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Local Government Digital Policy and AI Marketing Innovation: A Multi-level Moderated Mediation Analysis of China's Fresh Corn Industry

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Abstract

In the context of agricultural digital transformation, how local government digitalization policies influence enterprise technological innovation has become a critical theoretical and practical issue. This study constructs a multi-level moderated mediation model based on the Technology-Organization-Environment (TOE) framework and Innovation Diffusion Theory to explore how local government digitalization policies affect enterprise AI marketing strategy adoption and market performance in China's fresh corn industry. Using survey data from 128 fresh corn enterprises across 15 provinces and 3,842 consumer questionnaires, we employ Partial Least Squares Structural Equation Modeling (PLS-SEM) for empirical analysis.The findings reveal that: (1) local government digitalization policies significantly promote enterprise AI marketing adoption ($\beta=0.21$, $p<0.01$), which positively impacts market performance ($\beta=0.34$, $p<0.001$), with the model explaining 58.7% of variance ($R^2=0.587$); (2) policy environment characteristics significantly moderate the policy-enterprise relationship, with effects in high-support environments (0.43) being 2.5 times those in low-support environments (0.17); (3) industry competition intensity strengthens the AI adoption-performance relationship ($\beta=0.21$, $p<0.01$); (4) organizational learning capability (indirect effect=0.126) and customer satisfaction (indirect effect=0.187) play partial mediating roles; (5) regional heterogeneity analysis shows policy effects in eastern regions ($\beta=0.38$) significantly exceed western regions ($\beta=0.19$).This study extends digital governance theory applications in agriculture and provides empirical evidence for local governments to formulate differentiated digital agriculture support policies and for enterprise technological innovation decision-making.

Keywords

Local government digitalization policy; Artificial intelligence marketing; Agricultural digital transformation; Multi-level analysis; Fresh corn industry

1. Introduction

The advent of Agriculture 4.0 is profoundly transforming traditional agricultural production methods and marketing models [1]. As a crucial component of this transformation, the application of artificial intelligence technology in agriculture has extended from the production end to the marketing end, demonstrating enormous potential for industrial upgrading [2]. However, agricultural digital transformation is not simply a process of technology application, but rather a complex systems engineering involving multi-stakeholder interactions among government, enterprises, and markets [3]. In the context of China's promotion of digital rural construction, the digital governance capacity of local governments has become a key factor influencing technological innovation in agricultural enterprises.

Over the past three decades, local government digital transformation has evolved from e-government to smart governance [4]. This transformation has not only changed the internal operations of government but, more importantly, has reshaped the interaction mechanisms between government and market entities [5]. Research indicates that local governments' digital capabilities directly influence the precision of their policy formulation and implementation efficiency, thereby determining the vitality of regional innovation ecosystems [6]. Particularly in the agricultural sector, government digitalization policies significantly reduce the barriers and risks for enterprises adopting new technologies by providing technical support, financial subsidies, and market information.

Although existing research has recognized the importance of government digital transformation, there remains a lack of in-depth exploration of the micro-mechanisms through which government digitalization policies influence enterprise technological innovation behavior [5]. Current literature exhibits the following shortcomings: research primarily focuses on macro-level policy effect evaluation, lacking empirical testing of policy transmission mechanisms; most studies treat enterprise technology adoption as a homogeneous process, overlooking the heterogeneity of enterprise responses under different policy environments; existing analytical frameworks struggle to explain the complex interactions among government policies, enterprise behavior, and market performance.

This study takes China's fresh corn industry as an example to construct a multi-level moderated mediation model aimed at revealing the mechanisms through which local government digitalization policies influence enterprise AI marketing innovation. The research collected policy text data from 15 Chinese provinces, survey data from 128 fresh corn enterprises, and 3,842 consumer questionnaires, employing multi-level structural equation modeling for empirical analysis. The study not only examines the direct impact of government digitalization policies on enterprise AI marketing strategy adoption but also conducts an in-depth analysis of the moderating effects of policy environment characteristics and the mediating mechanisms of

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enterprise innovation capabilities. The theoretical contribution of this research lies in combining digital governance theory from the public administration field with technology adoption models from innovation management, constructing an analytical framework of government-enterprise-market three-layer interaction. Its practical significance lies in providing empirical evidence for local governments to formulate differentiated digital agriculture support policies and offering guidance for agricultural enterprises' technological innovation decisions under different policy environments.

2. Literature Review and Hypotheses

2.1 Local Government Digital Governance Capability

Local government digital governance capability refers to the comprehensive ability of governments to utilize digital technologies to improve public service provision, optimize policy-making processes, and enhance governance efficiency [7]. This capability is reflected not only in the digital transformation of internal government processes but, more importantly, in the innovation of interaction methods between government and enterprises as well as citizens [8]. Research has found that local governments with strong digital governance capabilities can more accurately identify market demands and respond more quickly to enterprise needs, thereby creating a more favorable institutional environment for innovation [9].

