Journal of Digital Intelligence and Economic Growth
Website: https://www.jdieg.com
Vol. 2 No. 3, September 2025, 33-51

ISSN (P r i n t): 3058-3535
ISSN (Online): 3058-6518
DOI: https://doi.org/10.63768/jdieg.v2i3.003

Data Element Flow and Urban-Rural Industrial Integration Efficiency: An Inverted U-Shaped Impact and Transmission Mechanism Study

Donghong Li *

Ph.D. Student, Dept. of Global Business, Kyonggi University, Suwon, South Korea

Abstract: The flow of data elements, driven by data resources, plays a crucial role in facilitating urban-rural factor mobility and optimizing resource allocation, thereby exerting a profound impact on urban-rural industrial integration efficiency. Based on provincial panel data from China spanning 1998 to 2023, this study systematically examines the impact of data element flow on urban-rural industrial integration efficiency and explores the transmission mechanism of traditional factor mobility and allocation. The findings reveal that: (1) There exists a significant inverted U-shaped relationship between data element flow and urban-rural industrial integration efficiency. While data element flow initially enhances integration efficiency, its marginal benefits diminish after exceeding a critical threshold, eventually leading to a negative impact; (2) The mobility and allocation of traditional urban-rural factors serve as key transmission mechanisms. Unidirectional flows reinforce the suppressive effect of data element flow, whereas bidirectional mobility and optimized allocation significantly enhance industrial integration efficiency; (3) Digital technology innovation and factor marketization play a moderating role in the inverted U-shaped impact, as improvements in both factors effectively mitigate the negative effects of excessive data element flow while strengthening its positive influence. The findings provide essential theoretical support and practical insights for optimizing digital economy policies, promoting efficient factor mobility, and advancing urban-rural industrial integration strategies, along with relevant policy recommendations.

Keywords: Data Element Flow; Urban-Rural Industrial Coordination; Inverted U-Shaped Relationship; Factor Allocation; Nonlinear Effects; Digital Transformation

* Author Correspondence: Donghong Li (lidonghonghanguo@163.com)
Received 13 March 2025, Revised 19 May 2025, Accepted 20 June 2025

1 Introduction

Urban-rural integration is a central objective of China's rural revitalization strategy, serving as a crucial pathway for promoting regional coordination, narrowing the urban-rural divide, and achieving common prosperity (Antonić and Djukić, 2018). As the core component of this integration, industrial integration not only drives rural industrial upgrading and advances agricultural modernization but also optimizes resource allocation and strengthens regional economic competitiveness (Salvati and Carlucci, 2011). In recent years, with the comprehensive implementation of the rural revitalization strategy, China's urban-rural industrial relations have gradually shifted from a fragmented development model to a more coordinated integration model (Shi et al., 2021). However, significant structural barriers continue to hinder urban-rural industrial integration, including the incomplete dismantling of the urban-rural dual structure, restricted factor mobility, underdeveloped rural industries, and lagging infrastructure (Baffoe, 2019). Specifically, inefficient factor allocation continues to impede balanced urban-rural industrial integration, highlighting the need for refined coordination mechanisms (Simwanda and Murayama, 2018; Javaid et al., 2024).

In the era of the digital economy, data has emerged as the "fifth production factor" alongside land, labor, capital, and technology, playing a transformative role in industrial upgrading and economic restructuring (Simwanda and Murayama, 2018; Xia et al., 2024). Projections indicate that China's total data volume will grow from 7.5 ZB in 2018 to 48.6 ZB by 2025, representing 27.8% of the global total. In 2023, the country's digital economy reached 53.9 trillion yuan, contributing 42.8% to GDP (Yang et al., 2020; Raihan et al., 2024). This exponential growth in data elements underscores their critical role in resource allocation, industrial upgrading, and regional coordination. Nevertheless, despite the abundance of data resources, the market-oriented allocation of data in China remains underdeveloped, and the potential value of data elements has yet to be fully realized. The accessibility and mobility of data elements are highly uneven across regions, adversely affecting the efficiency of industrial integration and intensifying structural disparities between urban and rural industrial development (Bennett et al., 2018).

As a unique "digital bridge" between urban and rural areas, data transcends traditional spatial and temporal constraints, effectively facilitating the bidirectional flow of production factors and injecting new momentum into urban-rural integration (Che et al., 2017; Dong et al., 2024). Data-driven empowerment enables industries in both urban and rural areas to overcome conventional spatial barriers, achieve more precise industrial matching, and enhance integration efficiency (Chen et al., 2018). However, numerous challenges continue to impede the mobility of data elements, including data security risks, data monopolies, and an immature market-oriented data allocation mechanism (Yan et al., 2018). Furthermore, the urban-rural digital divide has become a critical obstacle to improving industrial integration efficiency (Chen and Wang, 2019). On one hand, rural areas suffer from significant deficits in digital infrastructure, network coverage, digital technology adoption, and data accessibility, which limit the free flow of data elements. On the other hand, disparities in digital literacy, information acquisition, and application capabilities between urban and rural residents hinder data circulation efficiency, constraining the deep integration of urban and rural industries (Yang et al., 2020).

Despite its importance, systematic research exploring the relationship between data element flow and urban-rural industrial integration efficiency remains limited, particularly regarding the transmission mechanisms through which data element mobility influences integration efficiency via factor mobility and allocation (Yang et al., 2021). Addressing this research gap, this study aims to investigate the impact of data element flow on urban-rural industrial integration efficiency while exploring the underlying transmission mechanisms. Specifically, this study first develops a theoretical framework to elucidate the functional pathways through which data element flow affects industrial integration efficiency. It then conducts an empirical analysis using provincial panel data from China spanning 1998 to 2023, systematically assessing the direct impact of data element flow on integration efficiency and examining the mediating roles of traditional urban-rural factor mobility and allocation. The findings of this study provide theoretical insights and practical policy recommendations for optimizing the market-oriented allocation of data elements, enhancing data resource utilization efficiency, and promoting urban-rural integration. Moreover, this study offers fresh perspectives and practical implications for advancing coordinated urban-rural industrial development and accelerating rural revitalization (Chen et al., 2020).

2 Literature Review

2.1 Research on Data Factor Flow

In recent years, research on data factor flow has primarily focused on its measurement methods and economic and social impacts. Existing literature has constructed various measurement frameworks to quantify data factor flow and examined how it facilitates resource optimization and enhances industrial integration efficiency, providing significant theoretical support for improving data flow mechanisms.

Regarding measurement methods, researchers have mainly employed comprehensive index methods, suitability evaluation models, and gravity models for quantitative analysis (Yin et al., 2016). The comprehensive index method typically involves constructing a data factor flow index to assess data movement across regions or industries (Antonić and Djukić, 2018). Some studies, for instance, have developed indices based on dimensions such as digital infrastructure, network coverage, and policy environment to characterize the overall trend of data flow. The suitability evaluation model, on the other hand, emphasizes assessing the appropriateness and compatibility of data factor flow by evaluating factors such as entities, platforms, technology, and institutional frameworks, thereby forecasting its future trajectory (Zhang et al., 2019; Baffoe, 2019). Meanwhile, the gravity model is widely used to measure the spatial correlation of data factor flow, where researchers incorporate variables such as enterprise profits and internet penetration rates to analyze data movement across regions and reveal its spatial distribution characteristics (Dai et al., 2015). Findings indicate that China's data factor flow exhibits a "core-periphery" structure, meaning data factors predominantly accumulate in economically developed regions, whereas their circulation efficiency in less-developed areas remains relatively low, leading to significant regional disparities in data flow.

