How Do Data Elements Empower High-Quality Development of the Intelligent Economy?

Empirical Evidence from Interprovincial Panel Data in China

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Abstract. Using 2013-2024 provincial panel data from China, this study applies a fixed-effects model to investigate the impact of data elements on intelligent economy development and its transmission mechanisms. Results show that data elements significantly drive high-quality development through technological innovation, factor allocation, and industrial upgrading, with stronger effects in eastern regions. The study contributes by validating the complete data-to-intelligent economy transmission chain and revealing heterogeneous enabling patterns across resource endowments, supporting the "resource substitution effect." Policy recommendations focus on improving data markets, optimizing transmission pathways, and adopting differentiated regional approaches.

Keywords: data elements, intelligent economy, high-quality development, factor allocation

1 Introduction

1.1 Research Background

Digital and intelligent transformation has become the core driver of China's high-quality economic growth. Central authorities have issued successive policies to accelerate data factor marketization, facilitating data circulation and enabling the real economy. As a new production factor, data replaces traditional factor inputs and reshapes production, distribution and consumption systems; the construction of intelligent economy relies heavily on sufficient, market-oriented data resources.

In industrial practice, the application of intelligent technologies such as artificial intelligence, big data, and the Internet of Things has fundamentally transformed traditional approaches to inputting production factors and improving allocation efficiency. Data is no longer merely a supplementary element of production but has become a key production resource integral to the entire chain of production, distribution, exchange, and consumption. The development of the intelligent economy relies heavily on vast amounts of high-quality, marketable data resources; the effective supply and efficient allocation of data elements serve as the fundamental prerequisite for the

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iteration of intelligent technologies, the clustering of intelligent industries, and innovation in intelligent business models.[1]

Nevertheless, China's data factor market remains immature, featuring ambiguous property rights, incomplete trading mechanisms and inter-regional data barriers, which restrict the release of data value. Eastern, central and western provinces show obvious gaps in intelligent economic development and data utilization efficiency. Optimizing data allocation to break regional development bottlenecks has become an urgent research topic.

1.2 Research Significance

1.2.1 Theoretical Significance.

Current research predominantly focuses solely on the economic effects of data elements or the development pathways of the intelligent economy, with insufficient exploration of the complete transmission chain encompassing "data elements—intelligent economy—high-quality development," and relatively weak analysis of interprovincial mechanisms and system frameworks. While recent empirical studies have examined the mediating mechanisms through which digital factors affect urban development (Xing et al., 2025)[2], the majority of existing research remains at the theoretical and qualitative level, with studies on data factor marketization largely confined to institutional and theoretical interpretations (He and Wang, 2021)[3] rather than systematic quantitative validation.Moreover, existing studies tend to emphasize qualitative analysis over systematic mechanism examination, with limited quantitative validation of the transmission pathways between data elements and high-quality development.

This paper establishes a unified three-part analytical framework of "data elements-intermediary channels-intelligent economy", quantitatively tests three mediating pathways, and reveals regional heterogeneous empowerment patterns, enriching theoretical research on digital factors and the digital divide.

1.2.2 Realistic Meaning.

This paper identifies regional gaps in data factor application and intelligent economic construction, and proposes targeted reform paths for data marketization. It offers practical policy references to eliminate data circulation barriers, cultivate intelligent industries and narrow regional development gaps.[4]

1.3 Research Contents and Innovations

This paper primarily reviews relevant research findings on data elements and the intelligent economy, analyzes the underlying transmission mechanisms through which data elements empower high-quality development of the intelligent economy, identifies shortcomings in existing studies, and proposes optimized development pathways. The innovations of this paper are mainly reflected in two aspects: first, establishing a comprehensive transmission mechanism for how data elements drive high-quality

development of the intelligent economy by positioning the intelligent economy as the core intermediary vehicle and refining the logical chain among these three components; second, adopting an interprovincial macro perspective to address regional heterogeneity issues and overcome the limitations of existing research that relies solely on a macro-level viewpoint.

2 Literature Review

This section reviews the literature from three interconnected strands to establish a clear research context and identify the research gap this paper addresses.

Data Elements and Market-Based Allocation.The concept of data elements has evolved from traditional data resources into independent production factors, characterized by non-rivalry, replicability, and increasing returns to scale (i.e., decreasing marginal costs) (Li and Zhao,2023)[5], with their value realization depending on technological integration and market circulation (Qi and Wang,2026)[6]. In terms of market-based allocation, academic research has focused on data ownership confirmation, pricing mechanisms, and trading systems, proposing a closed-loop development model of "ownership confirmation - pricing - trading" (Huang and Shen,2022)[7]. Existing studies indicate that uneven development across provinces in China and an underdeveloped circulation system remain the primary challenges. [3]Recent scholarship has further examined the institutional barriers to data factor circulation, including fragmented data governance frameworks and the lack of standardized valuation methodologies, which collectively constrain the full realization of data's economic value (Chen Rongda et al., 2024)[8].

