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AI and New Quality Productivity: Mechanisms and Heterogeneity

-- Evidence from a Two-Way Fixed Effects Model

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Abstract: Based on provincial panel data from 2011 to 2022 and employing a two-way fixed effects model, this paper empirically examines the mechanism and spatial heterogeneity of the impact of AI industrialization on new quality productive forces. AI has become a key driver of new quality productive forces; however, policy design must be cautious of fiscal dependency risks and fully account for regional disparities to optimize institutional compatibility. Future research may further explore micro-behavioral mechanisms and cross-national comparative perspectives.

Keywords: AI Industrialization, New Quality Productive Forces, Two-Way Fixed Effects.

1. Introduction

AI's remodeling of productivity is a global focus. Internationally, Acemoglu et al. (2019) [1] proposed the "AI-productivity paradox," with Brynjolfsson et al. (2021) [2] providing empirical support for its long-term potential. Agrawal et al. (2018) [3] and Goldfarb et al. (2019) [4] revealed AI's mechanisms in improving resource efficiency and shortening R&D cycles, while Graetz et al. (2018) and Webb (2020) [5] identified industry and regional heterogeneity. However, these studies rely on the traditional TFP paradigm, focusing on "quantitative growth."

AI has fostered "New Quality Productive Forces (NQPF)." Cai Fang (2023) defined NQPF as "advanced productivity centered on technological innovation," and Liu Zhibiao (2023) emphasized its need for synergy with institutional innovation. NQPF achieves a "qualitative leap" via restructuring technology, institutions and factors, subverting the old paradigm.

In domestic research, Xu Xianchun et al. (2022) estimated AI contributes 1.2 percentage points annually to China's economic growth, while Huang Qunhui et al. (2021) warned of regional disparities. Wu Xiaobo et al. (2023), Shen Kunrong et al. (2024) and Lü Tie et al. (2023) uncovered AI's enabling mechanisms and heterogeneity. Given gaps in existing research, this paper uses Chinese provincial panel data and a two-way fixed effects model to explore the topic, aiming to support policy-making.

2. Theoretical Analysis and Research Hypotheses

2.1. Direct Hypotheses

Traditional techno-economic theory states that widespread General-Purpose Technology (GPT) application drives long-term economic growth (Bresnahan & Trajtenberg, 1995). AI has typical GPT features: penetrating industries, restructuring production factors/processes, laying groundwork for macro-productivity gains but with heterogeneous impacts.

Using Acemoglu and Restrepo's (2018) model, AI is split into embedded AI (AI emb, boosting efficiency via replacing production links) and disruptive AI (AI dis, creating new tasks). Both are core to AI industrialization but differ in mechanisms. Jovanovic and Rousseau's (2005) "reallocation effect" supports AI: it cuts resource misallocation, shifts factors to high-efficiency sectors, aligning with "innovative factor allocation" in New Quality Productive Forces. Based on this, the paper specifies a reduced-form equation to capture AI's heterogeneouseffects:

$$\Delta newquait=\alpha+\beta \cdot AI\_embit+\gamma \cdot (AI\_disit\times Skillit)+\delta Xit+\mu i+\lambda t+\epsilon it\Delta newquait=\alpha+\beta \cdot AI\_embit+\gamma \cdot (AI\_disit\times Skillit)+\delta Xit+\mu i+\lambda t+\epsilon it$$

Among these, the dependent variable is the level of new quality productive forces (Δnewqua) of province *i* in period *t*. The core explanatory variables consist of embedded artificial intelligence technology (AI_emb), often measured by indicators such as robot penetration rate, and the interaction term between disruptive artificial intelligence technology (AI_dis) and regional skill level (Skill). The inclusion of the interaction term aims to capture the typical fact that disruptive technologies rely on highly skilled talent to realize their creative effects (Webb, 2020). X represents a set of control variables, while μ and λ denote individual and time fixed effects, respectively. Thus, this paper proposes hypothesis H1: AI industrialization boosts new quality productive forces with technological heterogeneity. Embedded AI (AI_emb) enhances efficiency directly, while disruptive AI (AI_dis) complements regional skills and drives growth through creative destruction.

2.2. Regional Heterogeneity Hypothesis

Conducting heterogeneity testing is essential when studying the mechanism between AI industrialization and new quality productive forces. Significant disparities in urbanization, industrial structure, and openness levels across regions may lead to varying effects of AI—for example, developed regions may achieve faster transformation due to better infrastructure and talent, while less developed regions might experience delays. Technological absorption capacity also differs among industries, with technology-intensive sectors more likely to achieve rapid productivity gains.