In terms of impact, optimizing data factor flow enhances urban-rural factor mobility, improves resource allocation efficiency, and drives industrial integration (Che et al., 2017). Due to its low-cost replication and rapid transmission capabilities, data factor flow accelerates information dissemination, fosters interregional industrial cooperation, and breaks traditional spatial barriers to factor mobility (Fang, 2022). For example, data factor flow promotes knowledge spillover and information sharing, strengthening synergies between industries across regions and improving overall resource allocation efficiency (Chen et al., 2018). However, data factor flow also exhibits an aggregation effect, where data resources tend to cluster in cities with well-developed infrastructure and strong economies. This aggregation pattern results in an unequal distribution of data resources between urban and rural areas, exacerbating structural disparities in industrial development (He et al., 2019).

Within the context of urban-rural integration, the role of data factor flow remains phased (Zhang et al., 2022). In the short term, due to the lag in rural digital infrastructure development, the digital divide, and information asymmetry, data factor flow may widen urban-rural disparities, leading to a temporary inhibitory effect on industrial integration efficiency (Chen and Wang, 2019). However, in the long run, as data factor markets mature, digital infrastructure improves, and data flow regulations become more standardized, the diffusion effect of data factors will gradually emerge, providing new momentum for urban-rural industrial integration (Herberholz and Phuntsho, 2018).

Thus, the impact of data factor flow on urban-rural industrial integration efficiency may follow an inverse U-shaped relationship. In the early stages, data factor flow significantly enhances industrial integration efficiency, but once it surpasses a certain threshold, its marginal benefits may diminish. At excessive levels, resource misallocation and market monopolization may arise, negatively impacting integration efficiency (Chen et al., 2020).

Based on this, the following research hypotheses are proposed：

Hypothesis 1a: China is currently in a phase where data factor flow promotes urban-rural industrial integration efficiency.

Hypothesis 1b: The relationship between data factor flow and urban-rural industrial integration efficiency follows an inverse U-shaped pattern, meaning that in the early stages, data factor flow significantly enhances integration efficiency, but beyond a certain threshold, its impact transitions from positive to negative.

2.2 Research on Urban-Rural Industrial Integration Efficiency

Research on urban-rural industrial integration efficiency primarily focuses on two core dimensions: urban-rural integration efficiency and urban-rural industrial integration. Urban-rural integration efficiency concerns the overall economic synergy between urban and rural areas, while urban-rural industrial integration emphasizes the internal resource flow and coordination mechanisms within the industrial system (Fang, 2022).

Regarding urban-rural integration efficiency, scholars widely use the Data Envelopment Analysis (DEA) model to measure the efficiency of urban-rural integration development, incorporating multidimensional indicators such as fiscal expenditure, economic development, and social structure to assess the level of urban-rural coordinated development. Some studies further use the Efficiency-Based Measure (EBM) model to calculate urban-rural integration efficiency, revealing the spatio-temporal evolution trends and influencing factors of urban-rural integration levels. Studies show that the overall efficiency of urban-rural integration varies significantly across regions, mainly due to the combined effects of urban-rural economic development levels, industrial structure, the degree of factor marketization, and government regulation (He et al., 2019).

In terms of urban-rural industrial integration, scholars typically use comprehensive indicator methods to measure the degree of industrial integration. Research has found that the extent of urban-rural industrial integration is closely related to economic development levels, marketization, and infrastructure development. The essence of urban-rural industrial integration depends on the free flow and optimal allocation of production factors, aiming for deep coupling and coordinated development of urban and rural industries (Hommes and Boelens, 2017). However, due to the long-standing urban-rural economic dual structure, urban-rural industrial integration efficiency still faces many limitations. Cities, with their advantages in resources such as economy, technology, talent, and capital, become the hubs for industrial factors, while rural industries face developmental lag due to factors such as capital shortage, labor outflow, and slow technological innovation (Ji et al., 2019). Urban-rural industrial integration presents a typical "core-periphery" model, where cities attract high-quality resources due to industrial agglomeration effects, while rural industries face development bottlenecks, leading to overall low urban-rural industrial integration efficiency (Hommes and Boelens, 2017).

In recent years, the rapid development of data factors has provided new momentum for urban-rural industrial integration (Marans, 2015). Based on the theory of information asymmetry, the flow of data factors can break urban-rural information barriers, alleviate information asymmetry, and improve the flow efficiency of urban-rural factors. The development of digital technology has made data resources more accessible, transferable, and analyzable, thereby improving urban-rural information asymmetry, optimizing urban-rural factor matching, and increasing industrial integration efficiency (Ji et al., 2019). On the other hand, based on the theory of new economic geography's core-periphery theory, the flow of data factors also influences urban-rural industrial integration efficiency through "cumulative causality effects" (Peng et al., 2018). In the early stages, data resources mainly concentrate in economically developed cities, leading to an imbalance in urban-rural industrial development. However, as data factor flow further optimizes, the spillover effects of data factors gradually emerge, driving rural industry upgrading and ultimately promoting deep urban-rural industrial integration (Salvati and Carlucci, 2011).

However, the impact of data factor flow may have phased characteristics, meaning that in the early stages of data flow, the aggregation effect of data resources may exacerbate the imbalance in urban-rural industrial development. Once data factor flow reaches a critical point, its diffusion effects will gradually be released, promoting urban-rural industrial integration (Li, 2012). Therefore, the influence of data factor flow on urban-rural industrial integration efficiency may exhibit an inverse U-shaped relationship: in the early stage, optimizing data flow helps enhance urban-rural industrial integration efficiency, but when data flow reaches a certain level, factors such as data market imbalance and excessive concentration may lead to a decrease in urban-rural industrial integration efficiency (Yan et al., 2018).

Based on this, the following research hypotheses are proposed：

Hypothesis 2a: Data factor flow influences urban-rural industrial integration efficiency through the inverse U-shaped relationship of urban-rural factor flow.

Hypothesis 2b: Data factor flow influences urban-rural industrial integration efficiency by improving the efficiency of urban-rural factor allocation.