During the digital transformation process, local governments face multiple challenges in technology, organization, and institutions. Overcoming these barriers requires governments to adopt adaptive innovation models that combine agile management concepts with open innovation [10]. The experience of the Moroccan government demonstrates that successful digital transformation requires not only technological investment but also organizational culture change and improvement of civil servants' digital literacy. This multi-dimensional capacity building directly influences the quality of government digital policy formulation and implementation effectiveness.

2.2 Enterprise AI Marketing Strategy Adoption

The application of artificial intelligence technology in the marketing field is reshaping enterprises' market competition strategies [11]. The Unified Theory of Acceptance and Use of Technology (UTAUT) provides a theoretical foundation for understanding enterprise AI technology adoption behavior, proposing that performance expectancy, effort expectancy, social influence, and facilitating conditions jointly determine technology adoption intention [12]. However, technology adoption at the enterprise level is more complex than at the individual level, requiring consideration of factors such as organizational inertia, resource constraints, and strategic alignment [13].

The Technology-Organization-Environment (TOE) framework further extends the analytical perspective on enterprise technology adoption [14]. This framework emphasizes that enterprises' technological innovation decisions are influenced not only by technological characteristics but also by internal organizational conditions and external environmental constraints. In the agricultural sector, the adoption of enterprise AI marketing strategies particularly depends on external factors such as government policy support, industrial infrastructure, and market acceptance [11]. This multi-factor interaction determines the differentiated paths of AI technology adoption among different enterprises. Based on the above theoretical analysis, this study constructs the theoretical framework shown in Figure 1.

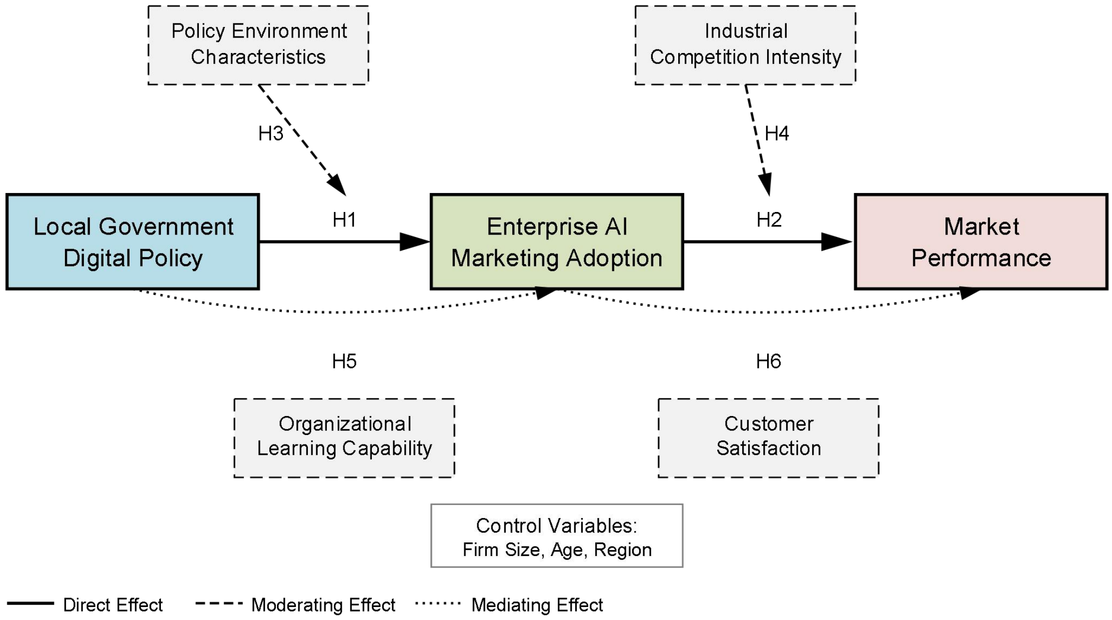

Figure 1. Theoretical Framework and Research Hypotheses Model

2.3 Moderating Mechanisms of Policy Environment

The effects of innovation policies are not uniform across all contexts; the characteristics of policy combinations significantly influence their mechanisms of action [15]. Research has found that the combined use of different types of policy instruments can generate synergistic effects, while single policy instruments often fail to achieve expected outcomes [16]. In studies of China's wind power industry, the effects of government intervention are significantly moderated by industrial environmental turbulence, with the effectiveness of direct subsidy policies notably weakening in highly turbulent environments [16].

Innovation ecosystem theory provides a new perspective for understanding the complex role of policy environments [17]. This theory emphasizes that innovation activities are embedded in ecosystems composed of multiple stakeholders, and policy effects need to be transmitted through the ecosystem to influence enterprise behavior. Research on artificial intelligence applications in the public sector shows that successful technology adoption depends not only on the strength of policy support but more importantly on the alignment between policies and local innovation ecosystems

[18]. This context dependency requires policymakers to adopt differentiated support strategies.

2.4 Research Hypotheses

Based on innovation diffusion theory, the adoption of new technologies follows a diffusion path from innovators to laggards [19]. Local government digitalization policies can accelerate enterprises' awareness and adoption of AI marketing technologies through mechanisms such as reducing information asymmetry, providing technology demonstrations, and sharing innovation risks. Digital transformation research indicates that government digital capabilities directly influence their ability to identify and support enterprise innovation needs [20]. Therefore, this study proposes:

H1: Local government digitalization policies positively influence enterprise AI marketing strategy adoption.