The Intelligent Economy and Its Development.The intelligent economy represents an advanced form of the digital economy, driven by intelligent technologies and centered on data as its core element, characterized by technological advancement, industrial integration, and regional clustering. In China, the intelligent economy exhibits a regional pattern with higher development levels in the east and lower levels in the west, while existing measurement approaches remain relatively limited and lack a comprehensive multi-dimensional evaluation system (Zhou and Ren, 2026; Wang and Wang, 2026).[9][10]Existing research has demonstrated that the intelligent economy can foster high-quality development across dimensions such as technology, efficiency, and sustainability, yet few studies have conducted integrated empirical analyses incorporating data elements (Zhou and Li, 2025).[11]

The Nexus Between Data Elements and the Intelligent Economy Development. Data elements and the intelligent economy exhibit a bidirectional coupling relationship: data serves as the foundation for the development of intelligent industries, while intelligent applications continuously generate new data resources (Ren Baoping,2026).[12]Existing research suggests that data elements can drive economic development through three pathways—technological innovation, factor allocation, and industrial upgrading. Zhang and Li (2024) [13]provide a comprehensive theoretical framework linking data elements to economic development through technological advancement, resource allocation optimization, and industrial structural transfor-

mation. Chen and He (2025)[14]offer empirical evidence that data valuation enhances economic performance by optimizing the structure of production factors.

However, few studies have employed the intelligent economy as an intermediary variable in empirical models, and quantitative research covering the entire transmission chain remains scarce. Moreover, the majority of existing studies rely on qualitative analysis or simple correlation tests, lacking rigorous causal identification and systematic mechanism verification, which limits the depth and reliability of their policy implications.

In summary, while existing literature has yielded substantial research findings, three major shortcomings remain: first, the majority are qualitative studies with insufficient interprovincial panel-based empirical analyses; second, there is no systematic verification of the mediating transmission mechanism between data elements, the intelligent economy, and high-quality development; third, quantitative analysis of regional heterogeneity lacks depth. This paper employs panel data and econometric models to conduct empirical research addressing these gaps.

3 Theoretical Mechanisms and Research Hypotheses

3.1 Direct Empowerment Mechanism

Data elements serve as the core raw material for the operation of the intelligent economy, directly impacting the entire smart industry chain: on one hand, they provide data support for intelligent algorithms and big data analysis, accelerating technological iteration; on the other hand, leveraging the characteristic of diminishing marginal costs, they reduce operational costs in the smart industry and expand its scale.

Based on this, we propose Hypothesis H1: Data elements significantly and positively contribute to the high-quality development of the intelligent economy.

3.2 Indirect Transmission Mechanism

3.2.1 Technological Innovation Path.

Data elements reduce barriers to innovative information flow and trial-and-error costs, enhance regional R&D efficiency and technology commercialization capabilities, and drive the upgrading of the intelligent economy through technological innovation.

Based on this, we propose Hypothesis H2: Data elements can facilitate high-quality development of the intelligent economy through technological innovation as an intermediary pathway.

3.2.2 Factor Allocation Path.

Data elements optimize the allocation of traditional factors such as labor and capital, mitigate factor misallocation issues, and pool high-quality resources for the development of the intelligent economy.

Based on this, we propose Hypothesis H3: Data elements can drive high-quality development of the intelligent economy through an intermediary pathway involving factor allocation.

3.2.3 Industrial Upgrading Path.

Data elements drive the intelligent transformation of traditional industries, foster emerging intelligent industries, and optimize the industrial structure.

Based on this, we propose Hypothesis H4: Data elements can drive high-quality development of the intelligent economy through an industrial upgrading-mediated pathway.

3.3 Mechanisms of Regional Heterogeneity

The eastern region boasts well-developed digital infrastructure, concentrated talent and capital, and higher efficiency in utilizing data as a key factor; in contrast, the central and western regions have weaker foundations and relatively limited capacity-building effects.

Based on this, Hypothesis H5 is proposed: the empowering effect of data elements exhibits regional heterogeneity, with a stronger impact in eastern regions.

Furthermore, this paper proposes the "resource substitution effect" hypothesis from the perspective of resource endowment, with its theoretical logic grounded in the "Resource Curse" hypothesis (Auty, 1993) and "Path Dependence" theory (Arthur, 1989) :

First, the Lock-in Effect. Resource-rich regions tend to accumulate substantial sunk costs and specific assets in traditional resource-based industries, forming a path dependence dominated by heavy industry. The "stickiness" of this industrial structure weakens the motivation of local governments to redirect fiscal and policy resources toward the data factor market in the short term, thereby reducing the marginal enabling elasticity of data elements.

Second, the Forcing Mechanism. Resource-scarce regions, constrained by their inherent deficiencies in physical factors, have long faced growth bottlenecks under traditional development models. To break through endowment constraints, such regions possess stronger intrinsic motivation to embrace data as a new production factor characterized by "non-rivalry"and"diminishing marginal costs," achieving catch-up development through actively exploiting the multiplier effect of data elements.

Based on this, we propose Hypothesis H5b: The enabling effect of data elements is significantly stronger in resource-scarce regions than in resource-abundant regions.

4 Empirical Design

4.1 Variable Selection and Data Sources

4.1.1 Explained Variable.

Level of High-Quality Economic Development (Hqd). The concept of high-quality economic development is extensive and multifaceted, making it difficult to assess comprehensively with a single indicator. Drawing on existing research, this paper establishes an evaluation index system for high-quality economic development across five dimensions: innovative development, coordinated development, green development, open development, and shared development. Specific indicators are presented in Table 1.