The relationship between data factor flow and urban-rural industrial integration efficiency is primarily discussed in terms of digital economy development, data factor circulation, and the mechanisms through which data factors influence urban-rural industrial integration (Li et al., 2014). As the digital economy rapidly develops, data, as a new form of production factor, is profoundly impacting urban-rural industrial patterns. Data factor flow not only optimizes urban-rural resource allocation but also breaks traditional spatial limitations on industrial development, fostering urban-rural industrial linkage (Phillipson et al., 2019). However, this process is not linear and involves staged and complex nonlinear impacts (Li et al., 2019). The cross-regional resource integration capability of the digital economy can improve the efficiency of urban-rural industrial factor matching. In the early stages of data factor flow, digital economy development promotes technology diffusion, information sharing, and industrial linkage, making urban-rural factor allocation more efficient, reducing the urban-rural industrial development gap, and enhancing urban-rural industrial integration efficiency (Li et al., 2019). However, as the level of data factor flow continues to rise, urban-rural industrial integration efficiency may be constrained by the highly concentrated effects of data. Due to cities' significant advantages in data resources, technological talent, and infrastructure, a "data siphon effect" may form, in which data resources, technological capital, and innovation factors accelerate toward cities. Meanwhile, rural areas, hindered by weak information infrastructure and limited data acquisition ability, struggle to absorb the spillover effects of data factors, ultimately leading to a decline in urban-rural industrial integration efficiency (Che et al., 2017).

Therefore, the impact of data factor flow on urban-rural industrial integration efficiency exhibits an inverse U-shape: in the early stages of data factor flow, data circulation promotes urban-rural industrial integration efficiency, but once data flow exceeds a critical threshold, the data aggregation effect starts to emerge. The imbalance in urban-rural factor flow intensifies, and urban-rural industrial integration efficiency decreases (Antonić and Djukić, 2018).

In practical applications of urban-rural industrial integration, optimizing data factor flow requires the use of digital technology innovation and factor marketization mechanisms to reduce the costs of data factor flow and improve the empowering role of data resources on traditional industrial factors (Long et al., 2022). When data factors are mainly concentrated in cities, and rural industries face restrictions due to uneven distribution of data resources, digital technology innovation plays a key role (Liu et al., 2015). Digital technology innovation not only improves the efficiency of data factor use but also enhances the sharing ability of data resources between urban and rural areas, allowing the spillover effects of data to better radiate to rural industries (Salvati and Carlucci, 2011). Meanwhile, improving the marketization of factors can also promote the rational flow of data factors, break down urban-rural data barriers, optimize the matching of urban-rural production factors, and reduce structural imbalances in the data flow process (Ma et al., 2020). Therefore, improving digital technology innovation and marketization levels can help mitigate the negative impact of data factor flow on urban-rural industrial integration efficiency, facilitating a more balanced distribution of data resources between urban and rural areas and achieving long-term balanced development of urban-rural industrial integration efficiency.

Based on this, the following hypothesis is proposed：

Hypothesis 3: Digital technology innovation and marketization levels can mitigate the suppressive effect of data factor flow on urban-rural industrial integration efficiency.

While existing studies have focused on data factor flow, urban-rural industrial integration efficiency, and their interactions, significant gaps remain (Long et al., 2022). First, research on data factor flow has mainly concentrated on the market scale and industrial development of data resources, with a lack of systematic analysis of the dynamic characteristics of data flow, factor circulation patterns, and the nonlinear impact of data factors on urban-rural industrial integration (Lysgård, 2019). Second, studies on urban-rural industrial integration efficiency remain confined to measuring integration levels, with limited exploration of the quality and efficiency of urban-rural industrial integration (Lysgård, 2019). Most current research uses comprehensive evaluation methods to measure urban-rural industrial integration, but has not systematically analyzed whether the resource input and output benefits of urban-rural industrial integration align, or how to optimize industrial integration efficiency (Peng et al., 2018). Moreover, research on the impact of data factor flow on urban-rural industrial integration efficiency is still in the theoretical discussion stage, with a lack of systematic empirical analysis (Ma et al., 2018). Most studies remain at a qualitative level and have not empirically tested the real effects of data factor flow on urban-rural industrial integration efficiency, especially in terms of examining the phase effects, nonlinear relationships, and transmission mechanisms of data factor flow (Salvati and Carlucci, 2011).

In response to these research gaps, this paper's contributions lie in three main areas. First, it constructs a mediating mechanism of urban-rural factor flow, systematically analyzing the inverse U-shaped impact of data factor flow on urban-rural industrial integration efficiency. Unlike traditional research that focuses solely on the direct impact of data factor flow on industrial integration, this study further explores how the flow and allocation efficiency of traditional factors (such as capital, labor, land, and technology) mediates data factor flow, providing a deeper theoretical explanation for the empowerment of urban-rural industrial integration by data factors. Second, the study examines the moderating role of digital technology innovation and marketization, revealing how data factor flow optimizes the allocation of production factors, thereby enhancing urban-rural industrial integration efficiency. By introducing digital technology innovation and marketization mechanisms, this research explores the different impact pathways of data factor flow on urban-rural industrial integration efficiency, filling a gap in existing research on moderating mechanisms. Finally, the study uses an improved gravity model to measure the data factor flow environment and combines it with an Efficiency-Based Measure (EBM) model to calculate urban-rural industrial integration efficiency, ensuring the rationality and robustness of data measurement and addressing gaps in existing research methodologies. Through these innovations, this study not only expands the theoretical research on data factor flow but also provides new theoretical support and practical guidance for optimizing data flow mechanisms and promoting urban-rural industrial integration.

3 Methodology

This study conducts an empirical analysis based on panel data from 27 provinces (municipalities and autonomous regions) in China from 1998 to 2023, excluding Xinjiang, Tibet, Qinghai, Yunnan, and Hong Kong, Macao, and Taiwan. The exclusion of these regions is based on both quantitative and qualitative considerations. Quantitatively, these regions exhibit significant data gaps, inconsistent records for key indicators, and limited availability of digital economy metrics, which would compromise data completeness and continuity. Qualitatively, these regions differ in economic structures, industrial development models, and policy environments—Hong Kong, Macao, and Taiwan operate under separate statistical systems, while Tibet and Xinjiang are characterized by resource-dependent economies with limited digital industrialization. By focusing on regions with comparable economic and digital development patterns, this study ensures the reliability, consistency, and interpretability of the empirical analysis.

3.1 Indicator Selection

This study uses the non-oriented super-efficiency EBM-GML model to measure urban-rural industrial integration efficiency. Existing studies primarily use two methods: Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). The DEA model avoids setting the production function form, preventing estimation bias caused by incorrect function specification. However, the traditional DEA method assumes a proportional change in input-output factors, which may lead to biased results. Therefore, this paper adopts the super-efficiency EBM-GML model for a more comprehensive measurement of urban-rural industrial integration efficiency.

The model consists of three components: (1) Input indicators, (2) Expected output indicators, and (3) Non-expected output indicators. Regarding the selection of input indicators, to consider both urban-rural and industrial characteristics, this study first selects the four basic production factors: labor, capital, technology, and land. Additionally, based on the practical situation of urban-rural industrial integration, the study includes energy, environment, transportation, and information factors to meet the dual attributes of urban-rural and industrial integration.

