

Research on the Impact of Data Elements on Rural Industrial Integration

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Abstract: This study investigates how data elements influence Rural Industrial Integration (RII). Using a random forest algorithm, we assess the development status of both data elements and RII across 30 provinces in China covering the period 2013-2023. A spatial Durbin model incorporating an economic-geographic distance weight matrix is then established for empirical investigation. The findings reveal four key points: First, data elements exert a significant facilitative influence on RII within local areas and also produce favorable spatial spillover impacts on adjacent regions. Second, the mechanism through which data elements elevate RII involves strengthening technological innovation and mitigating the misallocation of labor and capital factors. Third, human capital demonstrates a single-threshold characteristic in this relationship, whereby the promotional impact becomes more pronounced once the threshold is surpassed. Fourth, spatial heterogeneity exists: eastern areas display more evident spatial spillover effects, whereas central and western areas show stronger direct impacts but comparatively weaker spillover effects.

Keywords: Data Elements; Rural Industrial Integration; Technological Innovation; Factor Allocation; Human Capital.

1. Introduction

Achieving high-quality RII constitutes an essential route for advancing comprehensive rural revitalization and realizing agricultural modernization. Between 2015 and 2026, the annual No. 1 Central Documents have continuously underscored, for eleven consecutive years, Rural regions now face an urgent need to pursue coordinated progress across agriculture, industry, and services. In China, the integration of rural industries (RII) is marked by innovation-led momentum and a variety of developmental

pathways, which have given rise to practical models such as farm-produce processing, countryside tourism, and online commerce in rural communities. Such evolutions have enabled farmers to transition into comprehensive operators and cultivated a developmental landscape steered by diverse entities—family farms, cooperatives, and leading enterprises—backed by emerging factors and technologies. Nonetheless, notable obstacles remain: limited scale, inadequate integration degree, shallow integration depth, insufficient technological innovation, and loose benefit linkages. These problems constrain both the depth and breadth of industrial integration and hinder further enhancement of the rural economy. As data emerges as a novel pivotal production factor for economic growth, the digital economy centered on data elements offers fresh perspectives and pathways for RII.

Considerable scholarly attention has been directed toward the market-oriented reform of data elements. In 2022, the opinion concerning the establishment of foundational data systems to better harness the role of data elements explicitly stipulated the need to accelerate the construction of such systems, fully unlock the value potential embedded in data elements, and rapidly advance their incubation. In December 2023, the National Data Bureau together with 17 other departments jointly promulgated the "Data Element ×" Three-Year Action Plan (2024-2026), emphasizing the amplification, superimposition, and multiplication effects of data elements. The plan advocates promoting collaboration between data elements and factors such as labor and capital, and facilitating multi-agent reuse to drive high-quality industrial development. Employing data analysis and deep mining technologies to fully explore data value and release data efficacy can further advance product iteration innovation, restructure and upgrade business models, and effectively enhance the operational efficiency of micro-level entities.

Within this context, a critical question arises: how can the role of data elements be fully leveraged to expand the scale, elevate the quality, and improve the efficiency of RII? Furthermore, do these effects exhibit significant regional disparities? By addressing these inquiries, this paper seeks to elucidate the impact effects and underlying mechanisms through which data elements influence RII, thereby furnishing theoretical support and practical insights for the integration, transformation, and upgrading of China's rural industries.

2. Literature Review

As data has evolved into a novel pivotal production factor for economic development, scholarly investigation into data elements has progressively broadened from connotative characteristics and quantitative measurement to empowerment effects. Data elements are conceptualized as information carriers represented by binary bit strings utilized in production, possessing technical attributes such as virtuality and permeability, alongside economic attributes including non-rivalry, partial excludability, and externalities [1]. Moreover, they demonstrate cross-boundary integration both between data and between factors [2]. Grounded in these characteristics, data elements possess the dual properties of substantial increasing returns to scale and low-cost reuse. To gauge data development, researchers have employed approaches such as web crawling and questionnaires at the micro level to acquire data resources held by enterprises [3], and constructed multi-dimensional indicator systems based on the characteristics and roles of data elements at the macro level [4]. The empowerment effect of data elements is dualistic in nature. Internally within enterprises, data elements restructure productive forces and production relations—directly advancing production efficiency by strengthening enterprise learning capabilities and collaborative innovation capabilities, and indirectly augmenting output by optimizing the allocation of traditional factors [5, 6]. Externally, data elements broaden business scope and enhance product allocation efficiency by facilitating dynamic matching between supply and demand [7].

RII is conceptualized as a dynamic process spearheaded by new agricultural business entities, integrating resource factors through diverse means, with industrial chain extension, industrial

function expansion, and new business formation serving as typical pathways, thereby fostering robust agriculture, prosperous farmers, and beautiful rural areas. Building upon this definition, the degree of RII is generally quantified using multi-dimensional indicator systems [8]. RII models encompass vertical integration, horizontal integration, integrated integration, and permeative integration [9]. Notably, as digital technology has rendered industrial boundaries increasingly blurred, RII models are transitioning from conventional models toward composite models of re-integration and interdisciplinary integration models such as smart agriculture [10]. The driving factors underpinning RII can be categorized as internal factor inputs (labor, capital, land, etc.) and technological innovation in agricultural production, together with external market demand and transaction efficiency [11]. Relatively few studies have directly probed the relationship between the two, and pertinent insights are primarily scattered throughout literature examining the impacts of the digital economy on rural industrial development. These investigations concentrate on three principal dimensions. First, the digital economy facilitates RII. The digital economy has heightened the degree of RII and manifests significant spatial spillover effects [12]. Second, the digital economy plays a positive role in improving the efficiency of agricultural production. The digital economy can integrate and develop in tandem with agriculture, promote factor flow, alleviate rural factor constraints, improve factor allocation efficiency, and strengthen agricultural technological innovation [13]. Third, the digital economy aids in augmenting agricultural product allocation efficiency. The digital economy can diminish information asymmetry and effectively link urban and rural markets [14].