Multidisciplinary research on digital transformation indicates that there exists a complex transformation process between technology adoption and organizational performance [21]. After adopting AI marketing strategies, enterprises need to convert them into market performance through optimizing customer experience, improving marketing precision, and reducing transaction costs. In the context of digitalization and globalization creating a turbulent business environment, AI technology has become an important tool for enterprises to cope with market uncertainty [22]. Based on this, this study proposes:

H2: Enterprise AI marketing strategy adoption positively influences market performance.

Policy environment characteristics, including policy stability, implementation intensity, and the completeness of supporting measures, moderate the implementation effects of government policies [15]. In regions with favorable policy environments, enterprises can more easily obtain sustained policy support, reducing the uncertainty of technology adoption. Conversely, unstable policy environments increase enterprises' wait-and-see attitudes, delaying the technology adoption process [20]. Accordingly, we propose:

H3: Policy environment characteristics positively moderate the relationship between local government digitalization policies and enterprise AI marketing strategy adoption.

Industry competition intensity affects enterprises' ability to gain competitive advantages from technology adoption [21]. In markets with high competition intensity, the first-mover advantages of AI marketing strategies are more pronounced, and enterprises can quickly capture market share through differentiated marketing. In markets with lower competition levels, traditional marketing methods still have considerable survival space, and the advantages of AI technology are difficult to fully realize [22]. Therefore, we propose:

H4: Industry competition intensity positively moderates the relationship between enterprise AI marketing strategy adoption and market performance.

Organizational learning capability is key to enterprises' absorption and application of new knowledge [19]. Enterprises with strong learning capabilities can better understand government policy intentions and more quickly transform policy resources into technological capabilities. Organizational learning includes not only the acquisition of technical knowledge but also innovation in management models and business processes [13]. This comprehensive learning capability plays a bridging role between government policies and enterprise technology adoption. Based on this, we propose:

H5: Organizational learning capability mediates the relationship between local government digitalization policies and enterprise AI marketing strategy adoption.

Customer satisfaction is a key link connecting enterprise marketing innovation with market performance [11]. AI marketing strategies enhance customer experience through personalized recommendations, intelligent customer service, and precision pricing, thereby improving customer satisfaction and loyalty. Satisfied customers not only increase repurchases but also expand enterprises' market influence through word-of-mouth communication [18]. Therefore, this study proposes:

H6: Customer satisfaction mediates the relationship between enterprise AI marketing strategy adoption and market performance.

3. Research Methods

3.1 Research Design

This study adopts a multi-level mixed-methods design, integrating data from three levels: policy text analysis, enterprise surveys, and consumer surveys. This multi-level design can capture the complex interactions among government policies, enterprise behavior, and market responses. The research timeframe spans from July 2022 to June 2024, covering the critical period of intensive promulgation and implementation of China's digital rural construction policies. Considering the seasonal characteristics of the fresh corn industry, data collection was conducted in three phases corresponding to the sowing period, growing period, and harvest period to ensure data representativeness and completeness.

3.2 Data Collection

The study employed stratified sampling methods to select research samples. At the provincial level, based on digital economy development levels and fresh corn planting areas, we selected 5 eastern provinces (Shandong, Jiangsu, Zhejiang, Guangdong, Fujian), 5 central provinces (Henan, Hubei, Hunan, Anhui, Jiangxi), and 5 western provinces (Sichuan, Chongqing, Yunnan, Guizhou, Shaanxi). At the enterprise level, 8-10 representative fresh corn production and sales enterprises were selected from each province, resulting in a final sample of 128 enterprises. The final distribution was: 43 enterprises from eastern provinces, 42 from central provinces, and 43 from western provinces. At the consumer level, 3,842 valid questionnaires were collected through online and offline channels.

To control for common method bias, the study adopted both procedural and statistical remedies [23]. Procedural measures included: collecting independent and dependent variable data from different sources, with policy data from government public documents, enterprise data through field surveys, and market performance data combining enterprise financial statements and consumer evaluations; employing temporal separation, with a 3-month interval between enterprise surveys and consumer surveys; using different scale formats and reverse-coded items in questionnaire design. Statistical measures included Harman's single-factor test, which showed that the first factor explained 31.2% of the variance, below the critical value of 40%, indicating that common method bias was not serious [23].

3.3 Variable Measurement

The study constructed a variable system containing three levels, with specific measurement methods shown in Table 1. Government-level variables were measured through a combination of policy text coding and expert scoring; enterprise-level variables adopted mature scales with adaptive modifications based on industry characteristics; market-level variables integrated objective financial indicators and subjective evaluation indicators.