For expected output indicators, the level of urban-rural industrial integration is used as the primary measurement target. To assess the level of urban-rural industrial integration, the study adopts the entropy-weight TOPSIS method for comprehensive calculation from three dimensions: rural primary, secondary, and tertiary industry integration, urban secondary and tertiary industry integration, and urban-rural industry integration. Furthermore, negative indicators such as the urban-rural Engel's coefficient ratio, the urban-rural per capita income gap ratio, and the urban-rural consumption expenditure ratio are processed in a positive direction to ensure data comparability. The specific indicators are shown in Table 1.

For non-expected output, urban-rural industrial integration may lead to environmental pollution and ecological damage. Therefore, this study includes carbon emissions and industrial wastewater as non-expected output indicators to measure the impact of urban-rural industrial integration on the ecological environment. The specific input-output indicators for urban-rural industrial integration efficiency are presented in Table 2.

Table1. Urban-Rural Industrial Integration Level

Primary Indicator	Secondary Indicator	Tertiary Indicator	Attribute
Urban-Rural Industry Linked Development	Rural Industry Integration	Per Capita Agricultural Processing Enterprise Growth Rate	+
		Facility Agriculture Land Proportion	+
		Per Capita Agricultural Services Output	+
		Agricultural Machinery Equipment Penetration Rate	+
		Rural Labor Force Non-Agricultural Transition Rate	+
		Per Capita Agricultural Product Processing Output	+
		Rural Cooperative Rate	+
		Proportion of Agricultural, Forestry, Animal Husbandry, and Fishery Services in Agricultural Economy	+
	Urban Industrial Chain Integration	Industrial to Service Enterprise Ratio	+
		Manufacturing to Service Industry Integration Index	+
		New Industrial to Service Enterprise Ratio	+
		Total R&D Personnel in Industrial Enterprises	+
		Coordination Degree of Urban-Rural Industry Integration	+
	Urban-Rural Industry Integration Coordination	Urban-Rural Development Gap Index	+
		Urban-Rural Consumption Structure Ratio	+
		Urban-Rural Income Ratio	+
		Urban-Rural Consumption Level Ratio	+
		Urban Agricultural Employment Population	+

Table 2. Urban-Rural Industrial Integration Efficiency

Primary Indicator	Secondary Indicator	Tertiary Indicator
Input Factors	Human Resource Input	Urban-Rural Labor Force Scale (10,000 persons)
	Capital Input	Fixed Asset Investment (Billion RMB)
		General Budget Expenditure (Billion RMB)
	Technology Input	Number of Patent Applications and Authorizations
	Land Resource Input	Urban Construction and Agricultural Land (Square Kilometers)
	Energy Consumption	Industrial and Agricultural Water Usage (Billion Cubic Meters)
		Electricity Consumption (Billion kWh)
	Ecological Input	Forest Coverage Rate (%)
	Transportation Resource Input	Railway and Highway Length (10,000 km)
	Information Resource Input	Mobile Phone Exchange Capacity (10,000 units)
Expected Benefit Indicators	Urban-Rural Industry Coordination	-
Non-Ideal Output Indicators	Carbon Emissions	Total Carbon Emissions (10,000 tons)
	Industrial Wastewater Emissions	Industrial Wastewater Emissions (10,000 tons)

Data element flow（$DATA_{it}$）， is the prerequisite for the value realization of data elements. Its characteristics include low-cost replication, cross-regional circulation, and spatial spillover effects. Data elements exhibit significant regional agglomeration, where areas close to data-dense regions are more likely to gain support from data resources, thus forming a network effect of data flow. Efficient data element flow can promote the rational allocation of data elements, optimize the circulation of production factors, and enhance industrial integration efficiency.

To accurately measure data element flow at the provincial level, this study uses a modified gravity model for calculation. This method constructs a spatial correlation matrix of data elements at the provincial level to measure the intensity and direction of data flow between regions, effectively reflecting the spatial-temporal characteristics of data element flow. The gravity model for data element flow is expressed as follows：

$$data_{ijt} = G_{ijt} \times \frac{\sqrt{P_{it} \times D_{it}} \times \sqrt{P_{jt} \times D_{jt}}}{R_{ij}^2}，\ G_{ijt} = \frac{D_{it}}{D_{it} + D_{jt}}$$

$$DATA_{it} = w_1 \sum_{i=1}^{n} data_{ijt} + w_2 \sum_{j=1}^{n} data_{ijt}$$

$data_{ijt}$is the spatial association matrix of data elements, representing the spatial connection between city I and city j in year t. $G_{ijt}$is the modified empirical constant. D_{it} and $D_{jt}$are the data element stocks of city i and city j，respectively. D_{it} and $D_{jt}$are the data element attraction indexes for cities i and j, respectively. $R_{ij}^2$is the distance between the two cities. $DATA_{it}$ it represents the data element flow between cities. $\sum_{i=1}^{n} data_{ijt}$represents the data inflow, while $\sum_{j=1}^{n} data_{ijt}$ represents the data outflow，w_1、w_2 are weight factors，with $w_1 = w_2$=0.5. The combined inflow and outflow form the data element flow index for the region.

To alleviate the estimation bias caused by omitted variables, this study selects the following control variables: (1) Scientific and technological support (the proportion of technology expenditure in local fiscal budget) to measure the impact of technological investment on urban-rural industrial development; (2) Foreign Direct Investment (FDI as a percentage of GDP), reflecting the role of foreign capital in supporting industrial development direction and integration patterns; (3) Government intervention (the proportion of general public budget expenditure to GDP), to gauge the influence of government policies on industrial development and urban-rural integration; (4) Industrialization level (the proportion of industrial added value to GDP), which reflects the industrial structure of the region and its impact on urban-rural industrial integration; (5) Financial development level (the proportion of financial institution deposit and loan balance to GDP), measuring the role of the financial system in promoting industry financing and long-term development; (6) Education investment (the proportion of education expenditure to local fiscal budget), which reflects the key impact of talent and technological development on urban-rural industrial integration. These variables cover multiple dimensions, including technology, foreign investment, government regulation, industrial structure, financial support, and talent development, providing comprehensive support for empirical analysis.

In the mediation mechanism analysis, this study primarily explores the impact of data element flow on the bidirectional flow URF_{it} and configuration efficiency URE_{it} of traditional urban-rural elements. Traditional urban-rural elements include labor, capital, technology, and land. The study selects the bidirectional flow and configuration efficiency of these elements as intermediary variables.

Regarding the measurement of bidirectional flow of urban-rural elements, labor flow is measured by the ratio of rural non-agricultural employment to urban non-agricultural employment; capital flow is assessed by the proportion of agricultural fixed assets and the proportion of fiscal expenditure on agriculture in total fiscal expenditure, reflecting the flow of fixed assets and fiscal funds, respectively; technology flow is represented by the per capita agricultural machinery power in rural areas, indicating the penetration of technology into rural areas; land flow is measured by the proportion of urban construction land area to total urban area, reflecting the transformation of agricultural land to non-agricultural land. Finally, the entropy-weight TOPSIS method is used to construct a comprehensive index system for the bidirectional flow of urban-rural elements (Table 3).