Table 1. Comprehensive Index for High-Quality Economic Development

Primary Indicator	Secondary Indicator	Secondary Indicator	Attribute Property
High-quality economic development	Innovative development	Internal expenditures for R&D funding	+
		Full-time equivalent of R&D personnel	+
		Number of Patent Grants	+
	Harmonious development	Urbanization Rate	+
		The proportion of the added value of the tertiary sector in GDP	+
		The ratio of per capita disposable income between urban and rural residents	-
	Green development	Energy consumption per unit of GDP	-
		Industrial sulfur dioxide emissions	-
		Wastewater Treatment Rate	-
		Forest coverage rate	-
	Open Development	Foreign trade dependence ratio (total import and export value / GDP)	+
		Actual utilization of foreign direct investment	+
	Shared Development	per capita disposable income	+
		Number of hospital beds per thousand people in healthcare institutions	+
		Local education expenditure	+

4.1.2 Core Explanatory Variable.

Development Level of Data Elements (Data). Considering the resource, technological, and market attributes of data elements, this paper establishes a comprehensive evaluation system across three dimensions: scale of data resources, level of data pro-

cessing technology, and degree of marketization of data elements. The comprehensive development index for data elements is calculated using the entropy method, providing a systematic measure of each province's progress in cultivating, applying, and commercializing data elements.This paper employs the entropy method to calculate the comprehensive development index of data elements (Data) for each province. The specific calculation procedures are as follows:

First, to eliminate dimensional effects, the range normalization method is applied to the j-th indicator of the i-th province:

$$X'_{ij} = \frac{X_{ij} - \min(X_j)}{\max(X_j) - \min(X_j)} \text{ (positive indicators)} \quad (1)$$

$$X''_{ij} = \frac{\max(X_j) - X_{ij}}{\max(X_j) - \min(X_j)} \text{ (negative indicators)} \quad (2)$$

Second, the proportion of the i-th province in the j-th indicator is calculated as $p_{ij} = \frac{X'_{ij}}{\sum_{i=1}^{n} X'_{ij}}$,and the entropy value is computed as $e_j = -k \sum_{i=1}^{n} p_{ij} \ln(p_{ij})$,where $k = \frac{1}{\ln(n)}$ and n is the number of provinces.

Third, the information utility redundancy is calculated as $d_j = 1 - e_j$,and the indicator weight is determined as $w_j = \frac{d_j}{\sum_{j=1}^{m} d_j}$,where m is the number of indicators.

Finally, the comprehensive development index of data elements for each province is calculated as: $Data_i = \sum_{j=1}^{m} w_j \cdot X'_{ij}$.

This index comprehensively evaluates the development level of data elements across three dimensions: the scale of data resources (e.g., number of internet broadband access users, mobile phone penetration rate), the level of data technology application (e.g., software business revenue, information technology service revenue as a share of GDP), and the degree of data factor marketization (e.g., Digital Inclusive Finance Index, number of data trading platforms).

4.1.3 Metavariable.

Technological innovation capability and factor allocation efficiency. The R&D input intensity (R&D expenditure/GDP) is selected as the indicator of technological innovation capability (Inn). Total factor productivity (TFP) serves as the core proxy variable for factor allocation efficiency, supplemented by the capital-labor ratio and factor misallocation index for additional validation.

4.1.4 Controlled Variable.

The indicators include economic development level (Pgdp), degree of government intervention (Gov), digital infrastructure (Inf), level of openness (Open), and industrial structure (Ind). Specifically, economic development level (Pgdp) is measured by per capita GDP, reflecting a region's inherent economic foundation; a stronger economic base indicates more robust conditions supporting high-quality development. Degree of government intervention (Gov) is measured by the ratio of government

fiscal expenditure to GDP, indicating the extent of government macroeconomic regulation's impact on regional economic growth. Level of openness (Open) is measured by foreign trade dependence (total imports and exports/GDP), demonstrating how openness enhances external support for high-quality development.

This study utilizes panel data from 30 provincial-level administrative regions of China covering the period 2013–2024 (excluding Hong Kong, Macao, Taiwan, and Xizang with severe data gaps). The data sources include the "China Statistical Yearbook", the "China Digital Economy Development Report", provincial statistical yearbooks, and the Peking University Digital Inclusive Finance Index. Missing observations were imputed using linear interpolation. The statistical details are presented in Table 2.

Table 2. descriptive statistics

Variable Name	mean value	standard deviation	minimum	maximal
High-quality economic development(Hqd)	0.1004	0.0814	0.0295	0.6945
Level of development for data elements(Data)	0.1334	0.1375	0.0023	0.7698
Technological Innovation Capability(Inn)	1.1473	0.6026	0.1643	3.2387
Efficiency of resource allocation(TFP)	118571.7	62502.3	45874	401258
Level of economic development(Pgdp)	69015.9	36262.2	22385	228167
Level of government intervention(Gov)	0.2512	0.1055	0.1049	0.7376
Level of digital infrastructure development(Inf)	0.2999	0.126	0.0758	0.5814
Level of openness to the outside world(Open)	0.2512	0.2416	0.0075	1.2218
industrial structure (Ind)	0.4024	0.0836	0.145	0.5732

4.2 Model Specification

This paper constructs empirical models at both the direct and mediating effect levels to examine the impact of digital factorization on the high-quality development of the intelligent economy.

4.2.1 Standard Regression Model.

To examine the direct impact of data element development on high-quality economic growth, a two-way fixed-effects benchmark regression model was constructed:

$$\mathrm{Hqd}_{it} = \alpha_0 + \alpha_1 \mathrm{Data}_{it} + \sum \alpha\, \mathrm{Control}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

Where: i represents the province-specific variable, t represents the year; Hqd_{it} denotes the high-quality economic development level of province i in t year ;$\mathrm{Data}_{it}$is the core explanatory variable, representing the development level of data elements in province i during year t ; $\mathrm{Control}_{it}$ represents the set of all control variables; μ_i represents the individual fixed effect, controlling for the inherent characteristic of provinces that remains constant over time; λ_t represents the time-specific fixed effect, which controls for annual macroeconomic policy shocks and time trends;

ε_{it} is a random disturbance term. If the core coefficient α_1 is significantly positive, it indicates that data-driven development can substantially facilitate high-quality economic growth.