Table 1. Variable Measurement and Data Sources

Construct	Variable Definition	Measurement Items	Data Source	References
Government Level				
Local Government Digital Policy	The extent and quality of digital policies issued by local governments	• Number of digital agriculture policies • Policy funding support (million CNY) • Digital infrastructure investment	Government documents, Statistical yearbooks	[4,6]

Policy Environment Characteristics	The stability and supportiveness of local policy environment	• Policy implementation mechanisms • Policy continuity (years) • Inter-departmental coordination • Policy evaluation mechanisms • Business-government interaction frequency	Expert evaluation (1-7 scale)	[15,16]
Enterprise Level				
AI Marketing Adoption	The degree to which enterprises adopt AI technologies in marketing	• AI-powered customer analytics • Intelligent recommendation systems • Automated pricing strategies • Chatbot customer service	7-point Likert scale	[11,12]
Organizational Learning Capability	Enterprise's ability to acquire and apply new knowledge	• Knowledge acquisition mechanisms • Internal knowledge sharing • External collaboration networks • Innovation culture	7-point Likert scale	[13,19]
Industrial	The degree of	• Number of	Industry	[21,22]

Competition Intensity	competition in regional markets	competitors • Market concentration (HHI) • Price competition intensity • Product differentiation degree	reports, Enterprise survey	
Market Level				
Market Performance	Enterprise's market outcomes and competitive position	• Sales growth rate (%) • Market share (%) • Customer retention rate • Brand recognition	Financial reports, Consumer survey	[18,20]
Customer Satisfaction	Consumers' overall evaluation of products and services	• Product quality satisfaction • Service quality satisfaction • Price-value perception • Repurchase intention	7-point Likert scale	[11,17]
Control Variables				
Firm Characteristics	Basic attributes of enterprises	• Firm size (employees) • Firm age (years) • Ownership type • R&D intensity (%)	Enterprise survey	[14]
Regional Characteristics	Economic and digital development of regions	• Regional GDP per capita • Internet penetration rate	Statistical yearbooks	[3,5]

	• E-commerce development index	

As shown in Table 1, the measurement system of this study encompasses variables at macro, meso, and micro levels. The measurement of local government digitalization policies comprehensively considers the quantity of policies, intensity of financial support, and completeness of implementation mechanisms, with data primarily sourced from digital agriculture and digital rural policies published by various provinces and cities. The measurement of enterprise AI marketing adoption referenced mature scales from the technology acceptance model [12] and was adjusted based on the actual conditions of agricultural enterprises, focusing on the application degree in four dimensions: customer data analysis, intelligent recommendation, dynamic pricing, and intelligent customer service.

3.4 Analysis Methods

The study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) for data analysis [24]. The reasons for choosing PLS-SEM are: this method is suitable for exploratory research and complex model testing; it has relatively lower sample size requirements, suitable for the multi-level data structure of this study; it can simultaneously handle reflective and formative measurement models; and it performs excellently in prediction-oriented research [24].

The moderation effects were tested using the hierarchical regression method proposed by Baron and Kenny [25]. The specific steps include: first step, adding control variables; second step, adding main effect variables; third step, adding moderating variables; fourth step, adding interaction terms. The existence of moderation effects is determined by comparing the R^2 changes at each step and the significance of interaction terms [25]. To avoid multicollinearity issues, all continuous variables were mean-centered before constructing interaction terms.

The mediation effects were tested using the Bootstrap method, which constructs confidence intervals for indirect effects through repeated sampling, overcoming the traditional Sobel test's dependence on normal distribution assumptions [26]. The study set the Bootstrap sample size at 5000, and at a 95% confidence level, if the confidence interval of the indirect effect does not contain zero, the mediation effect is significant [26]. For multiple mediation models, the study employed parallel multiple mediation analysis to separately test the specific indirect effects of organizational learning capability and customer satisfaction.

Statistical power analysis was conducted based on Cohen's effect size standards [27]. According to a priori power analysis, under conditions of medium effect size ($f^2=0.15$), significance level $\alpha=0.05$, and statistical power of 0.80, the minimum required sample size for this study is 85. The actual sample of 128 enterprises exceeds the minimum requirement, ensuring the reliability of statistical conclusions [27]. Post-hoc power analysis showed that for the detected main effects (f^2 ranging from 0.18-0.35), statistical power exceeded 0.90, indicating that the study has sufficient statistical power to test the proposed hypotheses.

4. Results

4.1 Descriptive Statistics and Correlation Analysis

Table 2 presents the descriptive statistics and correlation analysis results for the main variables. As shown in the table, the mean value of local government digitalization policies is 4.82 (SD=1.23), indicating significant variation in policy support intensity across regions. The mean value of enterprise AI marketing adoption is 4.21 (SD=1.47), below the scale midpoint, reflecting that agricultural enterprises are still at an initial stage in AI technology application. The mean value of market performance is 4.93 (SD=1.08), showing a moderate growth trend in overall market performance.