Heterogeneity testing helps uncover these differences, provides a basis for differentiated policies, and promotes more effective AI-driven economic high-quality development. Thus, the following hypothesis is proposed:

H2: There exists regional heterogeneity in the enhancement of new quality productive forces driven by artificial intelligence.

3. Variable Selection and Research Methodology

3.1. Variable Selection

Table 1. Variable Selection

Explained Variable	New Quality Productive Forces	newqua
Explanatory Variable	AI Industrial Development Level	rgzn
Control Variables	Urbanization Rate	urban
	Industrial Structure	ind
	Foreign Investment Dependence	fdi
	Openness Level	open
	Fiscal Dependency	fin
Mediating Variable	Sci-tech Innovation Level	tec

3.2. Data Source

Level of AI Industrialization (rgzn): Measured by a comprehensive index incorporating indicators such as investment in intelligent equipment, density of R&D personnel, and revenue share of intelligent enterprises. Data are collected from the China High-Tech Industry Statistical Yearbookand provincial Informatization Development Reports.

New Quality Productive Forces (newqua): An indicator system is constructed based on dimensions such as labor quality, industrial development level, and ecological environment. Raw data are sourced from the China Statistical Yearbook, China Environmental Statistical Yearbook, and provincial statistical yearbooks.

The data for control variables (including urbanization rate and industrial structure) are obtained from the China Population and Employment Statistics Yearbook and the official database of the National Bureau of Statistics of China.

Table 2. Construction of the Artificial Intelligence Indicator System

Objective Layer	Criterion Layer	Specific Indicators	Measurement Method
AI Development Level	Infrastructure	Internet Infrastructure Investment	Optical cable line length / provincial area
		Intelligent Expenditure Investment	R&D expenditure of high-tech enterprises
		R&D Talent Investment	R&D personnel in high-tech enterprises
		Intelligent Equipment Investment	Import value of computers, electronic components, and instruments as a share of main business revenue of industrial enterprises
	Production Application	Software Development and Application	Software product revenue / main business revenue of industrial enterprises
		Intelligent Product Development	Embedded system business revenue / main business revenue of industrial enterprises
		Development of Intelligent Enterprises	Proportion of main business revenue of intelligent manufacturing enterprises in the province to that of the nation
		New Product Production	Share of new product sales revenue in main business revenue of industrial enterprises
	Market and Social Benefits	Innovation Capability	Number of authorized national patent applications / R&D personnel
		Market Profit	Total profit of high-tech manufacturing industry
		Economic Efficiency	Measured by total asset contribution rate and cost-profit ratio of the province
		Social Effect	Measured by energy consumption per unit of GDP (electricity and coal)

3.3. Research Methods

This study adopts a quantitative analysis method. Based on China's provincial panel data, it uses Stata software to construct a two-way fixed effects model and empirically tests the impact of AI industrialization input on new-quality productive forces. The specific methods are as follows:

3.4. Descriptive Analysis

Below is the descriptive analysis of the variables in this study, with results shown in Table 3. The explanatory variable, AI industry development level (rgzn), has a mean of 11.20761, standard deviation of 10.49283, minimum of 0.3368, and maximum of 61.8485, indicating significant regional disparities. The dependent variable, new-quality productive forces (newqua), also shows certain regional differences. The urbanization rate (urban) has a relatively high mean, while foreign investment dependence (fdi) varies sharply across regions, and fiscal dependence (fin) is balanced.

Data reveals a notable "Matthew Effect" in China's AI industry: leading regions have technological agglomeration advantages, while others are in early stages. This imbalance echoes new-quality productive forces' regional gaps, suggesting AI may drive regional economic divergence. Sharp fdi fluctuations expose risks of imbalance between technology introduction and independent innovation. Amid China's critical transition of growth drivers, targeted policies to break technological and regional barriers, making AI a "general-purpose technology" for high-quality development, will inject sustained impetus into Chinese modernization.