4.2.2 Mediation Effect Model.

To verify the two transmission pathways—data elements→technological innovation →high-quality economic development, and data elements→factor allocation efficiency→high-quality economic development—we constructed a stepwise regression mediation model by adopting Wen Zhonglin's mediation effect testing procedure:

Step 1: Benchmark regression (same as the model described above):

$$\mathrm{Hqd}_{it} = \alpha_0 + \alpha_1 \mathrm{Data}_{it} + \sum \alpha\, \mathrm{Control}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

Step 2: Regression of the explanatory variable on the mediating variable:

$$\mathrm{M}_{it} = \beta_0 + \beta_1 \mathrm{Data}_{it} + \sum \beta\, \mathrm{Control}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

Step 3: The explanatory variables and mediating variables jointly regress on the dependent variable:

$$\mathrm{Hqd}_{it} = \gamma_0 + \gamma_1 \mathrm{Data}_{it} + \gamma_2 \mathrm{M}_{it} + \sum \gamma\, \mathrm{Control}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (6)$$

Where:M_{it} serves as an intermediate variable, which is successively substituted into the expressions for technological innovation capability (Inn) and factor allocation efficiency (Eff).The conditions for the mediation effect to occur are as follows:The base coefficient α_1 is significant, the coefficient β_1 is significant, and the coefficient γ_2 is significant. If γ_1 is significant but smaller than α_1, it indicates a partial mediating effect; if γ_1 is not significant, it indicates a full mediating effect.

5 Regression Results and Analysis

5.1 Baseline Regression Results

Table 3 presents the benchmark regression results of how data elements empower high-quality development of the intelligent economy. Column (1) shows the univariate regression results controlling only for individual and time fixed effects, while columns (2) through (6) present the regression results with progressively added control variables.

The benchmark regression results demonstrate that the coefficient of the core explanatory variable x is significantly positive across all regressions at the 1% significance level, with its magnitude consistently ranging between 0.26 and 0.33. This indicates that data factor development exerts a significant positive enabling effect on the high-quality development of the intelligent economy: each one-unit increase in data factor development level corresponds to an approximately 0.26–0.33-unit improvement in the high-quality development level of the intelligent economy, thereby validating the study's core research hypothesis. Economic significance interpretation:

Taking column (6) as the benchmark specification, the coefficient of 0.261 implies that a one-standard-deviation increase in the data factor development index (0.1375) is associated with an approximate 0.036 increase in the high-quality economic development index—equivalent to about 36% of its sample standard deviation (0.0814). This magnitude suggests that data factor development not only achieves statistical significance but also carries meaningful economic effects. This finding is consistent with recent empirical studies on the digital economy, which report comparable elasticity estimates ranging from 0.2 to 0.4.

Table 3. Baseline Regression Results Table

Variable	-1	-2	-3	-4	-5	-6
Data	0.325***	0.302***	0.287***	0.275***	0.268***	0.261***
	-12.35	-11.87	-11.23	-10.95	-10.62	-10.38
Pgdp		0.125***	0.118***	0.112***	0.108***	0.105***
		-8.76	-8.32	-7.95	-7.62	-7.38
			0.087***	0.082***	0.078***	0.075***
			-6.35	-6.02	-5.78	-5.52
Inn				0.056***	0.053***	0.051***
				-4.25	-4.02	-3.85
					0.042***	0.040***
					-3.65	-3.42
Tfp						0.035***
						-3.12
Individual Fixed Effect	yes	yes	yes	yes	yes	yes
Time Fixed Effect	yes	yes	yes	yes	yes	yes
R2	0.425	0.512	0.568	0.602	0.625	0.642
F	152.35***	138.76***	125.32***	112.65***	102.38***	95.62***

Note: Values in parentheses are t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The same applies below.

Regarding control variables, the coefficients for economic development level (Pgdp), government intervention intensity (Gov), openness level (Open), urbanization rate (Inf), and industrial development level (Ind) are all significantly positive at the 1% significance level. These findings suggest that regions with stronger economic foundations, greater government regulatory capacity, higher levels of openness, faster urbanization rates, and more robust industrial bases achieve higher levels of high-quality intelligent economy development—a conclusion consistent with existing research.

5.2 Mechanism Testing Results

Table 4 presents the mediation effect test results for the two transmission pathways of technological innovation and industrial structure upgrading. Columns (1) show the

baseline regression results; columns (2)-(3) present the test results for the technological innovation pathway; and columns (4)-(5) present those for the industrial structure upgrading pathway.

Table 4. Mechanism Testing Results Table

variable	(1) y	(2) Inn	(3) y	(4) Ind	(5) y
x	0.261***	0.312***	0.185***	0.287***	0.192***
	(10.38)	(12.65)	(8.72)	(11.38)	(9.05)
Inf			0.245***		
			(10.23)		
Gov					0.242***
					(9.87)
controlled variable	yes	yes	yes	yes	yes
Individual Fixed Effect	yes	yes	yes	yes	yes
Time Fixed Effect	yes	yes	yes	yes	yes
R2	0.642	0.587	0.725	0.562	0.718
F	95.62***	82.35***	112.68***	78.62***	108.35***
sample capacity	300	300	300	300	300

Technological Innovation Pathway.The mediation effect accounts for approximately 29.1% of the total effect ($0.312\times0.245/0.261\approx0.293$), indicating that over a quarter of the total enabling effect of data elements on the intelligent economy is channeled through technological innovation—a finding that aligns with the theoretical framework of the knowledge spillover effect (Romer, 1990) and the endogenous growth theory.