In summary, existing scholarship has laid an important foundation for research on RII and data elements, yet two aspects warrant further expansion and deepening. First, the majority of extant studies analyze the impact of the digital economy from a single perspective of either production efficiency or allocation efficiency, lacking systematic investigation from the dual perspectives of both. Second, current scholars predominantly conduct research from the vantage point of the digital economy, with insufficient attention devoted to the association between data elements and industrial innovation value chain integration, and limited focus on the spatial

dependence of data element spillovers. This study takes data elements as the entry point to explore their effects on industrial innovation value chain integration.

3. Mechanism of Data Elements Affecting Rural Industrial Integration

3.1 Direct Mechanism

Endogenous growth theory posits that technological progress constitutes the core driving force for economic growth. As data emerges as a novel pivotal production factor for economic development, its digital empowerment through the Internet, cloud computing, and big data can furnish robust technological support for RII. Data elements constitute a critical foundation of the digital economy, and related research indicates their positive role in advancing RII.

From the standpoint of factor integration, the amalgamation of data elements with traditional production factors (labor, capital, land, etc.) can optimize resource allocation and transform the production modalities of rural industries. In the course of mutual integration, the multiplier effect of data elements is activated, thereby fostering the diversified development of rural industries and giving rise to new models of industrial development. From the perspective of subject integration, diverse rural industrial subjects—such as farmer cooperatives and agricultural enterprises—can shatter information silos among industrial subjects by establishing data sharing mechanisms, achieve data interoperability, furnish comprehensive information support for various industries, and surmount the predicament of single-dimensional development in rural industries.

Furthermore, the positive externalities, permeability, and dynamic evolution characteristics of data elements can effectively break through temporal and spatial constraints, facilitate the formation of closely linked regional economic activities, and provide key support for the construction of high-quality regional development models. For example, Zhang et al. (2025) argued that market-based allocation of data elements directly advances high-quality development of rural industries in local areas and, through two channels—green innovation and market connectivity—also creates spatial spillover effects, thereby promoting cooperation and integration across regions [15]. Building upon the foregoing analysis, we propose the first

hypothesis:

H1a: Data elements exert a positive promotional effect on driving RII.

H1b: Data elements positively advance RII in neighboring regions, generating spillover effects.

3.2 Indirect Mechanism

According to endogenous growth theory, technological progress stems from knowledge accumulation and R&D investment within the economy. As a novel pivotal production factor, data elements, with their strong permeability and reusability, substantially promote the flow and spillover of knowledge, rendering information more transparent and thereby enhancing decision-making efficiency and accuracy, significantly diminishing information acquisition costs in innovation activities, and ultimately driving technological progress to become the endogenous core driving force of economic growth. The embedded informational worth of data components can drive a deep-seated, enduring, and efficiency-oriented reshaping of how rural industries develop, enabling systemic breakthroughs by analyzing data and combining production factors including land, capital, and labor. Allocating data factors through market mechanisms can help enterprises establish innovation systems and enable innovation to play a more constructive role in market-based development.

Technological, managerial, and business-model innovation serve as the primary drivers of RII. Through spillovers in markets, talent, and society, they promote the convergence of technology and products, business integration, and market integration. Empirical evidence indicates that technological innovation exerts a notable positive influence on RII and can reinforce its spatial spillover. As an emerging factor of production, data elements combine with inputs such as labor, capital, land, and technology. Across agricultural production, processing, and sales, data sharing and analytics allow advanced agricultural technologies and managerial experience to be rapidly diffused and applied, actively enabling innovation, raising productivity, and generating synergistic effects that drive quality improvements in RII. Therefore, we advance the second hypothesis:

H2: Data elements empower innovation and promote RII.

Moreover, as an emerging factor of production involved in distribution, data supports efficient

movement and optimal allocation, thereby restructuring conventional inputs—land, labor, capital, and technology—and boosting their efficiency. Because data is highly reproducible and cheap to spread, once it is created, many actors may use it concurrently without depleting extra material resources; it therefore constitutes a low-cost and reusable asset. Its non-excludable property likewise allows simultaneous use by numerous parties. With the help of data platforms and information networks, diverse actors can rapidly exchange agricultural technology, market information, and management experience, which enables more accurate and efficient production and marketing decisions, better resource allocation, and reduced resource waste. Data elements can, on the one hand, stimulate technological progress by optimizing the distribution of traditional production factors; on the other hand, they can become deeply embedded with such factors to achieve high-level interconnection, thus advancing technological innovation, enhancing productivity, and easing factor misallocation.

The enhancement of resource allocation efficiency plays an important role in promoting RII and the diversified development of the rural economy. For example, Li (2023) found that alleviating land and labor misallocation can enhance the human capital support for industrial integration and significantly improve the level of high-quality agricultural development [16]. Using a spatial Durbin model, Zhou et al. (2024) found that better allocation of agricultural factors not only improves the green utilization efficiency of local cultivated land but also facilitates cross-regional integration of rural industrial chains [17]. Based on this, we propose the third hypothesis:

H3a: Data elements promote RII by alleviating labor factor misallocation.

H3b: Data elements promote RII by alleviating capital factor misallocation.

3.3 Threshold Effect

A high level of human capital promotes technological transformation and progress, enhances productivity, and accelerates industrial integration. As an emerging form of production factor, data elements exhibit very obvious technology-driven characteristics. In the process of acquiring and utilizing data elements, certain digital processing capabilities are required so that the functions or value of data elements can be fully explored and rationally utilized. On the one

hand, the formation of a data circulation market attracts external digital technology talents to concentrate in rural areas, directly increasing the proportion of local digital talents and optimizing the human capital structure, reserving key human resources for industrial upgrading. Meanwhile, the application of data elements promotes the penetration of Internet and big data technologies into the agricultural supply side, helping to alleviate the dilemma of insufficient digital literacy and skilled human capital shortages among farmers. By implementing digital transformation strategies, rural industries restructure production, operation, and management processes with data technology, improving the efficiency of data element investment, while the improvement of human capital further reduces data usage costs and enhances its value conversion capability and marginal returns. On the other hand, the regional human capital level determines the degree to which the potential of data elements is released. The marketization of data elements not only increases the effective supply of new production factors but also profoundly affects the supply quality and methods of traditional human capital, and addresses the urgent demand for professional talents in new agricultural business forms through the agglomeration of digital talents. The realization of data elements depends on collaborative allocation with other factors, especially requiring the improvement of labor digital skills as a prerequisite. Only workers with higher digital literacy can better achieve the coordinated development of data and labor, maximize factor allocation efficiency, and empower RII and high-quality development. Therefore, human capital serves as the primary driver for advancing data elements and RII. Moreover, human capital levels exert an influence on how RII evolves. Accordingly, this paper advances the fourth hypothesis:

H4: Human capital has a threshold effect in the impact of data elements on RII.