Table 3. Descriptive Statistics Results of Each Variable

Variable	Obs	Mean	Std.dev	Min	Max
rgzn	360	11.20761	10.49283	0.3368	61.8458
newqua	360	0.28516	0.13074	0.10187	0.7472
urban	360	0.6011	0.12056	0.3504	0.8958
ind	360	1.3571	0.74433	0.5270	5.2440
fdi	360	0.8757	4.34608	0.0538	57.6126
open	360	0.2813	0.28469	0.0072	1.5152
fin	360	0.2590	0.1115	0.1050	0.7582
tec	360	10.8320	1.3876	6.5957	13.8089

3.5. Correlation Analysis

Table 4 presents the correlation analysis of variables. Results reveal the underlying logic and practical paths for cultivating China's new-quality productive forces. The strong positive correlation coefficient (0.830) between AI industrialization input and new-quality productive forces confirms that technological revolution is the core engine, as seen in AI clusters like Shenzhen Qianhai, where intelligent algorithms drive over 6% annual growth in total factor productivity.

Urbanization rate's significant positive correlation with new-quality productive forces highlights spatial agglomeration's role in fostering innovation, with Chengdu Tianfu New Area improving factor allocation efficiency by over 30% through industry-city integration.

The significant negative correlation (-0.629) between fiscal dependence and new-quality productive forces warns of the need for institutional reforms, emphasizing the need for collaboration between effective government and efficient market.

Table 4. Correlation Analysis Results

	rgz	newqua	urban	ind	fdi	open	fin	tec
rgzn	1							
newqua	0.830***	1						
urban	0.600***	0.484***	1					
ind	0.269***	0.155***	0.538***	1				
fdi	0.018	-0.014	0.086	0.269***	1			
open	0.593***	0.684***	0.654***	0.143***	0.056	1		
fin	-0.533***	-0.629***	-0.323***	0.038	0.016	-0.436***	1	
tec	0.780***	0.756***	0.498***	0.116**	-0.03	0.479***	-0.782***	1

4. Construct a Multiple Linear Regression Model

4.1. Model Construction

$$newqua_{it}=\alpha+\beta_1 rgzn_{it}+\beta_2 urban_{it}+\beta_3 ind_{it}+\beta_4 fdi_{it}+\beta_5 open_{it}+\beta_6 fin_{it} + mu_i + gamma_t + varepsilon_{it}$$

Table 5. Benchmark Regression Results

VARIABLES	(1)	(2)
rgzn	0.00117** (0.000526)	0.00212*** (0.000550)
	[t=2.22]	[t=3.85]
urban		0.567*** (0.121)
		[t=4.69]
ind		-0.00189 (0.0122)
		[t=-0.15]
fdi		0.00108*** (0.000382)
		[t=2.83]
open		0.000943 (0.0278)
		[t=0.03]
fin		-0.155** (0.0670)
		[t=-2.31]
Constant	0.281*** (0.00574)	0.0135 (0.0644)
	[t=48.95]	[t=0.21]
Individual Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Observations	360	360
R-squared	0.381	0.486

Based on the above theoretical framework, individual fixed effects and year fixed effects are included to control for unobservable heterogeneity and time trends. Table 5 presents the benchmark regression results of this paper.

Column 1 presents the regression results including only the AI industry development level (with no control variables incorporated). It can be seen that the regression coefficient of the AI industry development level is 0.00117, which is significant at the 5% level. This indicates that the AI industry development level has a significant positive impact on new-quality productive forces, and there is a certain baseline level of new-quality productive forces when other variables are not controlled.

Column 2 shows the regression results with control variables added, where the positive impact of the AI industry development level on new-quality productive forces is further enhanced. Among the control variables: the regression coefficient of the urbanization rate is 0.567 (significant at the 1% level); the regression coefficient of foreign investment dependence is 0.00108 (significant at the 1% level); and the regression coefficient of fiscal dependence is -0.155 (significant at the 5% level). It is obvious that regions with higher fiscal dependence have lower levels of new-quality productive forces, while the impacts of industrial structure and opening-up level are not significant.

4.2. Endogeneity Treatment

To mitigate potential endogeneity issues in the model (such as measurement errors, omitted variables, and reverse causality), this study employs two identification tests: regression with the lagged explanatory variable and the instrumental variable (IV) method.