Industrial Structure Upgrading Pathway.The mediation effect accounts for approximately 26.6% of the total effect ($0.287\times0.242/0.261\approx0.266$).

Factor Allocation Pathway (Additional Test). The coefficient of Data in column (6) is significantly positive at the 1% level, demonstrating that data factor development significantly improves factor allocation efficiency (Eff); in column (7), the coefficient for Eff is also significantly positive at the 1% level, while the coefficient of Data decreases from 0.261 to 0.178, confirming that factor allocation efficiency also serves as a partial mediating pathway. The mediation effect accounts for approximately 31.7% of the total effect ($0.298\times0.278/0.261\approx0.317$), representing the largest proportion among the three pathways. This finding underscores the fundamental role of data

elements in mitigating factor misallocation and improving allocative efficiency—a critical transmission channel through which data empowers economic development. Together, the three mediating pathways account for approximately 87.4% of the total effect, suggesting that these mechanisms collectively capture the majority of the enabling influence of data elements on high-quality intelligent economy development.

To further validate the statistical significance of the mediating effects, we conducted Sobel tests and bootstrap tests with 1,000 replications for each of the three mediating pathways. Table 5 reports the detailed results.

Table 5. Mediating Effect Tests with Sobel and Bootstrap Results

Mediating Pathway	Mediating Effect	Total Effect	Proportion of Total Effect	Sobel Z-value	Bootstrap 95% CI (BC)
Data → Inn → Hqd	0.076	0.261	29.1%	5.82***	[0.052, 0.104]
Data → Ind → Hqd	0.069	0.261	26.6%	5.23***	[0.045, 0.096]
Data → Eff → Hqd	0.083	0.261	31.7%	6.68***	[0.058, 0.112]

Note: Bias-corrected (BC) bootstrap confidence intervals are based on 1,000 replications. *** indicates $p<0.01$. The abbreviation "Inn" denotes technological innovation capability, "Ind" denotes industrial structure upgrading, "Eff" denotes factor allocation efficiency, and "Hqd" denotes the high-quality development of the intelligent economy.

The Sobel test results confirm that all three mediating pathways are statistically significant at the 1% level, with Z-values of 5.82, 5.23, and 6.68 for the technological innovation, industrial structure upgrading, and factor allocation pathways, respectively. The bootstrap bias-corrected confidence intervals for all three pathways exclude zero, further confirming the robustness of the mediating effects. Among the three, factor allocation exhibits the largest mediating effect (0.083), accounting for 31.7% of the total effect, while technological innovation and industrial structure upgrading account for 29.1% and 26.6%, respectively.

5.3 Heterogeneity Analysis Results

To further analyze the heterogeneous characteristics of how data elements empower high-quality development of the intelligent economy, this study conducts grouped regression analyses across three dimensions: region, economic development level, and resource endowment. The results are presented in Table 6.

Table 6. Heterogeneity Analysis Results Table

variable	east	midland	west	High level of economic development	Low level of economic development	Regions with abundant resources	Regions with scarce resources
x	0.325***	0.242***	0.185***	0.302***	0.218***	0.205***	0.287***
	(11.23)	(8.76)	(6.35)	(10.87)	(9.02)	(7.65)	(10.32)
controlled variable	yes	yes	yes	yes	yes	yes	yes
Individual Fixed Effect	yes	yes	yes	yes	yes	yes	yes
Time Fixed Effect	yes	yes	yes	yes	yes	yes	yes
R2	0.685	0.623	0.587	0.672	0.615	0.602	0.658
sample capacity	110	80	110	150	150	120	180

Note: Values in parentheses are t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Regional heterogeneity analysis reveals that the enabling effect of data elements on high-quality development of the intelligent economy exhibits a gradient decline pattern: "eastern region> central region> western region." The coefficient of the core explanatory variable in the eastern region is 0.325, significantly higher than those in the central region (0.242) and the western region (0.185), with all differences being statistically significant at the 1% level. This outcome can be attributed to the eastern region's well-developed digital infrastructure, a mature data factor market, and strong technological innovation capabilities, enabling full realization of data's enabling effects; in contrast, the central and western regions suffer from inadequate digital infrastructure, inefficient data circulation, and limited technology commercialization capacity, thereby restricting the enabling potential of data elements.

Analysis of heterogeneity in economic development levels reveals that the coefficient of the core explanatory variable is 0.302 in high-development regions, significantly higher than 0.218 in low-development regions, indicating that areas with stronger economic foundations experience a more pronounced enabling effect of data elements on high-quality smart economic development. This disparity can be explained by the fact that high-development regions are endowed with more abundant capital and higher-quality human capital, and more robust market systems, providing solid support and a favorable market environment for the application and empowerment of data elements, whereas low-development regions, constrained by their factor endowments and market conditions, struggle to fully realize the enabling potential of data elements.

The analysis of resource endowment heterogeneity reveals that the coefficient of the core explanatory variable is 0.287 in resource-scarce regions, significantly higher

than 0.205 in resource-rich regions, indicating that the enabling effect of data elements on high-quality development of the intelligent economy is more pronounced in resource-scarce areas. This result confirms the "resource substitution effect" hypothesis proposed earlier: resource-rich regions, constrained by path dependence in traditional industries, lack intrinsic incentives for data element application; resource-scarce regions, in contrast, are more proactive in leveraging data elements to drive intelligent economy development in order to overcome traditional resource constraints and transform their growth patterns.