3.4 Geographical Heterogeneity

From a geographical standpoint, the impact of digital elements on RII levels is highly heterogeneous, shaped by regional economic development, natural resource conditions, and topography. Data elements have two attributes: the crowding-out effect and the digital divide. In China, the spatial distribution of data elements shows a clear ladder-like pattern, with notable

regional disparities. As an economic pioneer, the eastern region has relatively well-established data infrastructure, abundant data resources, and high data application levels. This allows eastern agriculture to achieve digital transformation and innovation upgrading more rapidly under the impetus of data elements. In contrast, the central and western regions lag in data infrastructure, data resources, and application levels, which constrains RII to a certain extent. Moreover, pronounced differences in resource endowments across regions lead to significant gaps in the application of data elements. Accordingly, we propose the fifth hypothesis:

H5: The impact of data elements on RII exhibits geographical heterogeneity.

The theoretical mechanism diagram obtained from the above analysis is shown in Figure 1.

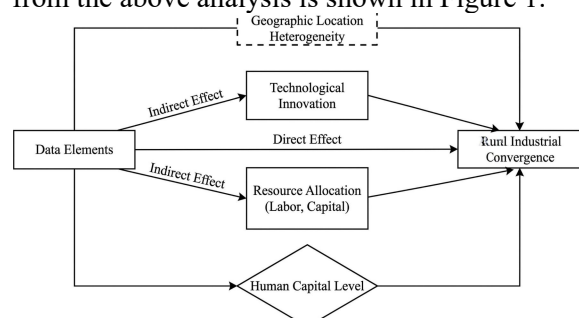


Figure 1. Mechanism of Data Elements Affecting Rural Industrial Integration

4. Research Design

4.1 Variable Measurement

(1) Data Element Allocation Level

Drawing on existing literature and considering data availability and completeness, we construct a multi-indicator system from the dual characteristics of data elements (Table 1). The data element evaluation indicator system constructed comprises three dimensions: data infrastructure generation, data element development and application, and data element management and utilization, covering 12 objective indicators including the number of Internet domain names, number of Internet web pages, number of IPv4 addresses, number of Internet broadband access users, number of enterprise-owned websites, number of above-scale electronic information manufacturing enterprises, information technology service revenue, e-commerce sales, digital inclusive finance index, software business revenue, R&D expenditure of above-scale industrial enterprises, and number of patent applications granted.

Table 1. Indicator System of Data Elements

Primary Indicator	Secondary Indicator	Attribute	Weight
Data Infrastructure Generation	Number of Internet domain names (10,000)	Positive	0.1656
	Number of Internet web pages (10,000)	Positive	0.0875
	Number of IPv4 addresses (10,000)	Positive	0.0830
	Number of Internet broadband access users (10,000)	Positive	0.0792
Data Element Development and Application	Number of enterprise-owned websites	Positive	0.0674
	Number of above-scale electronic information manufacturing enterprises	Positive	0.0756
	Information technology service revenue (10,000 yuan)	Positive	0.0752
	E-commerce sales	Positive	0.0737
Data Element Management and Utilization	Digital inclusive finance index	Positive	0.0722
	Software business revenue (10,000 yuan)	Positive	0.0784
	R&D expenditure of above-scale industrial enterprises	Positive	0.0692
	Number of patent applications granted	Positive	0.0731

Note: Indicator weights of regional data element allocation level are calculated through the random forest algorithm.

(2) Rural Industrial Integration Development

A quality–efficiency indicator system is established in this study to assess RII. It consists of 11 objective measures, namely the ratio of primary industry value added to GDP, the agricultural output ratio, per capita agricultural machinery power, the main revenue of leisure agriculture, the level of facility agriculture, the number of rural Internet access households, the share of output value from specialized and auxiliary activities in agriculture, forestry, animal husbandry, and fishery, the Engel coefficient for rural households, the urban-to-rural ratio of per capita income, the urban-to-rural ratio of per capita consumption expenditure, and the intensity of fertilizer application. This framework

highlights both the economic output efficiency of integration process (Table 2).
RII and quality enhancement within the

Table 2. Indicator System of Rural Industrial Integration

Dimension	Sub-dimension	Indicator	Attribute	Weight
Rural Industrial Integration Efficiency	Rural Industrial Chain	primary industry value added as a share of GDP	Negative	0.3489
		Agricultural output ratio	Positive	0.0593
		Per capita agricultural machinery power	Positive	0.0862
	Agricultural Multi-functionality Expansion	Main revenue of leisure agriculture	Positive	0.0783
		Level of facility agriculture	Positive	0.0692
	Growth of Emerging Agricultural Business Models	Number of rural Internet access households	Positive	0.0697
		Output value of specialized/auxiliary activities / total output value of agriculture, forestry, animal husbandry and fishery	Positive	0.0642
Rural Industrial Integration Quality		Rural household Engel coefficient	Negative	0.0516
	Urban-Rural Integration	Ratio of per capita income of urban and rural residents	Positive	0.0593
		Ratio of per capita consumption expenditure of urban and rural residents	Positive	0.0526
	Green Development	Fertilizer application intensity	Negative	0.0608

Note: Indicator weights of regional rural industrial integration are calculated through the random forest algorithm.

4.2 Measurement Method

This study employs the random forest algorithm to calculate the weights of each indicator in the evaluation indicator systems for RII level and data element allocation level. The specific steps are as follows:

First, the maximum-minimum method is used to perform dimensionless processing and translation processing on the original data of each indicator. Second, regarding the determination of indicator weights, we employ the random forest algorithm for weighting. Multiple sub-sample sets are generated through the Bootstrap method and decision trees are constructed: assuming the original dataset contains N samples and m independent variables, the Bootstrap resampling method is used to draw n_{tree} samples with replacement from the original dataset for constructing n_{tree} decision trees. At each node of each decision tree, m_{try} ($m_{\text{try}} < m$) pre-selected variables are randomly selected for node splitting, and all decision trees are grown to maximum depth without pruning. Finally, these n_{tree} decision trees constitute the random forest. During the Bootstrap resampling process, samples not drawn constitute the test dataset (i.e., out-of-bag data), which is used to evaluate the performance of the random forest regression

algorithm. Meanwhile, by calculating the error rate of out-of-bag data, the variable importance measure (VIM) of each variable is obtained, thereby determining the weight of each indicator. Finally, according to the importance scores of feature variables within each decision tree, the standardized weights of each feature variable are calculated. The composite weight value of each sample is then computed through weighted summation.