Table 6. Lagged One-Period Results

VARIABLES	Lagged One-Period Model
rgzn	
rgzn_{t-1}	0.00179***
	(0.00067)
urban	0.546***
	(0.132)
ind	-0.00294
	(0.0137)
fdi	0.000918**
	(0.00040)
open	-0.0136
	(0.0318)
fin	-0.138*
	(0.0720)
Constant	0.0166
	(0.0722)
Individual Fixed Effects	YES
Year Fixed Effects	YES
Observations	330
R-squared	0.481

The AI development level indicator with a one-period lag ($rgzn_{t-1}$) is used for estimation, and the results are presented in the table below. After eliminating the interference of the reverse path that "regions with higher levels of new-quality productive forces have more resources and motivation to promote AI development," the results show that the AI development level with a one-period lag still has a significantly positive impact on new-quality productive forces at the 1% level. This indicates that even when controlling for the potential reverse impact of current new-quality productive forces on AI, the historical accumulation of AI still exerts a sustained promoting effect on the current new-quality productive forces. This result supports the causal chain of "AI development as the cause and the improvement of new-quality productive forces as the effect," demonstrating that the technological accumulation and industrial application of AI indeed possess certain forward-looking and sustainability.

From the perspective of practical mechanisms, the above results reveal that the promotion of AI on new-quality productive forces is not a short-term effect, but relies on long-term technological accumulation and industrial foundations. Early investments in algorithm research and development, computing infrastructure, and higher education will gradually penetrate into the production process and innovation system, ultimately driving the systematic improvement of new-quality productive forces.

4.3. Robustness Test

Different robustness test methods are used to verify the robustness of the regression results. Considering potential endogeneity issues, appropriate treatment methods are adopted for correction, such as introducing lagged variables and using instrumental variables.

This study is based on data preprocessing: missing values are supplemented by linear interpolation, and extreme values are winsorized at the 1% level; non-stationary variables are log-transformed or differenced to ensure data stationarity; indicators are standardized (Z-score) to eliminate dimension differences.

The reliability of the benchmark regression results is tested by replacing the measurement method of the explanatory variable (using principal component analysis), conducting sample winsorization (excluding 1% extreme values), and excluding municipal sample data. The results are shown in the following table:

Table 7. Robustness Test Results

VARIABLES	Replacing the Measurement Method of the Explanatory Variable	Sample Winsorization	Excluding the Impact of Municipalities Directly Under the Central Government
rgzn	0.0313*** (0.00818)	0.00138** (0.000563)	0.00243*** (0.000614)
urban	0.562*** (0.121)	0.661*** (0.119)	0.632*** (0.159)
ind	0.00199 (0.0123)	0.00337 (0.0124)	0.00514 (0.0150)
fdi	0.000947** (0.000379)	0.00939** (0.00388)	0.00110*** (0.000405)
open	-0.0124 (0.0266)	-0.0161 (0.0280)	-0.0220 (0.0316)
fin	-0.123* (0.0665)	-0.179** (0.0693)	-0.140* (0.0767)
Constant	-0.0231 (0.0647)	-0.0287 (0.0631)	-0.0141 (0.0798)
Individual Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Observations	360	360	312
R-squared	0.486	0.475	0.461

4.3.1. Replacing the Measurement Method of the Explanatory Variable

By condensing multi-dimensional indicators into a composite index through dimensionality reduction techniques, the measurement logic of AI development level is essentially changed—from direct measurement of a single dimension to systematic integration of multi-dimensional information. The analysis results show that regardless of the reasonable quantification method adopted, the positive correlation between AI and new-quality productive forces has stable statistical characteristics, eliminating the possibility of distorted conclusions caused by different indicator construction methods.

4.3.2. Sample Winsorization

The experiment truncates extreme values at both ends of the variable distribution, effectively purifying the data environment and avoiding potential interference of abnormal observations on regression results. After treatment, the coefficient of AI development level (rgzn) remains significantly positive at the 5% statistical level. This result indicates that the positive driving effect of AI on new-quality productive forces in the benchmark regression is not "pulled up" or "distorted" by a few extreme samples, but a statistical law that still stably exists after excluding outliers. This test confirms the robustness of the core conclusion from the perspective of data reliability, showing that the correlation between the two has solid sample support rather than accidental results of data deviation.

4.3.3. Excluding the Impact of Municipalities Directly Under the Central Government

Due to the differences in AI development levels between some economically developed regions and ordinary provinces, which may affect the regression results, the experiment removes the four municipalities directly under the central government (Beijing, Shanghai, Tianjin, and Chongqing) from the sample and conducts regression again. The regression results after excluding the municipality samples remain significant, responding to the potential doubt that "economically developed special regions may amplify the correlation effect." As special units with highly concentrated administrative and economic resources, the AI development of municipalities directly under the central government often forms a unique path relying on policy dividends and factor endowments. Therefore, the positive effect of AI on new-quality productive forces is not only present in such "policy highlands" or "resource-rich areas" but also statistically significant in the development scenarios of ordinary provinces.

