86	0.89	0.59	0.71 (vs. OI)
Non-Financial Performance (NFP)	5	0.87	0.90	0.61	0.79 (vs. MR)

Notes: Alpha=Cronbach’s alpha; CR=composite reliability; AVE=average variance extracted; HTMT=heterotrait-monotrait ratio.

4.3 Structural model results

Table 4 presents the structural path coefficients, t-values, p-values, 95% confidence intervals (CI), and hypothesis decisions. All five AI-related capabilities exhibit positive and significant relationships with non-financial performance, supporting H1–H5.

AI technological advantage (TA): $\beta=0.18$, $t=3.26$, $p<0.01$, CI=[0.07, 0.29] → H1 supportedAI organizational infrastructure (OI): $\beta=0.24$, $t=4.12$, $p<0.001$, CI=[0.13, 0.35] → H2 supported.Environmental pressure (EP): $\beta=0.12$, $t=2.31$, $p<0.05$, CI=[0.02, 0.22] → H3 supported.AI innovation capability (IC): $\beta=0.27$, $t=4.58$, $p<0.001$, CI=[0.16, 0.38] → H4 supported.AI market responsiveness (MR): $\beta=0.31$, $t=5.03$, $p<0.001$, CI=[0.20, 0.42] → H5 supported.

The model explains 68.4% of the variance in non-financial performance ($R^2=0.684$), indicating strong predictive power. Control variables had minimal effects: firm age ($\beta=0.05$, $p=0.23$), sector (agri-products vs. others: $\beta=-0.03$ to 0.07, $p>0.05$), platform scope ($\beta=0.08$, $p=0.11$), and digital investment intensity ($\beta=0.06$, $p=0.18$).

Table 4

Structural paths and hypothesis decisions

Path	Beta	t	p	CI (95%)	Decision
TA → NFP	0.18	3.26	0.001	[0.07, 0.29]	H1 Supported
OI → NFP	0.24	4.12	0.000	[0.13, 0.35]	H2 Supported
EP → NFP	0.12	2.31	0.021	[0.02, 0.22]	H3 Supported
IC → NFP	0.27	4.58	0.000	[0.16, 0.38]	H4 Supported
MR → NFP	0.31	5.03	0.000	[0.20, 0.42]	H5 Supported
Controls (Firm Age)	0.05	1.22	0.223	[-0.03, 0.13]	NS
Controls (Platform Scope)	0.08	1.61	0.108	[-0.01, 0.17]	NS
Controls (Digital Investment)	0.06	1.36	0.175	[-0.02, 0.14]	NS
R^2 (NFP)	0.684				
Q^2 (NFP)	0.421				

Notes: Beta=standardized path coefficient; t=t-value (bootstrapped, 5,000 resamples); p=p-value; CI=confidence interval; NS=not significant; Q^2=Stone-Geisser's Q^2 (values >0 indicate predictive relevance).

4.4 Moderation results

Table 5 presents the moderation effects of government policy support (GP) on the capability–performance relationships. All five interaction terms are positive and significant, supporting H6a–H6e.

TA × GP → NFP: β=0.11, t=2.45, $p<0.05$, CI=[0.02, 0.20] → H6a supported

OI × GP → NFP: β=0.15, t=3.02, $p<0.01$, CI=[0.05, 0.25] → H6b supported

EP × GP → NFP: β=0.09, t=2.18, $p<0.05$, CI=[0.01, 0.17] → H6c supported

IC × GP → NFP: β=0.17, t=3.36, $p<0.001$, CI=[0.07, 0.27] → H6d supported

MR × GP → NFP: β=0.19, t=3.74, $p<0.001$, CI=[0.09, 0.29] → H6e supported

To interpret the moderation effects, we plotted the relationships between each AI capability and non-financial performance at high (1 SD above mean) and low (1 SD below mean) levels of GP (see Figure 1). The plots show that the slopes of the capability–performance relationships are steeper for firms with high GP, indicating that policy support amplifies the positive effects of AI-related capabilities.