Table 3. Bidirectional Flow of Urban-Rural Elements

Labor Flow	Ratio of Rural Non-Agricultural Employment to Urban Non-Agricultural Employment
Capital Flow	Proportion of Agricultural Fixed Asset Investment
	Proportion of Fiscal Agricultural Expenditure in Total Fiscal Budget
Technology Flow	Per Capita Agricultural Machinery Power
Land Flow	Proportion of Urban Construction Land to Total Urban Area

In measuring the efficiency of the spatial allocation of traditional urban-rural elements, this study uses the DEA-ML model to calculate the urban factor productivity, which reflects the spatial allocation efficiency of urban elements. Additionally, drawing on the benevolent cross-efficiency DEA model, the study divides urban and rural areas into two groups and calculates the urban-rural factor productivity based on the four elements: labor, capital, technology, and land. This method comprehensively assesses the overall allocation efficiency of traditional urban-rural elements. It not only aligns with the role of data factor flow in optimizing the allocation of urban-rural factors but also scientifically measures the factor matching degree in the process of urban-rural industrial integration (Table 4).

Table 4. Urban-Rural Factor Allocation Efficiency

Primary Indicator	Secondary Indicator	Tertiary Indicator	Account
Input Indicators	Rural Input	Labor	Rural Employment Population
		Capital	Agricultural Related Fixed Asset Investment and Fiscal Expenditure
		Technology	Total Agricultural Machinery Power
		Land	Total Cultivated Area
	Urban Input	Labor	Urban Employment Population
		Capital	Non-Agricultural Fixed Asset Investment and Fiscal Expenditure
		Technology	R&D Investment in Large-Scale Industrial Enterprises
		Land	Total Urban Construction Land Area
Output Indicators	Rural Output	Rural Output	Agricultural Added Value and Rural Resident Income
	Urban Output	Urban Output	Industrial and Service Industry Added Value and Urban Resident Income

In the examination of the moderating mechanism, this study focuses on the moderating effects of digital technology innovation level（DTI_{it}）and the degree of factor marketization（FMD_{it}）on data factor flow and urban-rural industrial integration efficiency. The level of digital technology innovation is measured by the number of patent authorizations for the digital economy in each province, reflecting the role of technological progress in promoting data flow. The degree of factor marketization is represented by the factor market development index, which assesses the moderating effects of market mechanisms in optimizing resource allocation, promoting factor flow, and enhancing urban-rural industrial integration efficiency.

3.2 Model Construction

To test Hypothesis 1a, this study constructs a two-way fixed effects model to analyze whether data factor flow exerts a suppressive effect on urban-rural industrial integration efficiency. The model is specified as follows：

$$URI_{it} = \alpha_0 + \alpha_1 DATA_{it} + \sum \alpha_j Control_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (1)$$

Where, URI_{it} represents urban-rural industrial integration efficiency (the core dependent variable), and $DATA_{it}$ _it represents data factor flow (the core independent variable)，α_1 reflects the extent of the impact of data factor flow on urban-rural industrial integration efficiency; $Control_{it}$ is a set of control variables, including factors such as scientific and technological support, foreign direct investment, government intervention, industrialization level, financial development level, and educational investment, which may affect urban-rural industrial integration efficiency; μ_i、 ν_t represent individual and time fixed effects, respectively; and ε_{it} is the random error term.

To test Hypothesis 1b, based on Equation (1), this study adds the quadratic term of data factor flow $DATA_{it}$to examine its U-shaped impact on urban-rural industrial integration efficiency. The specific model is as follows:

$$URI_{it} = \alpha_0 + \alpha_1 DATA_{it} + \alpha_2 DATA^2{}_{it} + \sum \alpha_j Control_{it} + \mu_i + \nu_t + \varepsilon_{it} \qquad (2)$$

In this model, $DATA^2{}_{it}$ represents the quadratic term of data factor flow, and α_2 reflects the U-shaped relationship between data factor flow and urban-rural industrial integration efficiency. The other variables remain consistent with those in Equation (1), including control variables, individual effects, time effects, and the random error term.

To test Hypotheses 2a and 2b, this study uses a two-step mediation effect test to enhance estimation robustness and accuracy, focusing on analyzing the impact of data factor flow on the bidirectional flow of urban-rural factors and urban-rural factor allocation efficiency.

First, based on Equations (1) and (2), the following model is constructed to examine the effect of data factor flow on the mediating variables:

$$M_{it} = \beta_0 + \beta_1 DATA_{it} + \sum \beta_j Control_{it} + \mu_i + \nu_t + \varepsilon_{it} \qquad (3)$$

$$M_{it} = \beta_0 + \beta_1 DATA_{it} + \beta_2 DATA^2{}_{it} + \sum \beta_j Control_{it} + \mu_i + \nu_t + \varepsilon_{it} \qquad (4)$$

In this model, M_{it} represents the mediating variable, which includes both the urban-rural factor flow and urban-rural factor allocation efficiency. The regression coefficient β_1 reflects the linear impact of data factor flow on the mediating variables, and β_2 reflects the U-shaped relationship. These two sets of equations, along with Equations (1) and (2), form a complete mediation effect model to ensure the scientific rigor and accuracy of the research conclusions.

To test Hypothesis 3, this study constructs the following moderation effect model based on Equation (1) to examine the impact of digital technology innovation level and factor marketization degree on the relationship between data factor flow and urban-rural industrial integration efficiency：

$$URI_{it} = \alpha_0 + \alpha_1 DATA_{it} + \alpha_2 Z_{it} + \alpha_3 DATA_{it} * Z_{it} + \sum \alpha_j Control_{it} + \mu_i + \nu_t + \varepsilon_{it} \qquad (5)$$

In this model, Z_{it} represents the moderating variables, which are the levels of digital technology innovation and factor marketization degree， $\alpha_3$reflects the strength of the moderating effect, indicating whether both can alleviate the inhibiting effect of data factor flow on urban-rural industrial integration efficiency.

4 Result

This study uses a two-way fixed effects model and conducts regression analysis on the first and second-order terms of data factor flow with clustered standard errors. Columns (1) and (2) of Table 5 show the regression results of the first-order term of data factor flow with and without control variables. The results indicate that, when control variables are not included, the effect of data factor flow on urban-rural industrial integration efficiency is significantly negative at the 10% level, and this effect remains significantly negative at the 5% level when control variables are included. This suggests that the inclusion of control variables reduces the impact of omitted variables, but data factor flow still operates in the suppression phase. Columns (3) and (4) show the regression results of the second-order term of data factor flow, where both the first and second-order terms are significant at the 1% level with opposite signs. This indicates that the impact of data factor flow on urban-rural industrial integration efficiency follows a U-shaped curve, initially promoting and later suppressing efficiency. Moreover, the significance of the second-order term is higher, suggesting that the promoting effect is weakening, although it remains greater than the suppressing effect. Overall, the impact of China's data factor flow on urban-rural industrial integration efficiency is currently transitioning from promotion to suppression, validating hypotheses 1a and 1b.