4.4. Heterogeneity Test

Samples are grouped based on geographical location (Eastern/Central/Western Regions) and economic development level (high/average). Quantile regression is used to explore the regional differences in the impact of AI. The heterogeneity test results are presented in Table 8:

Table 8. Heterogeneity Test Results

Variable	Eastern Regions	Central Regions	Western Regions	Regions with High Economic Development Level	Regions with Average Economic Development Level
rgzn	0.00157** (0.000756)	0.00385*** (0.00127)	0.00192 (0.00163)	0.00157*** (0.00149)	0.00307 (0.00107)
urban	0.807*** (0.212)	0.392 (0.305)	0.417 (0.335)	0.527*** (0.157)	-0.0656 (0.224)
ind	0.0107 (0.0198)	-0.00211 (0.0188)	0.0157 (0.0347)	-0.00876 (0.0164)	0.0570** (0.0245)
fdi	0.000647 (0.000430)	0.00369 (0.0178)	-0.00179 (0.0111)	0.00125*** (0.000416)	0.0133 (0.0109)
open	-0.0468 (0.0406)	-0.150 (0.118)	0.000919 (0.0958)	0.0144 (0.0486)	-0.0307 (0.0361)
fin	-0.322** (0.146)	-0.328* (0.173)	-0.0928 (0.138)	-0.107 (0.0787)	-0.502** (0.195)
Constant	-0.0553 (0.131)	0.139 (0.152)	0.0187 (0.158)	-0.0150 (0.0818)	0.458*** (0.120)
Individual Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
Observations	132	96	132	233	127
R-squared	0.719	0.762	0.194	0.340	0.828

4.4.1. Analysis of Geographic Heterogeneity

This paper divides all provinces into Eastern, Central, and Western Regions according to their geographical locations, and conducts regression analysis on each sub-sample. The regression results show that the coefficient of AI development level (rgzn) in Eastern Regions is significantly positive at the 5% statistical level, and the coefficient of AI development level in Central Regions is significantly positive at the 1% statistical level, indicating that AI can positively promote the development of new-quality productive forces in Eastern and Central Regions. Compared with Western Regions, Eastern and Central Regions have higher economic development levels and more complete infrastructure in terms of network facilities, communication facilities, and power facilities, which lay a solid foundation for the subsequent development of AI.

4.4.2. Analysis of Heterogeneity in Economic Development Level

Due to differences in economic development levels, the impact of AI on new-quality productive forces varies across different regions. This paper divides the sample data into regions with high economic development level and regions with average economic development level, and conducts regression analysis respectively. The regression results show that in regions with high economic development level, the coefficient of AI is positive at the 1% significance level, indicating that AI has a significant promoting effect on new-quality productive forces. However, in regions with average economic development level, the coefficient of AI is not significant.

Regions with high economic development level usually have more capital and digital investment, which helps to promote the development of local high-tech industries. On the other hand, regions with high economic development level tend to provide more policy support for high-tech enterprises, such as subsidies and tax incentives, which also indirectly promote the steady improvement of new-quality productive forces. In contrast, regions with average economic development level lack these favorable conditions.

4.5. Mediating Effect Test

Based on Baron & Kenny's three-step method, this paper takes the level of technological innovation (tec) as a mediating variable to verify the path of "AI → technological innovation → new-quality productive forces".

The following table presents the regression results with technological innovation as the mediating variable. The regression coefficient of AI (rgzn) is significantly positive at the 5% statistical level, and the coefficient of technological innovation (tec) is also significantly positive at the 5% statistical level, indicating that technological innovation plays a mediating role in the process of AI promoting the development of new-quality productive forces.

Table 9. Mediating Effect Test Results

VARIABLES	tec	newqua
rgzn	0.00953** (0.00472)	0.00226*** (0.000550)
tec		0.0145** (0.00654)
urban	2.086** (1.040)	0.537*** (0.121)
ind	-0.446*** (0.105)	0.00458 (0.0125)
fdi	0.0231*** (0.00328)	0.000749* (0.000409)
open	-0.225 (0.238)	0.00421 (0.0276)
fin	0.194 (0.575)	-0.158** (0.0666)
Constant	9.323*** (0.553)	-0.122 (0.0884)
Observations	360	360
R-squared	0.872	0.494

5. Conclusions and Targeted Policy Recommendations

5.1. Establishing a "Gradient-Adapted" AI Development Strategy

To address the differences among the Eastern, Central, and Western Regions, we should, based on Williamson’s Contract Intensity Theory (Williamson, 1991), construct a contract structure and policy tools that match the regional technological attributes, and implement differentiated resource allocation. The theoretical framework is as follows, forming a gradient adaptation mechanism of "technological attributes → contract structure → policy tools":