Table 4

Moderation results

Interaction	Beta	t	p	CI (95%)	Interpretation
TA × GP → NFP	0.11	2.45	0.015	[0.02, 0.20]	GP strengthens the positive effect of TA on NFP
OI × GP → NFP	0.15	3.02	0.003	[0.05, 0.25]	GP strengthens the positive effect of OI on NFP
EP × GP → NFP	0.09	2.18	0.030	[0.01, 0.17]	GP strengthens the positive effect of EP on NFP
IC × GP → NFP	0.17	3.36	0.001	[0.07, 0.27]	GP strengthens the positive effect of IC on NFP
MR × GP → NFP	0.19	3.74	0.000	[0.09, 0.29]	GP strengthens the positive effect of MR on NFP
ΔR^2 (NFP)	0.072			Additional variance explained by interactions	

Notes: Beta=standardized interaction coefficient; ΔR^2=change in R^2 due to interaction terms (from 0.684 to 0.756).

4.5 Robustness checks

Robustness checks confirmed the stability of the results:

OLS regression: Replicating the model with non-financial performance as a composite score (mean of NFP items) yielded consistent results (all capability coefficients positive and significant, interaction terms positive and significant; R^2=0.652).

Multicollinearity: VIF values for all predictors (including interactions) ranged from 1.31 to 2.14, well below 5.0, indicating no multicollinearity issues.

Sector sensitivity: Subgroup analyses by sector (agri-products vs. non-agri-products) showed consistent path coefficients (β ranges: 0.16–0.33 for capabilities, 0.08–0.20 for interactions), confirming no sector-specific biases.

Platform scope sensitivity: Subgroup analyses by platform scope (single vs. multi-platform) yielded similar results (β ranges: 0.17–0.32 for capabilities, 0.09–0.18 for interactions), indicating the model's generalizability across platform strategies.

5 DISCUSSION AND IMPLICATIONS

5.1 Theoretical implications

The study's findings contribute to the literature on AI adoption and SME performance in several key ways. First, by integrating the TOE framework with Dynamic Capabilities Theory, we provide a nuanced explanation of how structural readiness (AI technological advantage, organizational infrastructure) and adaptive capabilities (innovation capability, market responsiveness) jointly drive non-financial performance. This integration addresses a critical gap in prior research, which often treats AI adoption as a unidimensional construct rather than a set of actionable capabilities.

Second, the results highlight the relative importance of adaptive capabilities (AI innovation capability: β=0.27; AI market responsiveness: β=0.31) compared with structural readiness (technological advantage: β=0.18; organizational infrastructure: β=0.24) and environmental pressure (β=0.12). This finding supports Dynamic Capabilities Theory's emphasis on sensing and transforming as key mechanisms for value creation in dynamic environments (Warner & Wäger, 2019), suggesting that SMEs cannot rely solely on technology adoption or organizational readiness.

Beyond these aggregate findings, this study advances AI adoption research by reconceptualizing AI use in SMEs as a multidimensional capability system rather than a binary adoption decision. Much of the existing literature on AI and SMEs focuses on whether firms adopt AI technologies and whether such adoption improves performance outcomes. While informative, this stream of research tends to overlook substantial heterogeneity in how AI is deployed, routinized, and leveraged within organizations. By decomposing AI-related capabilities into technological advantage, organizational infrastructure, innovation capability, and market responsiveness, this study provides a more fine-grained explanation of why SMEs with similar access to AI tools may experience markedly different performance outcomes. In particular, the empirical distinction between AI innovation capability and AI market responsiveness highlights two analytically distinct but complementary adaptive processes: experimentation-oriented capability building and real-time sensing-and-response. This distinction extends prior TOE-based studies by embedding dynamic capability development directly into the AI adoption framework.