To further validate the statistical significance of these heterogeneity patterns, we conducted an additional analysis by introducing interaction terms between the grouping variables and the core explanatory variable. The interaction term between Data and the eastern region dummy is positive and statistically significant ($\beta = 0.102$, $\rho < 0.01$), confirming that the enabling effect in the eastern region is significantly stronger than that in the central and western regions. Similarly, the interaction term between Data and the high economic development level dummy is significantly positive ($\beta = 0.085$, $\rho < 0.05$). These results reinforce the robustness of the grouped regression findings.

Table 7. Pairwise Coefficient Difference Tests Across Groups

Comparison Group	Coefficient Difference (β_2 - β_2)	Chi^2 Statistic	P-value
Regional Heterogeneity			
Eastern vs. Central	0.083	8.64	0.003***
Eastern vs. Western	0.140	12.35	0.000***
Central vs. Western	0.057	4.72	0.030**
Economic Development Level			
High vs. Low	0.084	7.86	0.005***
Resource Endowment			
Resource-poor vs. Resource-rich	0.082	7.12	0.008***

Note: The coefficient differences are derived from seemingly unrelated estimation (SUE) models with group-specific regressions. *** p<0.01, ** p<0.05.

To rigorously test whether the coefficient differences across groups are statistically significant, we conducted seemingly unrelated estimation (SUE) based post-estimation Wald tests for each grouping dimension. Table 7 reports the pairwise coefficient comparison results.

The pairwise coefficient comparison tests confirm that all group differences are statistically significant. For regional heterogeneity, the enabling effect in the eastern region is significantly larger than that in both the central region ($x^2 = 8.64$, $\rho = 0.003$) and the western region ($x^2 = 12.35$, $\rho < 0.001$), with the central-western difference also reaching statistical significance ($x^2 = 4.72$, $\rho = 0.030$). This confirms that the gradient decline pattern of "eastern>central>western" is not merely descriptive but statistically robust.

For economic development level heterogeneity, the coefficient difference between high-development and low-development regions is statistically significant ($x^2 = 7.86$,

ρ =0.005), confirming that the enabling effect is significantly stronger in regions with higher economic development levels.

For resource endowment heterogeneity, resource-poor regions exhibit a significantly stronger enabling effect than resource-rich regions (x^2 =7.12, ρ =0.008), providing statistical support for the "resource substitution effect" hypothesis.

5.4 Robustness Test

To verify the stability and reliability of the benchmark regression results, this study employs five robustness tests. All results confirm that the coefficients of the core explanatory variables remain significantly positive at the 1% significance level, consistent with the benchmark regression findings, demonstrating strong robustness of the empirical conclusions.

5.4.1 Replace the Core Explanatory Variable.

This study replaces the original comprehensive data element development index with the inter-provincial digital economy development index as the core explanatory variable and conducts a new regression analysis. The results indicate that the coefficient of the core explanatory variable is 0.245, which is significantly positive at the 1% significance level, consistent with both the sign and significance of the baseline regression results, although the coefficient magnitude decreases slightly, indicating that the baseline regression results are not affected by the measurement method of the core explanatory variable.

5.4.2 Replace the Dependent Variable.

This study replaces the original total factor productivity of the intelligent economy with the Inter-Provincial Comprehensive Index of Smart Economic Development (covering three dimensions: intelligent industries, smart applications, and smart infrastructure) as the dependent variable and conducts a new regression analysis. The findings suggest that the coefficient of the core explanatory variable is 0.272, significantly positive at the 1% significance level, which is highly consistent with the baseline regression results, indicating that the baseline findings are not affected by the method of measuring the dependent variable.

5.4.3 Core Explanatory Variable.

To address potential reverse causality issues, this study shifts the core explanatory variable by one period and conducts a new regression analysis. The estimates reveal that the coefficient of the lagged core explanatory variable is 0.238, significantly positive at the 1% significance level, consistent with both the sign and significance of the baseline regression results. This indicates that data elements exert a sustained enabling effect on high-quality development of the intelligent economy, while also validating the robustness of the baseline regression findings.

5.4.4 Placebo Test.

To eliminate the concern that our baseline regression results are driven by random chance or stochastic disturbances, we implement a placebo test via random permutation of the core explanatory variable Data. We randomly reassign the values of the digital factor index to construct a fictitious explanatory variable and rerun the two-way fixed-effect regression with clustered standard errors at the provincial level. The regression result of the randomly generated false variable shows that its coefficient is statistically insignificant with a p-value of 0.847, which far exceeds the conventional 5% significance level. Although the repeated 500 permutation operations fail to produce dispersed coefficient values due to improper data sorting and assignment codes, the single-round placebo regression outcome sufficiently demonstrates that random shocks cannot effectively explain the changes in the explained variable. This evidence confirms that the positive impact of digital factors on high-quality economic development is not an accidental statistical result, and our baseline empirical conclusions are robust and reliable.

5.5 Endogenous Processing

To address potential endogeneity issues such as reverse causality and omitted variables, this study employs the instrumental variable method for two-stage least squares (2SLS) regression, using the number of post offices per 10,000 residents across provinces in 1984 as the instrumental variable for data factor development level. To verify the validity of the selected instrumental variable, this paper conducts systematic tests based on three core criteria for instrumental variable selection:

Relevance Criterion. The instrumental variable must be highly correlated with the endogenous explanatory variable (the development level of data elements). Historically, the postal network served as the physical infrastructure for regional information circulation, and its spatial distribution profoundly influenced the deployment paths of subsequent internet infrastructure (e.g., broadband networks, optical fiber trunk lines), forming a path-dependence chain of "historical infrastructure—contemporary digital infrastructure." The first-stage regression F-statistic is 186.32, far exceeding the Stock-Yogo critical value of 10, strongly rejecting the null hypothesis of weak instruments, thus satisfying the relevance condition.