4.3 Empirical Model

RII development may vary across regions, and there may be continuity and dependence in industrial development and data element flow between adjacent regions. Moreover, the application of data elements not only drives the development of RII but can also affect adjacent regions through indirect spillover effects. Accordingly, this paper applies a spatial econometric approach to assess how data elements affect RII development and to capture cross-regional interactions and synergistic linkages. To confirm the model's appropriateness, LM, LR, Wald, and Hausman tests are additionally conducted. The model is specified as follows:

$$\text{Con_it} = \alpha_0 + \rho W \text{Con_it} + \alpha_1 \text{Data_it} + \theta_1 W \text{Data_it} + \alpha_2 X_{\text{it}} + \tau W X_{\text{it}} + \mu_i + \varphi_t + \varepsilon_{it} \quad (1)$$

In this specification, Con_it measures the development level of RII; $Data_it$ captures the allocation level of data elements; X_it denotes a set of control variables; and ε_it represents the spatial error term; μ_i and φ_t capture provincial and time fixed effects, respectively; ρ stands for the spatial autoregressive coefficient; τ denotes the spatial lag coefficient of the control variables; W represents the spatial weight matrix; and the remaining symbols are parameters.

In existing research, four principal types of spatial weight matrices are generally adopted to analyze spatial effects: spatial adjacency, geographical distance, and economic distance, and economic–geographic distance matrices. Economic processes such as knowledge spillovers, technological diffusion, industrial cooperation, and factor mobility are conditioned not only by geographic proximity but also strongly by economic proximity, as reflected in development level, industrial structure, and human capital. Meanwhile, regions that are geographically close usually maintain more frequent interaction and connection in physical-geographic and socioeconomic terms. A combined economic–geographic distance matrix can better capture these linkages and more effectively identify the cross-regional spillover effects of data elements. Accordingly, this study employs the economic–geographic distance spatial weight matrix as the spatial weight matrix.

To further test the transmission channel through which data elements empower RII, this paper follows the methodological framework of Jiang (2022) and develops a spatial mediation effect model that examines the linkage between core explanatory variables and mediating variables while incorporating spatial spillover effects [18]. This specification enables the estimation of both the direct influence of data elements and the indirect effects generated by interregional technology spillovers and resource flows via spatial interaction terms, thereby offering a more comprehensive account of the synergistic empowerment mechanism of data elements.

$$Media_it = \beta_0 + \rho_2 W Media_it + \beta_1 Data_it + \theta_1 W Data_it + \rho_2 X_it + \tau_1 W X_it + \mu_i + \varphi_t + \varepsilon_it \quad (2)$$

$$Con_it = \gamma_0 + \rho_3 W Con_it + \gamma_1 Data_it + \theta_2 W Data_it + \gamma_2 X_it + \gamma_2 Media_it + \tau_2 W X_it + \tau_3 W Media_it + \mu_i + \varphi_t + \varepsilon_it \quad (3)$$

where $Media_it$ represents the mediation variable. The meanings of the other symbols are similar to

those in Equation (1).

To rigorously examine whether the impact of data element allocation level exhibits nonlinear changes due to differences in human capital levels, We employ a panel threshold regression model, taking human capital (Cap) as the threshold variable for empirical analysis, and construct the following threshold model:

$$Con_it = \eta_0 + \eta_1 DataMit \times I(\ln Cap \leq \psi_1) + \eta_2 DataMit \times I(\psi_1 < \ln Cap \leq \psi_2) + \eta_3 DataMit \times I(\ln Cap > \psi_2) + \eta_4 X_it + \tau_t + \gamma_p + \varepsilon_it \quad (4)$$

4.4 Variable Selection and Data Sources

RII (Con), derived above, acts as the outcome variable, and the data element allocation level ($Data$), also defined earlier, functions as the key explanatory variable. Two mediating variables are considered. The first, technological innovation capability (Tec), is measured by regional R&D expenditure intensity. This measure mirrors how much importance a region attaches to innovation, how heavily it invests, and how well it supports innovation resources. With sufficient funding, a region can draw in and nurture research talent and acquire research equipment, thereby establishing a solid material base for producing advanced innovation results. The second, factor misallocation ($Kdis$ and $Ldis$), relates to the fact that the digital economy can allocate resources more efficiently by facilitating factor flows and advancing factor marketization, which in turn helps promote RII. Consequently, the capital factor misallocation index ($Kdis$) and labor factor misallocation index ($Ldis$) are adopted as proxy variables to explore the relationship among data elements, factor allocation, and RII.

To reduce omitted-variable bias, and following prior research, this study includes the following controls: urbanization level, financial support for agriculture, openness, economic development level, industrial structure upgrading, labor force level, and transportation infrastructure. Their measures are as follows: urbanization (Urb) is represented by the urban population share; openness ($Open$) by the proportion of imports and exports in regional GDP; economic development level ($\ln GDP$) by the logarithm of per capita GDP; advanced industrial structure (Ind) by the ratio of tertiary-sector value added to secondary-sector value added; labor force level ($\ln Lab$) by the logarithm of total provincial employment; and human capital (Hum) by the share of the

population with a college education or above in each province.

For data availability and continuity, the analytical sample consists of panel data covering 30 Chinese provinces from 2013 to 2023. The data are obtained from the China Statistical Yearbook, China Rural Statistical Yearbook, China Agricultural Machinery Industry Yearbook,

China Urban-Rural Construction Statistical Yearbook, China Transportation Statistical Yearbook, provincial statistical yearbooks, and the official website of the National Bureau of Statistics. A small number of missing values are filled through interpolation. Table 3 presents descriptive statistics for the relevant variables.