The study further contributes to performance theory in platform-mediated e-commerce contexts by foregrounding non-financial performance as a theoretically meaningful outcome of AI capability deployment. In digital platform ecosystems, metrics such as customer satisfaction, platform visibility, brand reputation, and responsiveness function as leading indicators of competitive positioning and algorithmic favorability, often preceding observable financial returns. Financial outcomes may lag or fluctuate due to platform fee structures, promotional cycles, and competitive intensity, whereas non-financial outcomes more directly reflect firms' adaptive alignment with platform rules and customer expectations. By demonstrating that AI-related capabilities explain a substantial proportion of variance in these non-financial outcomes, the findings suggest that the performance effects of AI adoption should be evaluated through customer-facing and market-facing metrics rather than short-term financial indicators alone. This perspective aligns performance measurement with the logic of algorithm-driven marketplaces and complements existing SME performance research.

Finally, the moderation results extend policy-oriented innovation research by positioning government policy support as a capability multiplier rather than merely an external facilitator of technology adoption. Existing studies often conceptualize policy support as a direct antecedent of AI adoption or as a background condition that lowers adoption costs. The present findings refine this view by showing that policy support systematically strengthens the conversion of AI-related capabilities into performance outcomes. In other words, public interventions influence not only whether SMEs adopt AI, but also how effectively they transform AI-related resources into adaptive actions and market-facing results. This effect is particularly salient for adaptive capabilities such as innovation capability and market responsiveness, suggesting that policies targeting training, collaboration, and access to shared digital infrastructure are especially effective in enhancing SMEs' dynamic capabilities. By integrating policy support into a capability-based explanation of AI value creation, this study offers a more granular theoretical account of inclusive digital transformation in resource-constrained inland regions.

Third, the moderation results confirm that government policy support acts as a "capability multiplier," strengthening the performance returns of all five AI-related capabilities. This extends prior research on policy support as a direct driver of AI adoption (e.g., Zhang et al., 2022) by showing that policy support also enhances the effectiveness of existing capabilities, particularly for resource-constrained inland SMEs. The finding that policy support has the strongest moderating effect on AI market responsiveness ($\beta=0.19$) and innovation capability ($\beta=0.17$) suggests that policies targeting training, collaboration, and resource access are particularly effective at enabling adaptive behaviors.

5.2 Managerial implications

For e-commerce SMEs in inland China and similar resource-constrained contexts, the findings offer actionable insights:

Prioritize adaptive capabilities: SMEs should invest in AI innovation (e.g., experimenting with AI-driven marketing content) and market responsiveness (e.g., real-time pricing adjustments via AI analytics), as these capabilities have the strongest direct effects on non-financial performance.

Build complementary structural readiness: To maximize the value of adaptive capabilities, SMEs should ensure AI tools are integrated smoothly with existing systems (technological advantage) and that employees have the skills and resources to use AI effectively (organizational infrastructure).

Leverage policy support: SMEs should actively engage with government initiatives such as training programs, subsidies, and public digital service platforms. The moderation results show that these policies amplify the impact of all AI-related capabilities, making them a cost-effective way to enhance performance.

Diagnose performance gaps: When non-financial performance is weak despite high environmental pressure, SMEs should assess their organizational infrastructure (e.g., employee training, cross-functional coordination). When infrastructure is strong but performance gains are limited, the focus should shift to innovation routines and responsiveness mechanisms.

5.3 Policy implications

The findings have important implications for policymakers aiming to promote inclusive digital transformation in inland regions:

Targeted support for adaptive capabilities: Policies should prioritize programs that enhance AI innovation and market responsiveness, such as innovation vouchers, collaboration grants with technology providers, and real-time data access initiatives.

Strengthen structural readiness: Training subsidies and IT resource grants can help SMEs build organizational infrastructure, while standards for AI tool compatibility can improve technological advantage.

Address regional heterogeneity: Given the variation in policy access across Sichuan's cities and counties, policymakers should expand outreach to low-support areas (e.g., Zigong, Leshan) through mobile training programs and online policy portals.

Measure non-financial outcomes: Policy evaluations should include non-financial metrics (e.g., customer satisfaction, platform visibility) alongside financial indicators, as these are early signals of sustained competitiveness for SMEs.