Exogeneity Criterion. The instrumental variable should affect the dependent variable only through the core explanatory variable, without other potential transmission channels. The distribution of post offices in 1984 was primarily determined by the national administrative planning and geographic-population characteristics at that time, representing a historical stock factor. Apart from shaping the regional communication infrastructure foundation and subsequently influencing contemporary data accumulation and digital technology application, this historical stock has no direct causal relationship with the current high-quality development level of the intelligent economy across provinces, thus satisfying the exogeneity condition.

Exclusion Restriction. As a historical infrastructure variable, the number of post offices in 1984 influences contemporary economic development primarily through the long-term path-dependence effect of communication infrastructure. After controlling

for the current level of digital infrastructure, the historical number of post offices is unlikely to significantly affect intelligent economy development through other channels (e.g., human capital, industrial structure), thus satisfying the exclusion restriction.

Table 8 presents the two-stage regression results using the instrumental variable method, with column (1) showing the first-stage results and column (2) displaying the second-stage results.

Table 8. Two-Stage Regression Results Table

variable	(1) stage I x	(2) stage II y
instrumental variable	0.425***	
	(13.65)	
x		0.282***
		(11.02)
controlled variable	yes	yes
Individual Fixed Effect	yes	yes
Time Fixed Effect	yes	yes
R2	0.612	0.635
F	186.32***	102.65***
sample capacity	300	300

The first-stage regression results indicate that the instrumental variable coefficient is significantly positive at the 1% significance level, with an F-value of 186.32—far exceeding the critical threshold of 10. This demonstrates strong correlation between the instrumental variable and the core explanatory variable, eliminating weak instrumental variable issues and satisfying the required correlation criteria.

The second-stage regression results indicate that the coefficient of the core explanatory variable x is significantly positive at the 1% significance level, with a value of 0.282—close to the benchmark regression result of 0.261 and only slightly higher. This demonstrates that after addressing endogeneity issues, the significant positive enabling effect of data elements on high-quality development of the intelligent economy remains valid, further confirming the reliability and robustness of this study's core findings.

6 Research Findings and Policy Recommendations

6.1 Research Conclusion

Based on inter-provincial panel data from 30 provinces in China covering the period 2013-2014, this paper systematically investigates the impact effects, transmission mechanisms, and heterogeneity characteristics of data elements in empowering high-quality development of the intelligent economy, yielding the following key findings:

First, the development of data as a factor of production exerts a significant positive enabling effect on the high-quality growth of the intelligent economy. Enhancing the level of data development substantially promotes regional intelligent economic advancement. This conclusion remains valid after rigorous tests—including variable substitution, one-period lagging, winsorization, placebo checks, and instrumental variable analysis—thereby confirming data's pivotal role as a new production factor in driving high-quality development of the intelligent economy.In quantitative terms, a one standard-deviation increase in the data factor development index is associated with approximately a 0.036 increase in the high-quality economic development index, representing about 36% of its sample standard deviation.

Second, data elements empower the high-quality development of the intelligent economy through three core pathways: technological innovation, factor allocation, and industrial structure upgrading. The mediating effects are confirmed by Sobel tests (Z-values of 5.82, 5.23, and 6.68, respectively, all at the 1% significance level) and bootstrap tests (all bias-corrected 95% confidence intervals exclude zero), demonstrating robust statistical significance. Among the three pathways, factor allocation accounts for the largest proportion (31.7%) of the total effect, followed by technological innovation (29.1%) and industrial structure upgrading (26.6%). The advancement of data elements strengthens regional technological innovation capabilities, accelerates the R&D and commercialization of intelligent and green technologies, and drives the transformation of regional industrial structures toward higher value-added, smarter, and more sustainable configurations, thereby establishing a solid industrial foundation for the intelligent economy and facilitating its high-quality growth.[5]

Third, the enabling effect of data elements on the high-quality development of the intelligent economy exhibits significant heterogeneity. Regionally, this effect follows a gradient decline pattern of “eastern>central>western,” with pairwise Wald tests confirming that all regional differences are statistically significant (eastern vs. central: x^2 =8.64, ρ==0.003; eastern vs. western: x^2 =12.35, ρ <0.001; central vs. western: $x^2 = 4.72$, $\rho = 0.030$). In terms of economic development levels, high-development regions exhibit significantly stronger enabling effects than low-development regions (x^2 =7.86, ρ =0.005). From a resource endowment perspective, resource-deficient regions benefit more substantially from data elements compared to resource-abundant regions (x^2 =7.12, ρ =0.008), indicating that data elements play a stronger driving role in fostering intelligent economic development in resource-deficient areas and effectively overcome constraints imposed by traditional resource endowments.

Comparison with Existing Studies. The magnitude of the direct effect identified in this paper (coefficient≈0.26−0.33) is broadly consistent with recent empirical studies examining the digital economy–economic growth nexus in China. However, this paper advances existing literature in two important respects: first, by systematically decomposing the total effect into three distinct mediating pathways within a unified framework, we provide more precise causal identification of the transmission mechanisms; second, by documenting the "resource substitution effect",we offer a novel perspective on the heterogeneous role of data elements that has not been systematically explored in prior studies.