Table 3. Descriptive Statistics of Variables

Variable Type	Variable Name	N	Mean	Std. Dev.	Min	Max
Explained Variable	Rural industrial integration (Con)	330	0.254	0.072	0.099	0.487
Core Explanatory Variable	Data elements (Data)	330	0.793	1.014	0.028	6.486
Mediation Variable	Technological innovation capability (Tec)	330	1.875	1.177	0.45	6.83
	Capital factor misallocation (Kdis)	330	-0.007	0.7372	-0.837	2.884
	Labor factor misallocation (Ldis)	330	-2.103	10.514	-64.763	7.518
Control Variable	Urbanization level (Urb)	330	0.619	0.113	0.379	0.896
	Degree of opening (Open)	330	0.258	0.254	0.0076	1.257
	Economic development level (lnGDP)	330	1.770	0.440	0.792	2.997
	Advanced industrial structure (Ind)	330	1.438	0.774	0.665	5.690
	Labor force level (lnLab)	330	2.021	0.108	1.713	2.182
	2021	0.131	0.086	0.244	0.010	
	2022	0.136	0.080	0.225	0.017	
	2023	0.128	0.092	0.217	0.020	

5. Empirical Results

5.1 Spatial Autocorrelation Test

The prerequisite for using spatial econometric methods is to test whether the data exhibits spatial autocorrelation. Accordingly, Moran's I is applied to examine spatial autocorrelation across the 30 provinces over the sample period. Table 4 reports the Moran's I values for data element allocation and RII in these 30 provinces from 2013 to 2023. From the global Moran's I index test results of data elements, the index values for each year are significantly positive. Meanwhile, the degree of RII from 2013 to 2023 also exhibits significant spatial correlation, with its Moran's I indices all being positive. The above results indicate that both data elements and RII exhibit positive spatial autocorrelation, further demonstrating the rationality of using a spatial econometric model to analyze the relationship between data elements and RII in this study.

Table 4. Moran's I Test of Data Elements and Rural Industrial Integration (2013-2023)

Year	Data Elements Moran's I	P-value	Rural Industrial Integration Moran's I	P-value
2013	0.148	0.066	0.196	0.036
2014	0.139	0.084	0.218	0.022
2015	0.160	0.052	0.235	0.014
2016	0.180	0.034	0.305	0.002
2017	0.195	0.023	0.284	0.003
2018	0.164	0.045	0.268	0.005
2019	0.144	0.065	0.265	0.006
2020	0.130	0.090	0.249	0.009

5.2 Spatial Econometric Model Selection Test

Before conducting regression analysis on the spatial Durbin model, systematic testing and scientific specification of the specific model form are performed. Table 5 displays the estimation diagnostics. The LM-family tests are significant at the 1% or 5% level, indicating that the necessary conditions for using either the SEM or the SLM are met. The LR statistic rejects the null, ruling out simplification to either the SEM or SLM. Moreover, the Wald statistic attains significance at the 1% level, reinforcing the view that the SDM is more suitable and fits better than the SAR and SEM. The Hausman test returns a negative value, suggesting that the random-effects null should be rejected in favor of fixed effects. Separate LR tests for spatial and time fixed effects both yield significant outcomes. Given these findings, the study adopts a Durbin model with spatiotemporal two-way fixed effects as the final specification.

Table 5. Spatial Econometric Model Selection Test Results

Spatial Econometric Model Test	Coefficient
LM-lag	30.6800***
Robust-LM-lag	30.6850***
Wald lag	99.42***
Wald error	117.95***
LM-error	7.6710***
Robust-LM-error	7.6760***
LR lag	100.46***

LR error	86.99***
LR SDM ind	55.21***
LR SDM time	606.40***
Hausman test	-16.63

Note: *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

5.3 Baseline Regression and Spatial Spillover Effect Decomposition

According to Table 6, data elements exert a direct influence on RII. Their coefficient is positive and significant at the 1% level, indicating that local data-factor development substantially promotes RII and providing support for H1a. Furthermore, ρ , the spatial autoregressive parameter, is significantly positive at the 1% level, which offers additional evidence of strong positive spatial autocorrelation in RII dynamics. Specifically, the local RII level and the industrial integration process in surrounding areas tend to move together and reinforce each other, with data elements functioning as the principal driving force and playing a key supportive role in this coordinated development. The spatial lag coefficient of data elements is also significantly positive at the 1% level, showing that data

elements produce a marked positive spatial spillover effect on neighboring regions' RII, thus supporting H1b.

For the control variables, urbanization enters with a positive coefficient that is significant at the 1% level, indicating that continued urban growth helps create favorable conditions for RII by generating agglomeration economies and enlarging market demand. Likewise, the openness variable is positively and significantly estimated at the 1% level, which suggests that stronger external openness enables the absorption of advanced technology and management expertise, thus advancing the transformation and upgrading of rural industries. The indicator for industrial structure upgrading also displays a positive coefficient significant at the 1% level, implying that improvements in industrial structure create supportive conditions for RII. By contrast, neither economic development level nor human capital has a statistically significant coefficient. Such insignificance may suggest that, at this stage, macroeconomic expansion and human capital accumulation have not yet delivered fully realized direct effects on RII.

Table 6. Baseline Regression and Effect Decomposition of Spatial Durbin Model

Variable	Spatial Durbin	Direct Effect	Indirect Effect	Total Effect
Data element	0.239*** (6.54)	0.281*** (6.78)	1.723** (3.28)	2.004*** (3.66)
Urbanization level	0.687*** (6.33)	0.660*** (6.18)	-0.983 (-0.93)	-0.323 (-0.30)
Degree of opening	0.0829*** (3.59)	0.0951*** (4.27)	0.405* (2.36)	0.500** (2.85)
Economic development level	-0.0592 (-1.86)	-0.0584 (-1.81)	0.0608 (0.27)	0.00242 (0.01)
Advanced industrial structure	0.0390*** (5.44)	0.0401*** (5.26)	0.0467 (0.66)	0.0867 (1.17)
Human capital	1.443 (1.66)	1.442 (1.65)	-2.147 (-0.62)	-0.705 (-0.20)
W*Data	0.700*** (3.76)			
ρ	0.523*** (4.65)			
σ^2_e	0.00025*** (12.14)			
Observations	330	330	330	330
R ²	0.255	0.255	0.255	0.255