6 CONCLUSION

This study develops and empirically tests a capability-oriented model linking five AI-related capability domains to the non-financial performance of e-commerce SMEs in Sichuan Province, China. By integrating the TOE framework with Dynamic Capabilities Theory and positioning government policy support as a moderator, the study provides a policy-sensitive explanation of inclusive digital transformation in resource-constrained inland contexts.

The results confirm that both structural readiness (AI technological advantage, organizational infrastructure) and adaptive capabilities (AI innovation capability, market responsiveness) are critical drivers of non-financial performance, with environmental pressure acting as a supplementary driver. Government policy support strengthens all capability–performance relationships, highlighting its role as a key enabler of AI value creation for SMEs.

Limitations of the study include the cross-sectional design (which limits causal inference), reliance on self-reported data, and focus on a single province. Future research should use longitudinal designs to capture temporal dynamics in capability development and performance, incorporate objective metrics (e.g., platform ratings, traffic data), and extend the model to other inland provinces for cross-regional comparison.

Notwithstanding these limitations, the study provides meaningful insights for managers, policymakers, and researchers interested in AI adoption and SME performance in emerging digital economies. By focusing on actionable capabilities and policy-sensitive mechanisms, the findings provide a foundation for inclusive digital transformation that can be adapted to other resource-constrained contexts worldwide.

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APPENDIX

Appendix A

Measurement Items

All items are measured on a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree).

Construct	Items	Code
AI technological advantage	Our AI tools integrate smoothly with our existing e-commerce systems.	TA1
AI technological advantage	AI tools improve service quality compared with prior methods.	TA2
AI technological advantage	AI tools can be expanded to support business growth.	TA3

AI technological advantage	AI tools are easy to use for our team.	TA4
AI organizational infrastructure	Top management actively supports AI-related initiatives.	OI1
AI organizational infrastructure	Employees receive sufficient training to use AI tools effectively.	OI2
AI organizational infrastructure	Our firm has sufficient IT resources to support AI deployment.	OI3
AI organizational infrastructure	We have reliable data sources to power AI applications.	OI4
AI organizational infrastructure	Departments collaborate effectively to implement AI tools.	OI5
Environmental pressure	Competitors' digital capabilities pressure us to upgrade AI practices.	EP1
Environmental pressure	Platform rules and algorithm changes require frequent adaptation.	EP2
Environmental pressure	Customers expect personalized experiences that AI can provide.	EP3
Environmental pressure	Regulatory requirements push us to adopt AI for compliance (e.g., data security).	EP4
AI innovation capability	We frequently experiment with new AI-enabled marketing content or formats.	IC1
AI innovation capability	We can translate data insights into new offerings or campaigns quickly.	IC2
AI innovation capability	We regularly test AI-driven product recommendation strategies.	IC3
AI innovation capability	We adapt AI tools to develop unique customer engagement models.	IC4
AI market responsiveness	We adjust prices/promotions rapidly based on AI-supported analytics.	MR1
AI market responsiveness	We respond quickly to customer feedback using AI-supported tools.	MR2
AI market responsiveness	We update product assortments based on AI-predicted demand trends.	MR3
AI market responsiveness	We adjust content strategies in real time using AI analytics.	MR4
Government policy support	Local policies provide accessible support for SME AI adoption (e.g., training/subsidies).	GP1
Government policy support	Policy support is effective in reducing our AI adoption costs or barriers.	GP2
Government policy support	Public digital service platforms help us access AI resources.	GP3
Government policy support	Collaboration programs with universities/tech firms (supported by policies) benefit our AI use.	GP4
Non-financial performance	Customer satisfaction with our online service is high.	NFP1
Non-financial performance	Our brand reputation on platforms has improved in the past 12 months.	NFP2

Non-financial performance	We adapt quickly to market changes compared with key competitors.	NFP3
Non-financial performance	Our platform visibility (traffic/exposure) has improved in the past 12 months.	NFP4
Non-financial performance	We receive positive customer reviews at a higher rate than industry peers.	NFP5

Authors' Contribution

All authors contributed to the study design, data analysis, manuscript preparation, and final approval of the submitted version.

Data availability

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

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