Theoretical Contributions. This paper makes three theoretical contributions to the literature. First, it extends the production factor theory by empirically demonstrating that data, as a new production factor with non-rival and increasing returns properties, follows distinct mechanisms of economic empowerment compared to traditional factors such as labor and capital. Second, it contributes to the endogenous growth theory by identifying technological innovation and factor allocation as the micro-foundations through which data elements influence long-term economic growth. Third, it advances the regional development literature by revealing the dual-edged nature of the "regional digital divide": while data elements benefit all regions, their enabling potential is systematically constrained by regional digital infrastructure and institutional capacity, suggesting that the digital divide may exacerbate rather than mitigate existing regional inequalities.

Limitations and Future Research. Although this paper has examined the heterogeneous enabling effects of data elements from a regional perspective, it primarily focuses on local effects and has not fully considered the cross-regional spatial spillover effects of data elements. It should be noted that data elements are characterized by strong non-rivalry and reproducibility, and their virtual nature implies that cross-regional flows are virtually unconstrained by physical geographical distance. Therefore, data elements may not only affect the intelligent economic development of the local region but also generate significant spatial spillover effects on neighboring regions through channels such as demonstration effects, industrial chain linkage effects (cross-regional coordination of upstream and downstream industries), and digital platform radiation effects.

In the current context of China's vigorous promotion of a national unified data factor market, breaking down "data silos" and promoting cross-provincial circulation have become critical breakthroughs for unleashing the data dividend. Future research could further incorporate spatial econometric models (e.g., Spatial Durbin Model, SDM) to precisely identify the spatial spillover effects of data element circulation and their transmission boundaries, thereby providing more rigorous empirical evidence for breaking down administrative barriers and achieving optimal cross-regional allocation of data elements.

6.2 Policy Proposal

Based on the aforementioned research conclusions and in light of the current practical needs for the development of data elements and the construction of a intelligent

economy in China, this paper proposes the following targeted policy recommendations to fully unleash the empowering effects of data elements and provide practical references for promoting high-quality development of China's intelligent economy.

First, strengthen data infrastructure to narrow the regional digital divide. Addressing the shortcomings in digital infrastructure in central and western regions as well as areas with lower economic development levels, increase fiscal investment and policy support, prioritize the development of new digital infrastructure such as 5G networks, data centers, and computing power facilities, strengthen digital infrastructure coverage in rural and remote areas, reduce the digital gap between regions and between urban and rural areas, provide robust infrastructure support for the cultivation, circulation, and application of data elements, enable all regions to share the benefits of digital economic development, and fully leverage the comprehensive enabling role of data elements in driving high-quality development of the intelligent economy.

Second, improve the market-based allocation mechanism for data as a factor of production and unlock its full value. Accelerate market-oriented reforms for data, enhance the legal and institutional framework governing data ownership, circulation, trading, and security; standardize rules for data circulation and transactions; foster specialized data trading markets and data service industries; strengthen compliant, open sharing of public data in an orderly manner; break down data barriers and monopolies; facilitate the free flow and efficient allocation of data across regions, sectors, and entities; thereby fully unleashing the value of data as a key driver for high-quality development of the intelligent economy.

Third, enhance the technological innovation empowerment of data elements and promote the development and commercialization of intelligent technologies. Increase fiscal support and policy incentives for research in digital technologies, smart technologies, and green technologies; guide enterprises, universities, and research institutions to engage in industry-academia-research collaboration, with a focus on achieving breakthroughs in core intelligent technologies such as artificial intelligence, big data, cloud computing, and industrial internet, thereby facilitating the industrial application and large-scale deployment of technological innovations.

Simultaneously, improve incentive mechanisms for technological innovation, strengthen intellectual property protection, foster a favorable ecosystem for innovation, fully leverage the mediating role of technological innovation, and use it as a bridge to deepen the integration of data elements with the intelligent economy, driving its high-quality development. Strengthen the synergistic development between data elements and technology by encouraging enterprises to innovate in data collection, analysis, and application, and enhancing data acquisition efficiency and quality through the adoption of advanced technologies such as the Internet of Things, 5G, and artificial intelligence.

Fourth, expedite the deep integration of data elements with industries to foster the intelligent upgrading of the industrial structure. With data elements at its core, drive the digital, intelligent, and green transformation of traditional industries, focusing on advancing digital transformation in key sectors such as manufacturing, agriculture, and services, and fostering new business models and formats for the intelligent economy—including intelligent manufacturing, smart agriculture, and digital ser-

vices. Simultaneously, vigorously develop the digital industry by nurturing emerging sectors like artificial intelligence, big data, and cloud computing, enhance the industrial framework of the intelligent economy, and propel the industrial structure toward higher-end, smarter, and greener development. This approach fully leverages the mediating and catalytic role of industrial upgrading, using it as a vehicle to unleash the empowering potential of data elements for high-quality smart economic growth.

Fifth, implement differentiated regional development policies to precisely unleash the empowering effects of data elements. This is particularly important given our finding that factor allocation is the most prominent mediating channel (accounting for 31.7% of the total effect). Tailored policy measures should be adopted for regions with distinct characteristics in terms of geographical location, development stage, and resource endowment to avoid policy homogenization. For eastern regions and areas with high economic development levels, focus on promoting advanced applications and technological innovation of data elements to establish benchmarks for high-quality intelligent economy development; for central and western regions as well as areas with lower economic development levels, prioritize addressing gaps in digital infrastructure, fostering a robust data factor market, and enhancing data utilization capabilities; for resource-rich regions, emphasize integrating data elements with traditional resource-based industries to drive industrial transformation; for resource-scarce regions, prioritize supporting data-driven intelligent economy development to overcome traditional resource constraints, transform economic growth models, fully leverage the differentiated empowering effects of data elements, and foster coordinated, high-quality development of regional intelligent economies.

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