Note: Standard errors are in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

We further apply a partial differential equation decomposition approach to split the influence of data elements on RII into direct, indirect, and total effects. Regression results indicate that, in terms of direct effects, the data element allocation level has a significantly positive impact on RII and is significant at the 1% level, suggesting that enhancing a region's capacity for data element allocation can effectively advance RII development within the province. Meanwhile, the indirect effects show significantly positive spatial spillovers and are significant at the 5% level, indicating that data element development not only drives local RII but also positively affects

neighboring provinces. The beneficial effect of data element allocation on RII further generates cross-regional radiation effects through spatial transmission channels, ultimately making the total effect coefficient of this variable on RII significantly positive. Based on the effect decomposition, when a province's data element allocation level rises by 1 unit, it directly promotes local RII, increasing the province's RII level by 0.280 units; it also produces clear spatial spillover effects that positively empower RII development in adjacent provinces, raising their RII level by 1.723 units.

In summary, data elements not only directly drive

local RII but also promote the integrated development of neighboring regions through spatial spillover effects, forming a new pattern of regional coordinated development, that is, data elements have spatial spillover effects on RII.

5.4 Endogeneity Test

Given the potential two-way causality between data elements and RII, along with endogeneity arising from omitted key regressors, baseline estimates may be unreliable, and conventional estimation could undermine accuracy. To address this, the GS2SLS approach is adopted for endogeneity testing. Table 7 reports the GS2SLS estimates. The spatial lag of the dependent variable ($W \cdot RII$) has a significantly positive coefficient, implying pronounced spatial dependence in RII and aligning with the spatial autoregressive coefficient from the baseline model. The core explanatory variable, data elements, yields a coefficient of 0.214, significant at the 1% level. Although this value is smaller

than the baseline estimate, its sign and significance remain unchanged, reinforcing the robustness of the central conclusion that data elements foster RII.

Table 7. Endogeneity Test Results

Variable	GS2SLS
$W \cdot \text{Rural industrial integration}$	0.453*** (0.089)
Data element	0.214*** (0.035)
Urbanization level	0.016 (0.088)
Degree of opening	0.061*** (0.020)
Economic development level	0.039 (0.030)
Advanced industrial structure	0.015** (0.006)
Human capital	3.277*** (0.736)
Constant	-0.019 (0.040)
Observations	330

Note: Standard errors are in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

5.5 Robustness Test

To determine whether the baseline estimates are credible and robust, three robustness checks are conducted.

Table 8. Robustness Test Results

Variable	(1) Replaced Explained Variable	(2) Changed Spatial Matrix	(3) Changed Spatial Model
Data elements	0.438*** (8.98)	0.239*** (6.54)	0.285*** (8.12)
Urbanization level	0.721*** (4.38)	0.687*** (6.33)	0.385*** (4.00)
Degree of opening	0.186*** (5.47)	0.0829*** (3.59)	0.129*** (5.90)
Economic development level	-0.0349 (-0.83)	-0.0592 (-1.86)	-0.0201 (-0.70)
Advanced industrial structure	0.0514*** (4.76)	0.0390*** (5.44)	0.0403*** (6.24)
Human capital	4.793*** (4.02)	1.443 (1.66)	0.168 (0.96)
$W \cdot \text{Data elements}$	0.493** (3.10)	0.700*** (3.76)	0.285*** (8.12)
ρ	0.198* (2.31)	0.523*** (4.65)	0.219*** (3.61)
σ_2^2	0.00056*** (12.20)	0.00025*** (12.14)	0.00031*** (12.22)
Direct effect	0.463*** (9.31)	0.281*** (6.78)	0.290*** (8.07)
Indirect effect	0.690*** (4.07)	1.723** (3.28)	0.0783** (3.02)
Total effect	1.154*** (6.43)	2.004*** (3.66)	0.368*** (8.08)
Observations	330	330	330

Note: Standard errors are in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

(1) Substituting the key explanatory variable and the dependent variable. The entropy-weight TOPSIS approach is used to reconstruct the composite indicator systems for data elements and RII. Column (1) of Table 8 reports the estimates. The coefficients change only slightly in magnitude, while their signs and significance remain essentially stable.

(2) Replacing the spatial weight matrix. A spatial distance weighting matrix is adopted instead of the economic–geographic distance weighting matrix. Column (2) of Table 8 gives the results. The estimated coefficients of the explanatory variables remain significantly positive and are

broadly in line with earlier findings. These tests collectively indicate that the estimates obtained in this study are highly robust.

(3) Changing the spatial model. The core empirical specification is further replaced with a spatial autoregressive model, and the spatial effects of data element allocation on RII are re-estimated and tested. The outcomes appear in column (3) of Table 8. Under the spatial autoregressive specification, the regression results remain significant, offering further evidence for the credibility of the baseline estimates.

5.6 Mechanism Analysis

Table 9 presents the test results of mediation effects. From the test of the technological innovation capability transmission pathway, at the 1% significance level, the impact of data element allocation level on innovation capability is significantly positive, indicating that the innovation capability of data elements has a significant positive impact on RII. Combined with the previous theory, technological progress results from knowledge accumulation and R&D investment within the economy. As a new key production factor, data elements, with their strong permeability and reusability, greatly promote the flow and spillover of knowledge, significantly reduce information acquisition costs in innovation activities, and promote knowledge innovation and technological innovation by lowering innovation information barriers and accelerating knowledge diffusion, thereby promoting the deep integration of rural industries. That is, technological innovation capability plays a mediating role in the impact of data elements on RII. Therefore, the second hypothesis of this

study is confirmed.

From the test results of the factor misallocation transmission pathway, the regression coefficients of data element allocation level on labor factor misallocation and capital factor misallocation are both significantly negative at the 5% significance level. This result indicates that data element development has an obvious inhibitory effect on labor factor misallocation and capital factor misallocation. This is consistent with the research results of many scholars and can be explained as follows: data elements, with their high permeability, substitutability, and synergy, increase the demand for highly skilled talents, forming a gravitational effect and promoting the free flow and efficient allocation of labor resources. Regarding capital misallocation, data elements break through the spatial constraints of capital, can break down information barriers that transcend temporal and spatial limits, and stimulate the vitality of idle assets transforming into digital capital, thereby alleviating the degree of capital misallocation. Thus, hypotheses H3a and H3b are confirmed.