Table 5. Benchmark Regression Results

	（1）	（2）	（3）	（4）
	URI	URI	URI	URI
DATA	-0.1096*	-0.1288**	-0.6863***	-0.791***
	(-1.6633)	(-2.0696)	(-3.0513)	(-3.998)
$DATA^2$			1.15633***	1.4126***
			(2.2405)	(4.3707)
Technology Investment		1.0531		1.7029***
		(1.6925)		(2.9208)
Foreign Investment Inflows		0.5742***		0.5175**
		(3.2113)		(2.5163)
Government Fiscal Intervention		0.3087		0.335
		(1.5458)		(1.5588)
Industrialization Degree		0.0542		-0.0232
		(0.2738)		(-0.1499)
Financial Market Development		-0.0448		-0.0460
		(-1.1503)		(-1.6543)
Educational Expenditure		0.3962		0.4244
		(0.982)		(1.0158)
cons	1.0021***	0.7917***	1.0009***	0.9215***
	(256.4980)	(9.4549)	(235.3578)	(9.5267)
N	553	553	553	553
R 方	0.368	0.371	0.373	0.359

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

Although the quadratic term in the model is significant, this does not necessarily imply the existence of a U-shaped relationship between the variables. Therefore, in the first step, we test whether the coefficients of the linear and quadratic terms are of opposite signs and significant. The results in column (4) of Table 5 show that the coefficients have opposite signs and are both significant, so the first step test passes. In the second step, we test whether the slopes at both ends of the U-shaped curve are of opposite signs and significant. The results in Table 6 show that both slopes are significant and of opposite signs, so the second step test passes. Finally, in the third step, we test whether the turning point lies within the range of the variable values. The results in Table 6 show that the extreme point is within the value range and is significant, so the third step test passes. In conclusion, the U-test confirms that there is indeed a U-shaped relationship between data flow and urban-rural industrial integration efficiency (Figure 1).

Table 6. U-test

Turning Point			
0.3362452^{***}			
（4.00）			
Left of Turning Point			
Value	Slope	P-value	T-value
0.0000688	-0.7500783^{***}	0.001313	-3.453277
Right of Turning Point			
Value	Slope	P-value	T-value
0.6112576	0.7565461^{***}	0.042634	4.046853

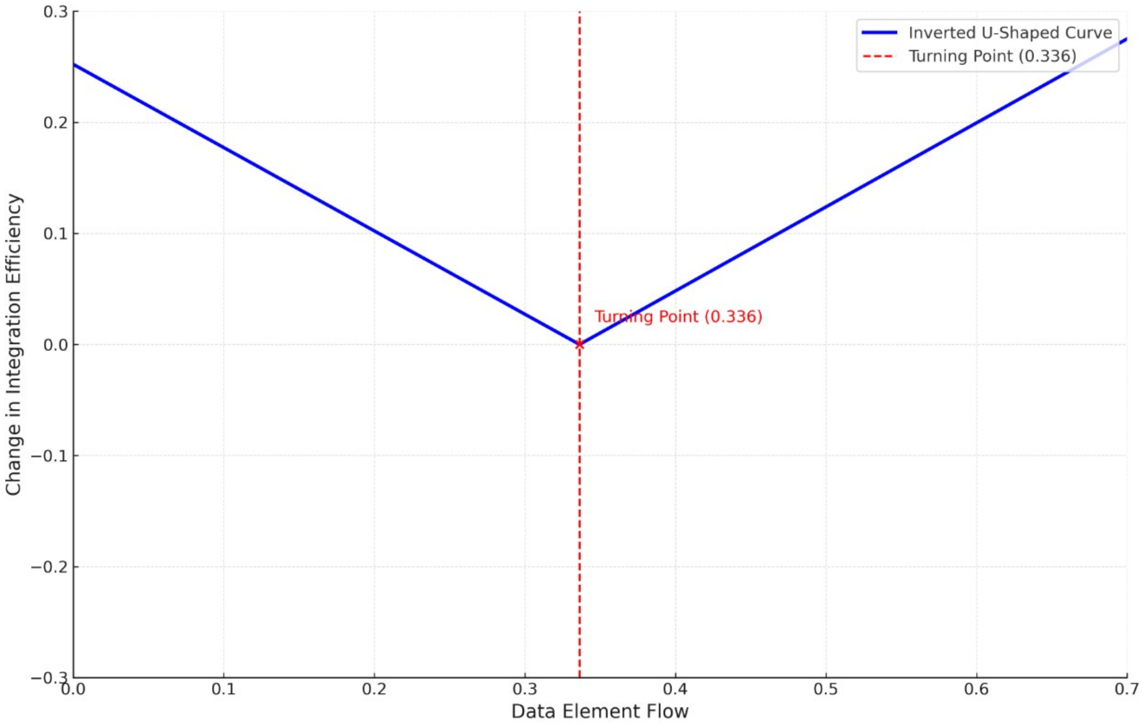

Figure 1. Inverted U-Shaped Impact Of Data Element Flow On Urban-Rural Industrial Integration Efficiency

To verify the robustness of the linear relationship and U-shaped relationship between data element flow and urban-rural industrial integration efficiency, various methods were employed in this study. First, by replacing the dependent variable and recalculating using the SBM-GML model, the results were consistent with the original EBM-GML index, eliminating the influence of the measurement method. Second, by excluding the years of the 2008 financial crisis and the 2020-2022 pandemic, the regression results remained stable, ensuring that special years did not interfere with the conclusions. In addition, after excluding municipalities directly under the central government, the direction and significance of the coefficients did not change, indicating that regional policy differences had no significant impact on the model. At the same time, 1% and 99% trimming were applied to all variables to eliminate the interference of extreme values on robustness, and the regression results remained consistent. Considering the potential lag effect of data element flow, the explanatory variables were further lagged by one period, and the conclusions remained robust, which helped alleviate endogeneity issues. Finally, the Tobit model was used for regression, and no significant changes were observed, verifying the reliability of the model choice. Overall, all robustness tests showed that the linear relationship and U-shaped relationship between data element flow and urban-rural industrial integration efficiency were robust and significant at least at the 10% level, ensuring the stability and reliability of the research conclusions.

Table 7. Robustness Test

	Change the dependent variable		Exclude special years		exclude municipalities directly under the central government	
	（1）	（2）	（3）	（4）	（5）	（6）
	URI	URI	URI	URI	URI	URI
DATA	-0.3265*	-1.8163**	-0.4460***	-1.6563***	-0.1412*	-0.9383***
	(-1.8766)	(-2.6500)	(-3.2374)	(-3.2784)	(-1.7981)	(-3.1256)
$DATA^2$		2.8501**		5.4253***		1.5651***
		(2.6406)		(2.8463)		(3.2786)
Technology	0.5212	1.8431	1.5612**	2.1247***	1.4116*	2.2442***
Investment	(0.3317)	(1.44533)	(2.1599)	(2.8208)	(1.9943)	(3.1940)