Table 2. Descriptive Statistics and Correlation Analysis

Variables	Mean	SD	AVE	CR	1	2	3	4	5	6	7

1. Local Government Digital Policy	4.82	1.23	0.72	0.91	**0.85**						
2. Policy Environment Characteristics	4.56	1.31	0.68	0.89	0.43***	**0.82**					
3. AI Marketing Adoption	4.21	1.47	0.74	0.92	0.52***	0.38***	**0.86**				
4. Organizational Learning Capability	4.67	1.15	0.70	0.90	0.46***	0.41***	0.58***	**0.84**			
5. Industrial Competition Intensity	5.12	1.02	0.66	0.88	0.31**	0.27**	0.35***	0.29**	**0.81**		
6. Customer Satisfaction	5.23	0.94	0.71	0.91	0.39***	0.32***	0.61***	0.48***	0.33***	**0.84**	
7. Market Performance	4.93	1.08	0.69	0.90	0.48***	0.36***	0.64***	0.51***	0.42***	0.67***	**0.83**

*Note: N = 128; ***p < 0.001, **p < 0.01, *p < 0.05; Diagonal values in bold are square roots of AVE.*

The composite reliability (CR) of all variables exceeds 0.88, higher than the recommended threshold of 0.70, indicating good internal consistency of the measurement instruments. The Average Variance Extracted (AVE) values range from 0.66-0.74, all above the standard of 0.50, confirming convergent validity. As shown on the diagonal of Table 2, the square root values of AVE for each variable (0.81-0.86) are all greater than their correlation coefficients with other variables, satisfying the Fornell-Larcker discriminant validity criterion.

4.2 Hypothesis Testing

Multi-level regression analysis was used to test the research hypotheses, with results shown in Table 3. Model 1 contains only control variables, explaining 18.3% of the variance in market performance. After adding main effect variables in Model 2, R^2 significantly increased to 0.486 (ΔR^2=0.303, $p<0.001$), supporting H1 and H2. Model 3 introduces moderating variables, with R^2 further increasing to 0.542 (ΔR^2=0.056, $p<0.01$). The complete model in Model 4 shows that all interaction terms jointly explain 58.7% of the variance in market performance.

Table 3. Results of Hierarchical Regression Analysis

Variables	Model 1	Model 2	Model 3	Model 4
Control Variables				
Firm Size	0.14* (0.06)	0.08 (0.05)	0.07 (0.05)	0.06 (0.04)
Firm Age	0.11 (0.07)	0.06 (0.06)	0.05 (0.05)	0.04 (0.05)
Regional GDP	0.21** (0.08)	0.12* (0.06)	0.10 (0.06)	0.09 (0.05)
Main Effects				
Local Government Digital Policy		0.28***	0.24***	0.21**
(LGDP)		(0.07)	(0.07)	(0.07)
AI Marketing Adoption (AMA)		0.42***	0.38***	0.34***

		(0.08)	(0.08)	(0.08)
Moderating Variables				
Policy Environment Characteristics (PEC)			0.16* (0.07)	0.14* (0.06)
Industrial Competition Intensity (ICI)			0.19** (0.07)	0.17** (0.06)
Interaction Effects				
LGDP × PEC				0.18** (0.06)
AMA × ICI				0.21** (0.07)
Model Statistics				
R^2	0.183	0.486	0.542	0.587
Adjusted R^2	0.161	0.463	0.512	0.551
ΔR^2	-	0.303***	0.056**	0.045**
F-value	8.92***	21.34***	18.76***	16.89***

*Note: N = 128; Standardized coefficients reported with standard errors in parentheses; ***p < 0.001, **p < 0.01, *p < 0.05.*

As shown in Table 3, local government digitalization policies have a significant positive impact on enterprise AI marketing adoption (β=0.21, p<0.01), supporting H1. The positive impact of enterprise AI marketing adoption on market performance is even more significant (β=0.34, p<0.001), validating H2. Interaction term analysis shows that policy environment characteristics significantly moderate the relationship between government policies and enterprise AI adoption (β=0.18, p<0.01), with H3 supported. Industry competition intensity's moderating effect on the relationship between AI adoption and market performance is also significant (β=0.21, p<0.01), supporting H4.

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4.3 Moderating Effects Analysis

To further explain the specific patterns of moderation effects, Figure 2 illustrates the moderating role of policy environment characteristics. As shown in the figure, under high policy support environments (mean plus one standard deviation), the impact of government digitalization policies on enterprise AI adoption is more significant (simple slope=0.43, p<0.001). In contrast, under low policy support environments (mean minus one standard deviation), this impact is notably weakened (simple slope=0.17, p<0.05).