Table 9. Mediation Effect Results

Variable	Technological Innovation Capability	Labor Factor Misallocation	Capital Factor Misallocation
Data elements	3.7993*** (0.3698)	-2.0920** (1.0440)	-1.2583** (0.5531)
W*x	4.7016*** (1.4048)	-4.0499 (5.1128)	-6.5527* (3.7657)
Direct effect	3.6185*** (0.3730)	-2.4786* (1.3423)	-2.3241** (1.1586)
Indirect effect	3.2161*** (1.1846)	-15.5142 (18.5475)	-35.1971 (25.9013)
Total effect	6.8346*** (1.2774)	-17.9928 (19.4646)	-37.5211 (26.9417)
Rho	-0.2501*** (0.0941)	0.6415*** (0.0993)	0.7770*** (0.0653)
sigma ² _e	0.0245*** (0.0019)	0.2088*** (0.0173)	0.0539*** (0.0043)
Control variables	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes
Region fixed	Yes	Yes	Yes
R ²	0.1977	0.1977	0.1977
Observations	330	330	330

Note: Parentheses contain standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

5.7 Threshold Effect Analysis

The preceding regression findings indicate that the allocation level of data elements exerts a significant linear influence on RII development. Theoretical studies, however, suggest that the empowering role of data elements may be conditioned by the cognitive and technical capacities of integrating entities. In this sense, human capital may serve as a crucial restrictive or facilitating factor in how data elements drive RII. To determine whether a human capital threshold effect exists and how many thresholds are involved, this study performs 500 bootstrap resamples and applies the likelihood ratio test to

derive the statistic's P-value, which is then used to judge whether the threshold effect is valid (Table 10). The test outcomes are as follows: the single-threshold test yields an F-statistic of 69.36 with a P-value of 0.0000, significant at the 1% level; the double-threshold test produces an F-statistic of 25.41 with a P-value of 0.1067, failing to reach significance. Hence, a single human-capital-based threshold effect exists in the impact of data elements on RII, with the threshold estimate at 0.0284 and a confidence interval of (0.0282, 0.0286).

To confirm the reliability of the estimated threshold, this study employs the likelihood ratio (LR) test and visualizes the results via an LR

curve. The 95% confidence interval for the threshold parameter is derived by collecting all values of the test statistic t^* for which the corresponding LR statistic does not exceed the 5% critical value (7.35, marked as the dashed line in Figure 2). As Figure 2 illustrates, the LR curve

attains its minimum exactly at the estimated threshold point, and the LR value at this minimum is substantially below the 7.35 benchmark. This outcome strongly supports the validity of the identified threshold.

Table 10. Human Capital Threshold Effect Test

Threshold Type	F-value	P-value	5% Critical Value	1% Critical Value	Threshold Estimate	95% Confidence Interval
Single threshold	69.36	0.0000	29.3897	38.8607	0.0284	(0.0282, 0.0286)
Double threshold	25.41	0.1067	40.7178	67.6837	0.0284	(0.0282, 0.0286)

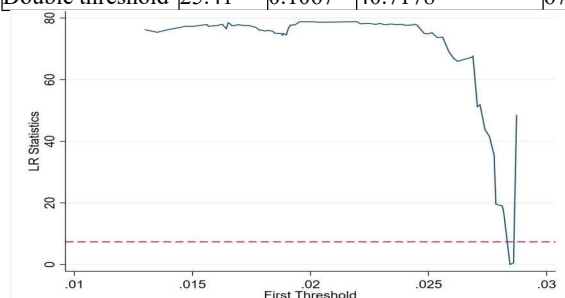


Figure 2. LR Curve of Human Capital Threshold Value

Table 11 presents the threshold regression results with human capital as the threshold variable. When the human capital level does not cross the threshold value, the impact effect of data elements on RII is 0.3803; when the human capital level crosses the threshold value, this impact effect increases to 0.5105. Taken together, the above threshold regression results, it can be found that regardless of the level of human capital, data elements can have a significant positive promoting effect on RII, and this empowerment effect exhibits obvious positive increasing characteristics, that is, as the regional human capital level continuously improves, the driving effect of data elements on RII also continuously strengthens. When the human capital level is low, entities such as enterprises, research institutions, and farmers have weak capabilities in applying data elements, making it difficult to exert economies of scale, and the improvement of resource factor utilization efficiency is constrained. When human capital reaches a certain level, enterprises, research institutions, and rural production operators can more effectively promote industrial chain extension and value chain upgrading through multiple channels such as technological innovation absorption capability, organizational management efficiency, and market development capability, and possess stronger capabilities and needs to accept and apply data resources, thereby promoting RII. Therefore, the improvement of human capital level can strengthen the promoting effect of data elements on RII, and hypothesis H4

is verified.

Table 11. Human Capital Threshold Regression Results

Variable	Regression Coefficient	t-value
Ln human capital ≤ 0.0284	0.3803***	10.83
Ln human capital ≥ 0.0284	0.5105***	14.26
Urbanization level	0.3439***	3.95
Degree of opening up	0.1751***	8.26
Economic development level	0.0072	0.29
Advanced industrial structure	0.0502***	8.17

5.8 Heterogeneity Analysis

Considering that there are significant differences in data element endowments, digital infrastructure, and rural industrial development foundations across regions, the effects and spatial spillover effects of data elements driving RII may exhibit regional heterogeneity. Accordingly, to compare how data elements generate multiplier effects on RII across different regions and to further interpret the empirical findings, this study conducts subsample regressions for the eastern, central, and western regions. The empirical results are reported in Table 12.