Foreign Investment Inflows	1.1640**	1.0280**	0.7395***	0.7338***	0.6256***	0.6532***
	(2.5285)	(2.1656)	(3.8488)	(3.8163)	(2.8154)	(3.3937)
Government	0.9416	0.9370*	-0.2332	-0.1447	0.3468*	0.3728*
Fiscal Intervention	(1.6952)	(1.7342)	(-0.5222)	(-0.6012)	(1.7405)	(1.8636)
Industrialization	-0.0183	-0.1778	0.2050*	0.1380	0.0105	-0.0506
Degree	(-0.0405)	(-0.4040)	(1.7331)	(1.1685)	(0.1800)	(-0.2702)
Financial Market	0.0370	0.0079	0.0081	-0.0030	-0.0465	-0.0619**
Development	(0.5919)	(0.1305)	(0.2856)	(-0.1734)	(-1.5205)	(-2.0642)
Educational	0.5340	0.5709	0.3719	0.3409	0.4274	0.5540
Expenditure	(0.6342)	(0.7047)	(0.7152)	(0.6719)	(0.8335)	(1.1500)
cons	0.7035***	0.7844***	0.8484***	0.8941***	0.8893***	0.9086***
	(3.4384)	(3.5907)	(8.2822)	(9.0426)	(8.0842)	(7.9853)
N	553	553	433	433	433	433
R^2	0.286	0.295	0.336	0.355	0.447	0.452

Table 8. Robustness Test

	1% and 99% Truncation		Lagged Explanatory Variables		Tobit	
	（7）	（8）	（9）	（10）	（11）	（12）
	URI	URI	URI	URI	URI	URI
DATA	-0.3253**	-1.2346***	-0.1781**	-1.0491***	-0.1298**	-0.8603***
	(-2.0562)	(-2.7645)	(-2.1580)	(-3.8835)	(-2.1275)	(-4.3967)
$DATA^2$		2.2960**		2.1728***		1.4009***
		(2.2484)		(4.0347)		(4.3223)
Technology	1.1354*	1.8528**	1.0324	1.6233**	1.0531*	1.7029***
Investment	(1.8130)	(2.0423)	(1.3779)	(2.4349)	(1.7315)	(2.9910)
Foreign Investment Inflows	0.9742***	0.8769***	0.6487***	0.5243**	0.5742***	0.5074**
	(3.1654)	(3.1685)	(3.1986)	(2.4317)	(3.2842)	(2.5767)
Government Fiscal	0.3532	0.3891	0.3263	0.3364	0.3567	0.3044
Intervention	(1.0962)	(1.0811)	(1.3628)	(1.4043)	(1.6050)	(1.6167)
Industrialization	0.0426	-0.0354	0.0394	-0.0227	0.0542	-0.0242
Degree	(0.0741)	(-0.1711)	(0.3676)	(-0.1288)	(0.3813)	(-0.1545)
Financial Market	-0.0653	-0.0692	-0.0376	-0.0520	-0.0338	-0.0460*
Development	(-1.1569)	(-1.4575)	(-1.1319)	(-1.6260)	(-1.1768)	(-1.6521)
Educational Expenditure	0.5346	0.5180	0.3787	0.4017	0.4062	0.4244
	(1.0562)	(1.0893)	(0.7623)	(0.8672)	(0.9148)	(1.0351)
cons	0.8852***	0.9124***	0.7647***	0.8068***	0.9110***	0.9399***
	(6.431)	(6.5419)	(7.0256)	(7.1183)	(11.7676)	(12.4734)
N	488	488	553	553	566	566
R^2	0.398	0.410	0.412	0.416		

To explore the mediation mechanism of data factor flow on urban-rural industrial integration efficiency, this paper conducts regression analysis on the bidirectional flow of urban-rural factors and the efficiency of urban-rural factor allocation to further verify the transmission effect of data factor flow in the process of urban-rural industrial integration. The study first conducts regression based on equations (3) and (4). The results show that the impact of data factor flow on the bidirectional flow of urban-rural factors presents a significant U-shaped relationship, where the coefficient of the first-order term is significantly negative, and the coefficient of the second-order term is significantly positive. This indicates that in the early stage of data factor flow, data resources are mainly concentrated in urban areas, which restricts rural factor flow and inhibits urban-rural industrial integration to some extent. However, as the level of data factor flow increases, the spillover effect of data gradually emerges, and rural areas' access to data resources improves, thereby promoting the bidirectional flow of urban-rural factors and enhancing the efficiency of urban-rural industrial integration.

Additionally, to further analyze the impact of data factor flow on the efficiency of urban-rural factor allocation, the study continues with regression analysis. The results show that data factor flow has a significant positive effect on the efficiency of urban-rural factor allocation, where the coefficient of the first-order term is significantly positive, and the coefficient of the second-order term is not significant. This suggests that data factor flow optimizes the matching of urban-rural factors, improves the efficiency of resource allocation, and contributes to the coordinated development of urban and rural industries. However, since the improvement in urban-rural factor allocation efficiency does not solely depend on data factor flow but is influenced by multiple factors such as infrastructure, market environment, and government policies, the impact of data factor flow on urban-rural factor allocation efficiency shows a relatively stable linear relationship rather than a U-shaped relationship.

Combining theoretical analysis and empirical results, both bidirectional flow of urban-rural factors and the efficiency of urban-rural factor allocation are key mechanisms through which data factor flow affects urban-rural industrial integration efficiency (Ma et al., 2020). In the early stages of data factor flow, data resources are highly concentrated in urban areas, which results in issues such as limited factor flow and poor information access in rural areas, hindering the bidirectional flow of urban-rural factors and affecting the improvement of urban-rural industrial integration efficiency. However, as the level of data factor flow increases, the spillover effect of data gradually emerges, and rural areas' absorption capacity for data improves, further driving the bidirectional flow of traditional urban-rural factors. By optimizing urban-rural resource allocation efficiency, this enhances the efficiency of urban-rural industrial integration (Marans, 2015). Therefore, the research results of this paper further verify the transmission path of data factor flow on urban-rural industrial integration efficiency. That is, data factor flow affects urban-rural industrial integration efficiency through the U-shaped relationship of bidirectional flow of urban-rural factors, while simultaneously promoting the coordinated development of urban-rural industries by improving the efficiency of urban-rural factor allocation. In summary, Hypotheses 2a and 2b are validated, and the findings provide important theoretical and empirical support for promoting the rational flow of data factors, optimizing urban-rural factor allocation, and enhancing urban-rural industrial integration efficiency.