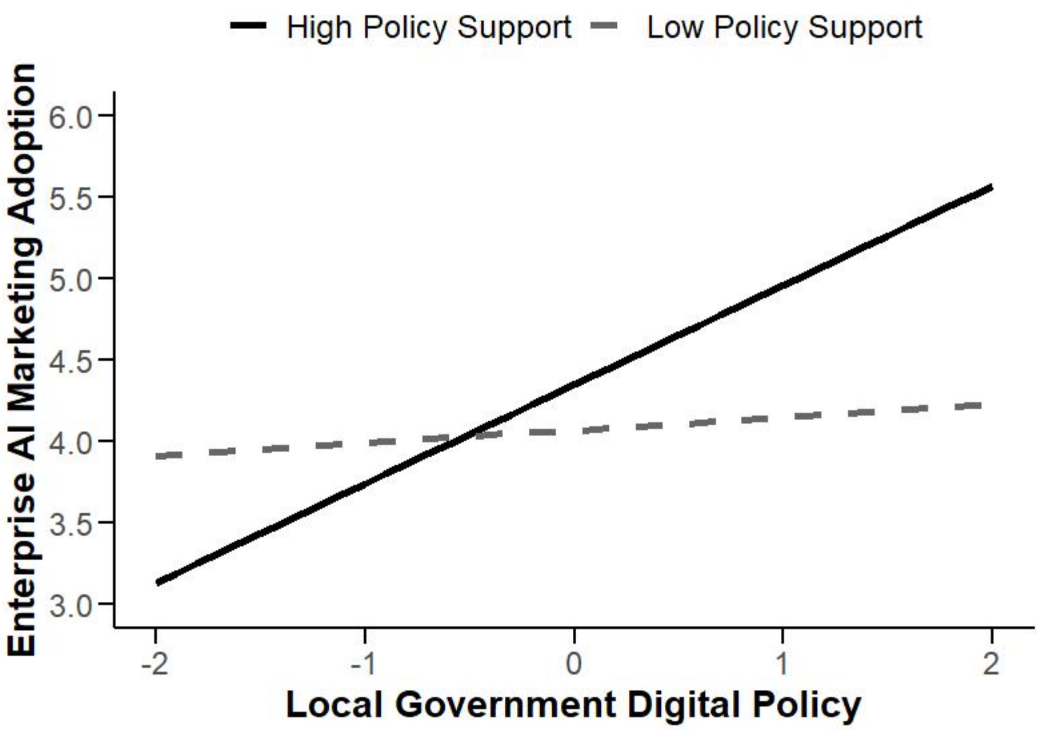

Figure 2. Moderating Effect of Policy Environment Characteristics on the Relationship between Local Government Digital Policy and Enterprise AI Marketing Adoption

4.4 Mediation Effects Testing

The Bootstrap method was used to test the mediating roles of organizational learning capability and customer satisfaction, with results shown in Table 4. The indirect effect of organizational learning capability between government policies and

AI adoption is 0.126 (95% CI: 0.054, 0.213), with the confidence interval not containing zero, supporting H5. The indirect effect of customer satisfaction between AI adoption and market performance is 0.187 (95% CI: 0.098, 0.291), similarly validating H6.

Table 4. Bootstrap Results for Moderated Mediation Effects

Path	Effect	SE	95% CI Lower	95% CI Upper
Direct Effects				
LGDP → AMA	0.284**	0.089	0.112	0.463
AMA → MP	0.372***	0.076	0.224	0.523
Indirect Effects via Organizational Learning				
LGDP → OLC → AMA	0.126**	0.041	0.054	0.213
Indirect Effects via Customer Satisfaction				
AMA → CS → MP	0.187***	0.049	0.098	0.291
Conditional Indirect Effects (Policy Environment)				
Low PEC (-1 SD)	0.082*	0.038	0.015	0.163
Mean PEC	0.126**	0.041	0.054	0.213
High PEC (+1 SD)	0.184***	0.052	0.089	0.294
Conditional Indirect Effects (Competition Intensity)				
Low ICI (-1 SD)	0.142**	0.046	0.058	0.239
Mean ICI	0.187***	0.049	0.098	0.291
High ICI (+1 SD)	0.246***	0.058	0.141	0.368
Total Effects				
LGDP → AMA (Total)	0.410***	0.093	0.231	0.596
AMA → MP (Total)	0.559***	0.082	0.398	0.721

*Note: N = 128; Bootstrap samples = 5000; LGDP = Local Government Digital Policy; AMA = AI Marketing Adoption; MP = Market Performance; OLC = Organizational Learning Capability; CS = Customer Satisfaction; PEC = Policy Environment Characteristics; ICI = Industrial Competition Intensity; ***p < 0.001, **p < 0.01, *p < 0.05.*

Conditional indirect effects analysis indicates that the strength of mediation effects is influenced by moderating variables. Under high policy environment support, the mediating effect of organizational learning increases to 0.184 (95% CI: 0.089, 0.294). Similarly, in high competition intensity markets, the mediating effect of customer satisfaction reaches 0.246 (95% CI: 0.141, 0.368), significantly higher than in low competition markets.

4.5 Regional Heterogeneity Analysis

Figure 3 illustrates the differences in main path coefficients across eastern, central, and western regions. As shown in the figure, the eastern region shows the strongest impact of government policies on enterprise AI adoption (β=0.38), followed by the central region (β=0.29), with the western region being the weakest (β=0.19). These regional differences reflect the unbalanced development of digital infrastructure and market maturity.