According to the direct-effect estimates, the allocation level of data elements generates a significantly positive boost to local RII across all three major regions—eastern, central, and western—thus offering preliminary support for H5. This suggests that data elements, as an emerging production factor, can empower RII irrespective of a region's development stage. The direct-effect coefficients for the central and western regions are markedly larger than that for the eastern region. In the east, rural industrial digitalization is relatively advanced, and the marginal returns to data element investment appear to be diminishing, whereas the central and western regions are undergoing a phase of rapid adoption and application of digital technologies. In terms of spatial spillovers, regional disparities are highly pronounced. In the eastern region, the indirect effect of data elements is positive and significant at the 1% level, suggesting that the

region's well-established digital infrastructure and strong cross-regional information connectivity create favorable conditions for the cross-regional flow of data elements and knowledge spillovers, thereby effectively stimulating RII in neighboring areas. The central region exhibits a negative indirect effect, while the western region shows a negative yet statistically insignificant indirect effect. This may arise because, in the process of data elements driving RII, there may be certain resource competition effects within the central region, and the "siphon effect" generated by data element agglomeration temporarily exceeds its "diffusion effect," inhibiting its positive spillover to neighboring regions. In the western region, due to imperfect digital infrastructure, the cross-regional flow and sharing mechanism of data elements is still not smooth, resulting in its spatial spillover effect not being fully manifested.

In summary, the impact of data elements on RII indeed exhibits significant geographical heterogeneity, and hypothesis H5 is verified. The eastern region should further leverage its spatial spillover advantages and strengthen regional collaboration and radiation-driven functions. While preserving their advantages in direct effects, the central and western regions should focus on removing the constraints on spatial spillovers, strengthening digital infrastructure, and fostering regional cooperation, so as to convert the considerable potential of data elements into genuine momentum for coordinated regional development. In advancing RII, it is essential to fully harness the multiplier effect of data elements, empower traditional production factor innovation, improve production efficiency, and select effective collaborative service models based on regional development conditions, exerting synergistic effects to drive the scale of RII.

Table 12. Heterogeneity Analysis Results

Variable	Eastern	Central	Western
Data elements	0.172*** (3.35)	1.636*** (8.79)	1.654*** (9.10)
W*x	0.501*** (3.50)	-1.035* (- 2.41)	-0.519 (-1.60)
Direct effect	0.207*** (3.49)	1.602*** (8.10)	1.652*** (8.73)
Indirect effect	0.760** (3.03)	-0.777 (- 1.36)	-0.432 (-1.25)
Total effect	0.967*** (3.32)	0.826 (1.25)	1.220** (2.70)
Control variables	Yes	Yes	Yes
rho	0.298*	0.274 (1.89)	0.0603

	(2.10)		(0.66)
sigma2_e	0.000189** * (7.36)	0.000115** * (6.27)	0.000139* ** (7.41)
R2	0.030	0.633	0.346
Observations	330	330	330

Note: Parentheses contain standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

6. Conclusions and Policy Recommendations

Driven by the swift evolution of digital technology and the growing maturity of data-factor market institutions, data elements, regarded as an emerging production factor, are profoundly transforming conventional agricultural production patterns and the rural industrial ecosystem. Against this backdrop, investigating how data elements empower rural industry integration (RII) and what effects they produce holds considerable theoretical significance and practical implications for implementing the rural revitalization strategy. Drawing on panel data for 30 Chinese provinces from 2013 to 2023, this study employs a spatial Durbin model to systematically evaluate how data elements affect RII levels and the transmission channels involved. The principal conclusions are as follows: (1) Data elements markedly raise local RII levels while also fostering RII growth in adjacent regions via spatial spillovers. (2) Data elements considerably strengthen RII by stimulating technological innovation and enhancing resource allocation efficiency. (3) In terms of threshold effects, human capital level displays a single-threshold effect in the process through which data elements affect RII. (4) The positive impact of data elements on RII demonstrates pronounced spatial heterogeneity. Based on the above conclusions, the following recommendations are proposed:

(1) Enhance the coupling between data factors and conventional inputs while fostering collaboration among diverse actors. Government authorities should facilitate the deep fusion of data elements with labor, capital, land, and other traditional production factors, dismantle information barriers by building multi-stakeholder data-sharing systems, and thereby raise the level of intelligent administration in rural industries. Partnerships between research organizations and firms should be encouraged to carry out R&D on data technologies across agricultural production, processing, and marketing, so that the multiplier effects of data

elements can be fully released and advanced technologies can be more widely adopted in rural industries. It is also necessary to advance smart management of conventional agricultural production, streamline processing operations, enhance product quality and market competitiveness, accomplish agricultural transformation and upgrading, and stimulate deep integration and innovative growth across rural industries.

(2) Establish and improve the data element market system and comprehensively enhance resource utilization efficiency. Promote the efficient flow and precise matching of agricultural production factors, clarify data property rights ownership, standardize data transaction processes, ensure that data elements meet the inherent requirements of unified openness and orderly competition, promote the efficient allocation of traditional and emerging factors across regions, eliminate factor misallocation and structural imbalance, and thereby promote the effective allocation of data elements in RII. By constructing a regionally integrated agricultural data resource system, integrating factor information such as land, labor, capital, and technology, effectively reduce resource misallocation caused by information asymmetry, guide factors to flow orderly to agricultural business forms and regions with high benefits and high integration degrees, thereby optimizing the distribution structure of agricultural industries and improving the overall efficiency of resource allocation.

(3) Develop interdisciplinary “Data Element × Agriculture” professionals and raise the digital literacy of rural residents. Greater efforts should be made to train rural data specialists, encourage universities to offer rural data science programs, and design policies for fostering interdisciplinary talent that steer production factors rationally toward RII. Internet platforms and online educational resources can be used to deliver targeted digital literacy training to rural populations; by combining classroom instruction with field-based teaching, basic knowledge of the digital economy and practical skills can be actively disseminated and applied, thereby strengthening the digital literacy of the local rural workforce. By expanding digital skills training, attracting professional talent, and enhancing the data literacy of relevant actors, it is possible to overcome human capital threshold constraints and maximize the efficiency with which data

elements drive industrial integration.

(4) Promote context-specific development of data-element infrastructure and build a solid support system for rural data elements. Differentiated RII policies should be formulated according to each region’s economic conditions, natural resource endowment, and topography. Eastern and coastal areas should make full use of their capital and technological strengths to foster the concentration of intelligent, high-value-added industries. In contrast, the central and western regions should give priority to using data elements to optimize resource allocation, boost productivity in labor-intensive and resource-based sectors, and steadily advance industrial integration. At the same time, transport and data infrastructure in the central and western zones should be upgraded to improve the efficiency of data transmission and application, ensure the effective use of data elements, support data sharing and openness, and facilitate the circulation and optimal allocation of data resources.

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