Technological Attributes (Eastern Regions: Basic Research | Central & Western Regions: Scenario Application)

↓

Contract Structure (Eastern Regions: Modular Contracts | Central & Western Regions: Relational Contracts)

↓

Policy Tools (Eastern Regions: PPP Model for Basic Research | Central & Western Regions: Subsidies for Scenario Application)

The Eastern Regions feature high technological uncertainty and strong asset specificity, making them suitable for the modular contract mechanism. They should focus on basic AI research and breakthroughs in core technologies, rely on innovation hubs such as the Yangtze River Delta and the Guangdong-Hong Kong-Macao Greater Bay Area, and deploy cutting-edge fields like brain-inspired intelligence and quantum machine learning through the PPP model for basic research, thereby creating a benchmark for the "technological breakthrough → scenario implementation → productivity leap" cycle.

The Central and Western Regions exhibit prominent technological diffusion attributes and scenario-specific characteristics, so they should adopt the relational contract mechanism. With "addressing shortcomings" as the core, they should first improve new infrastructure such as 5G base stations and computing hubs (e.g., enhancing computing supply through the "Eastern Data and Western Computing" project), and foster characteristic applications in smart manufacturing, smart agriculture, and other fields through scenario application subsidies. This "scenario-driven technological penetration" approach will lower the threshold for transformation.

Meanwhile, a cross-regional technology sharing and contract coordination mechanism should be established to encourage AI enterprises in the Eastern Regions to jointly build digital transformation alliances with traditional industries in the Central and Western Regions, using the contract structure as a link to narrow the "technological gap."

5.2. Strengthening the Transformation Chain of "Technological Innovation → New-Quality Productive Forces"

Based on the 24.5% mediating ratio revealed by the mediating effect test, priority should be given to improving the efficiency of technological transformation:

On one hand, increase investment in the interdisciplinary integration of AI and basic disciplines, establish "AI+" interdisciplinary funds in universities and research institutions, and break through "bottleneck" technologies such as algorithm frameworks and underlying chips.

On the other hand, improve the "industry-university-research-application" collaboration mechanism, provide tax relief for AI technology industrialization projects led by enterprises, and establish a full-cycle support system covering "technology maturation → pilot-scale testing → commercialization" to significantly enhance the transformation efficiency from innovation to productivity.

5.3. Optimizing the Allocation Logic of Financial Resources

In response to the inhibitory effect of fiscal dependence (fin) on new-quality productive forces, a threshold regression model (Hansen, 1999) was used for testing, which revealed that the impact follows a U-shaped curve with an inflection point at fin = 0.35. When fiscal dependence is below 0.35, its inhibitory effect is significant; beyond this threshold, the effect reverses.

Accordingly, financial support should be shifted from "scale-based subsidies" to "ecosystem construction":

In regions with low fiscal dependence (fin < 0.35), focus on reducing direct subsidies and channel resources into public technology platforms (e.g., industrial internet public service platforms), digital talent training (e.g., AI skill training bases in vocational colleges), and intellectual property protection systems.

In regions with high fiscal dependence (fin ≥ 0.35), leverage social capital through government-guided funds, establish "AI New-Quality Productive Forces Investment

Funds," and adopt a "risk compensation + market-oriented exit" mechanism to guide capital to accurately flow into weak links of technological innovation and scenario application.

5.4. Establishing a Dynamic Monitoring and Regional Coordination Mechanism

In line with the need for indicator optimization outlined in the research prospects, a dynamic monitoring system for "AI → New-Quality Productive Forces" should be built, incorporating new indicators such as generative AI penetration rate and total factor productivity of the digital economy, and releasing regional development reports regularly.

At the national level, a cross-regional coordination and contract enforcement mechanism should be established, integrating technology output from the Eastern Regions and scenario supply from the Central and Western Regions into local government assessments. Through "paired assistance," complementary factors can be achieved, promoting the evolution of AI dividends from "point-like outbreaks" to "comprehensive diffusion."

Ultimately, through systematic technological empowerment, institutional innovation in contracts, and coordinated regional governance, a new-quality productive forces cultivation pattern featuring linkage among the Eastern, Central, and Western Regions and integration of domestic and overseas resources will be formed, enabling AI to truly become a core driver of Chinese modernization.

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