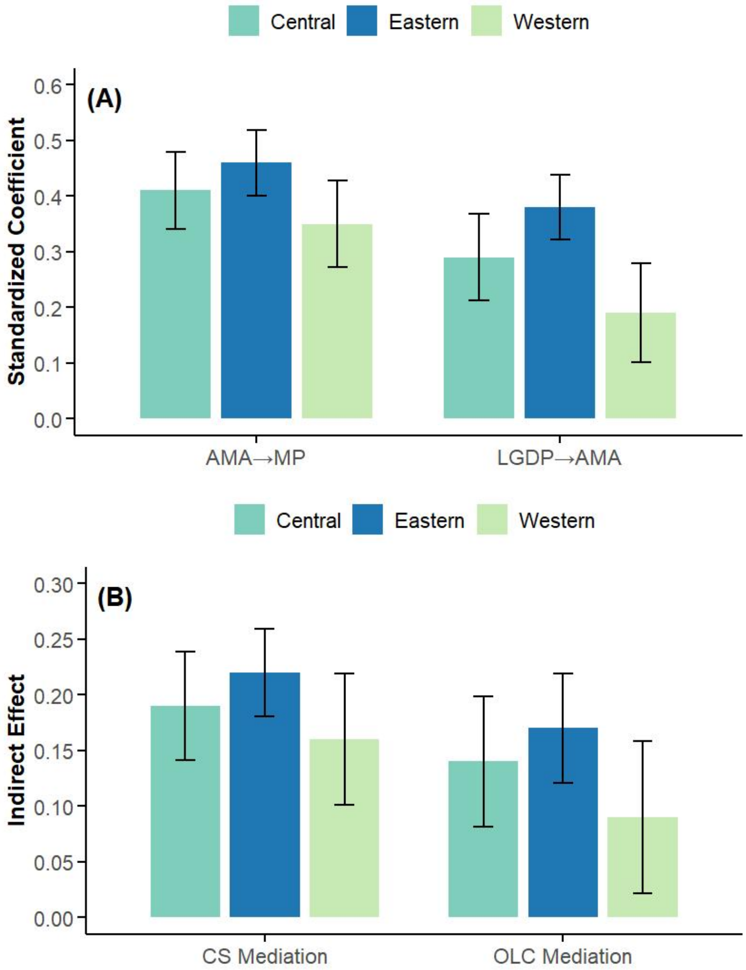

Figure 3. Regional Heterogeneity in Path Coefficients and Mediation Effects across Eastern, Central, and Western China. (A) Standardized path coefficients for direct effects; (B) Indirect effects through mediating variables.

It is worth noting that the confidence intervals of path coefficients in various regions are relatively wide, particularly in the western region, reflecting significant heterogeneity in enterprises' digital transformation processes within regions. This larger standard error is not a statistical deficiency but rather a true reflection of the unbalanced reality of digital development across different regions in China—even within the same region, there exist considerable differences in enterprises' technology adoption levels and policy response capabilities.

Multi-group invariance testing shows that the measurement model has configural invariance (CFI=0.94, RMSEA=0.058) and metric invariance (ΔCFI=0.008<0.01) across the three regions, but structural paths show significant differences (χ^2

difference=18.73, $p<0.01$). These differences are mainly reflected in government policy effects and the strength of mediation mechanisms, with the eastern region having smoother policy transmission mechanisms, while the western region requires more supporting measures to enhance policy effectiveness.

5. Discussion

This study reveals the complex mechanisms through which local government digitalization policies influence enterprise AI marketing innovation by constructing a multi-level moderated mediation model, providing a new theoretical perspective for understanding government-enterprise-market three-layer interactions. The finding that government digitalization policies have a positive impact on enterprise AI adoption ($\beta=0.21$, $p<0.01$) resonates with existing research on smart technologies creating public value [28]. However, this study further finds that this impact is neither linear nor homogeneous but is significantly moderated by policy environment characteristics. This finding extends the smart technology value creation framework proposed by Criado and Gil-Garcia, extending it from the public sector to the interaction level between government and market entities [28].

The mediating role of organizational learning capability reveals the key mechanism for transforming policies into enterprise behavior. Research shows that government policies need to stimulate enterprises' learning and absorption capabilities to effectively promote technological innovation, which is consistent with research conclusions on the digitalization of agricultural knowledge and advisory networks [29]. Fielke et al. emphasized the core role of knowledge networks in agricultural digitalization, while this study further confirms the bridging function of internal organizational learning mechanisms in transforming policy knowledge into innovation practice [29]. This perspective of internal and external knowledge integration provides a more comprehensive explanatory framework for understanding agricultural enterprises' technology adoption behavior.

Regional heterogeneity analysis results show that policy effects in the eastern region are significantly stronger than in the central and western regions, a finding that forms an interesting contrast with research on digital innovations for sustainable and resilient agricultural systems [30]. Finger pointed out differences in the application effects of digital innovation across different agricultural systems, while this study explains the causes of these differences from the perspective of policy transmission mechanisms [30]. The unbalanced development of digital infrastructure and regional differences in market maturity jointly shape the spatial heterogeneity of policy effects, providing a theoretical basis for formulating differentiated regional support strategies.

The research results have important practical guidance significance for policymakers and enterprise managers. The moderating effect of policy environment characteristics indicates that simply increasing policy quantity or financial investment cannot automatically translate into enterprise innovation; policy continuity, coordination, and evaluation mechanisms are equally important. This aligns with research findings on the "experience versus expectation" gap in smart farming technology applications [31]. Kernecker et al. found that European farmers' actual experience with smart farming technologies often falls below expectations, while this study provides a path to narrow this gap from a policy design perspective: enhancing enterprises' technology adoption willingness and capability by improving policy environment quality [31].

The mediating role of customer satisfaction emphasizes the importance of market orientation in technological innovation. Research shows that enterprise AI marketing strategies can only effectively translate into market performance by enhancing customer experience, a finding that resonates with research conclusions on internet use improving technical efficiency in banana production in China [32]. Zheng et al. found that internet technology improves agricultural production efficiency by improving information access and market connection, while this study further confirms the key role of positive customer feedback in reinforcing this efficiency improvement [32]. This suggests that enterprises should always focus on customer value creation when adopting AI technology, avoiding the pitfall of technology for technology's sake.

The moderating role of industry competition intensity provides guidance for enterprises' market positioning strategies. In highly competitive markets, the value of AI marketing strategies becomes more prominent, which has similar logic to research on digital finance promoting green control technology adoption by family farms [33]. Yu et al. found that digital finance promotes technology adoption by reducing financing constraints, while this study shows that competitive pressure is also an important external driver for enterprise technological innovation [33]. This dual-drive mechanism suggests that policymakers should introduce moderate market competition mechanisms while providing financial support to stimulate enterprises' innovation vitality.

Despite providing valuable theoretical and practical insights, this study still has some limitations that need to be improved in future research. The cross-sectional data used in the study cannot fully capture the dynamic evolution of policy effects, which is a common challenge in the application of PLS-SEM methods in marketing research [34]. Sarstedt et al., in reviewing PLS-SEM applications over the past decade, pointed out that the lack of longitudinal data limits the strength of causal inference [34]. Future research could adopt panel data or quasi-experimental designs to better identify the causal effects of policies, particularly examining the trajectory of changes in enterprise behavior before and after policy implementation.

Sample representativeness also deserves attention. The study focuses on the specific industry of fresh corn, and the external validity of its conclusions needs careful evaluation. PLS-SEM research guidelines emphasize the impact of sample characteristics on model estimation [35]. Becker et al. suggest that researchers should fully consider sample uniqueness when interpreting results [35]. Future research could extend the analytical framework to other agricultural product fields to test the robustness and universality of this study's findings, particularly whether policy transmission mechanisms change when industry characteristics differ significantly.

While multi-group analysis reveals regional differences, it insufficiently explores the deep mechanisms behind these differences. Multi-group analysis with more than two groups in PLS-SEM has special complexity [36]. Cheah et al. pointed out that when the number of groups increases, more refined analytical strategies are needed to identify difference patterns between groups [36]. Future research could adopt mixed methods, combining qualitative case studies to deeply analyze contextual factors of policy implementation in different regions, thereby providing more detailed policy recommendations.

There is still room for improvement in measurement instruments. Although the scales developed in this study show good reliability and validity, the measurement of some constructs (such as policy environment characteristics) still mainly relies on subjective evaluation. Future research could develop more objective measurement indicators, such as using text mining techniques to quantify policy text characteristics or constructing comprehensive policy environment indices. Additionally, introducing more mediating and moderating variables, such as entrepreneurship and social capital, might reveal richer mechanisms of action.

6. Conclusion

Based on data from 128 fresh corn enterprises across 15 Chinese provinces and 3,842 consumers, this study constructs a multi-level moderated mediation model to systematically reveal the mechanisms through which local government digitalization policies drive enterprise AI marketing innovation. Empirical results show that local government digitalization policies significantly promote enterprise AI marketing strategy adoption ($\beta=0.21$, $p<0.01$), while the impact of enterprise AI marketing adoption on market performance is even more significant ($\beta=0.34$, $p<0.001$), with the complete model explaining 58.7% of the variance in market performance. The study finds that policy environment characteristics and industry competition intensity respectively strengthen the connections between policy-enterprise and enterprise-market, with policy effects under high policy support environments (simple slope=0.43) being 2.5 times those under low support environments (simple slope=0.17). The mediating roles of organizational learning capability (indirect effect=0.126) and customer satisfaction (indirect effect=0.187) reveal the transmission paths of policy impact, and these mediation effects show significant differences under different moderating conditions, with the mediation effect of customer satisfaction in high-competition markets (0.246) being 73% higher than in low-competition markets (0.142). Regional heterogeneity analysis further shows that policy transmission efficiency in eastern regions (β=0.38) is twice that of western regions (β=0.19), reflecting regional imbalances in digital infrastructure and market environments. The theoretical contribution of this study lies in integrating digital governance theory from public administration with technology adoption models from innovation management, constructing a government-enterprise-market three-layer interaction analytical framework, and extending the theoretical boundaries of agricultural digital transformation. At the practical level, the research provides empirical evidence for local governments to formulate differentiated digital agriculture policies, emphasizing that policy design should focus on environmental quality construction rather than mere resource input, while enterprises should maintain market orientation in technological innovation, achieving sustainable development through enhancing customer value.

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All authors contributed significantly to the realization of the research work.

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Conflict of interest

The authors declare no conflict of interest.

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