Table 9. Mediation Mechanism Test

	（1）	（2）	（3）	（4）
	URF	URF	URE	URE
DATA	-0.1435***	-0.3625***	0.1321***	-0.0189
	(-5.0152)	(-5.1743)	(3.4263)	(-0.1432)
$DATA^2$		0.8971***		0.2456
		(3.3398)		(1.4762)
Technology Investment	1.3421***	1.5533***	-0.4248	-0.3033
	(5.7425)	(6.4553)	(-1.2461)	(-0.8924)
Foreign Investment Inflows	-0.3986***	-0.4125***	-0.3359**	-0.3487**
	(-3.5351)	(-3.5336)	(-1.9806)	(-2.0559)
Government Fiscal Intervention	-0.1717***	-0.1724***	-0.1848**	-0.1843**
	(-2.8133)	(-2.9662)	(-2.1338)	(-2.1815)
Industrialization Degree	-0.001	-0.0256	-0.1517**	-0.1668**
	(-0.0232)	(-0.5327)	(-2.2338)	(-2.4299)

Financial Market	0.051***	0.0412***	-0.0405**	-0.0449**
Development	(3.673)	(3.3881)	(-2.4521)	(-2.5797)
Educational Expenditure	-0.0912	-0.0855	0.1460	0.1335
	(-0.6335)	(-0.6016)	(0.6358)	(0.6527)
cons	0.1329***	0.1453***	0.9846***	0.9923***
	(3.9157)	(4.3787)	(20.5197)	(20.5844)
N	553	553	553	553
R^2	0.088	0.123	0.386	0.368

Currently, the negative impact of China's data factor flow on the efficiency of urban-rural industrial integration is still greater than its positive effect. How to effectively mitigate this negative impact and enhance the efficiency of urban-rural industrial integration has become a key issue. To address this, this paper constructs a moderating effect model based on equation (5) and focuses on analyzing the moderating roles of the degree of factor marketization and digital technology innovation level in the relationship between data factor flow and urban-rural industrial integration efficiency. The regression results show that the interaction terms between data factor flow and the degree of factor marketization, as well as digital technology innovation level, are significantly positive, indicating that both can effectively reduce the negative impact of data factor flow on urban-rural industrial integration efficiency. Furthermore, they promote the penetration of data factors into rural industries, improve the efficiency of urban-rural factor matching, and facilitate deeper urban-rural industrial integration. Therefore, the research results validate Hypothesis 3 and further demonstrate that the development of digital technology innovation and factor marketization can optimize the data factor flow environment, reduce the over-concentration of data resources, and strengthen the positive impact of data on urban-rural industrial integration, providing important support for improving the efficiency of urban-rural industrial integration.

Table 10. Moderating Effect Test

	（1）	（2）
	URI	URI
DATA	-1.1535**	-0.3669**
	(-2.4253)	(-2.5174)
FMD	-0.0058**	
	(-2.2319)	
DATA*FMD	0.0585**	
	(2.3364)	
DTI		-0.0181***
		(-5.79 75)
DATA*DTI		0.0573***
		(3.8223)
Technology Investment	1.8336**	2.0748**
	(2.4256)	(2.4597)
Foreign Investment Inflows	0.6667***	0.4455**
	(3.5045)	(2.2244)
Government Fiscal Intervention	0.2839	0.3523
	(1.4421)	(1.6123)
Industrialization Degree	0.0358	-0.0768
	(0.2496)	(-0.1423)
Financial Market Development	-0.0275	-0.0439
	(-0.8935)	(-1.6242)

Educational Expenditure	0.3127	0.6574
	(0.7854)	(1.6364)
cons	0.9435***	0.8900***
	(9.8499)	(9.8092)
N	553	553
R^2	0.386	0.395

5 Discussion

Data as the "fifth factor of production" in modern economic systems provides both new growth momentum and structural challenges in promoting the efficiency of urban-rural industrial integration (Murdoch, 2000). The research in this paper demonstrates that the impact of data factor flow on the efficiency of urban-rural industrial integration exhibits a typical inverted U-shaped relationship. In the initial stages of data factor flow, its optimization helps break down the barriers to the flow of urban and rural factors, promoting the bidirectional flow of urban-rural production factors and improving urban-rural industrial synergy, which significantly enhances urban-rural industrial integration efficiency. However, as the degree of data flow increases, the aggregation effect of data resources strengthens, which may lead to an over-concentration of data resources in cities, aggravating the imbalance in data utilization and technological innovation between urban and rural areas. This can result in resource misallocation, reducing the marginal contribution of data factors and even inhibiting the efficiency of urban-rural industrial integration (Peng et al., 2018). Nevertheless, China is still in a stage where the promoting effect of data factor flow on urban-rural industrial integration efficiency outweighs the inhibiting effect. Further analysis reveals that the flow and configuration efficiency of urban-rural factors are key transmission mechanisms in the influence of data factor flow on urban-rural industrial integration efficiency. In the early stages of data flow, the optimization of data circulation significantly promotes the bidirectional flow of urban and rural factors and improves factor matching efficiency. However, when data become overly concentrated in specific areas, resource misallocation gradually becomes evident, weakening the positive promotion of data factors on urban-rural industrial integration. Furthermore, digital technology innovation and the degree of factor marketization play important moderating roles in this process. A high level of digital technology innovation can enhance the spillover effects of data factors, promoting cross-regional sharing of data resources and improving the conversion efficiency of data in urban-rural industrial integration. More mature factor marketization mechanisms help reduce the cost of urban-rural factor circulation and alleviate the resource allocation imbalances that data factor flow may cause between urban and rural areas (Phillipson et al., 2019). Therefore, promoting digital technology innovation and the marketization of factors is of great significance in optimizing the data factor flow environment and improving urban-rural industrial integration efficiency.

This research contributes to the following three areas. First, it expands the research framework on data factor flow and urban-rural industrial integration efficiency, revealing the inverted U-shaped relationship between the two. Unlike previous research primarily focused on the level of urban-rural industrial integration, this paper explores how data factors influence the efficiency of urban-rural industrial integration at different stages, providing new perspectives for urban-rural integration development in the context of the digital economy. Second, the paper constructs a mediation mechanism between urban-rural factor flow and configuration efficiency, systematically explaining how data factor flow affects urban-rural industrial integration efficiency through the circulation and optimization of traditional production factors (labor, capital, technology, land). This mechanism analysis deepens the theoretical explanation of the role of data factor flow in adjusting the urban-rural economic structure and provides a scientific basis for urban-rural industrial policy formulation (Razin and Hasson, 1994). Additionally, this paper further explores the moderating effects of digital technology innovation and factor marketization, finding that both play key buffering roles in the relationship between data factor flow and urban-rural industrial integration efficiency. This study deepens the understanding of the complex mechanisms of data factor flow in the urban-rural integration process and provides empirical support.

6 Management Suggestions, Limitations, and Future Research

This paper provides the following management and policy recommendations to optimize the data factor flow environment and improve urban-rural industrial integration efficiency. First, efforts should be made to narrow the digital divide between urban and rural areas and optimize the free flow of data factors. The government should increase investment in rural digital infrastructure and promote the integrated development of urban and rural network infrastructure to enhance the capacity of rural areas to support data factors. At the same time, digital talent training should be strengthened, and rural residents' information technology application abilities should be improved through digital technology training and online education to ensure the fairness and accessibility of urban-rural data resource sharing. Second, the flow of urban and rural factors should be unblocked to improve factor configuration efficiency. By optimizing the circulation mechanisms of capital, technology, talent, and land, the deep integration of urban and rural industrial chains should be promoted. Moreover, the over-concentration of data factors in cities should be prevented to avoid the excessive aggregation of data resources in urban areas, thereby enhancing the empowerment of data to the real economy. Additionally, promoting digital technology innovation and factor marketization reform, strengthening policy support for the digitalization of rural industries, and encouraging the rational flow of urban and rural data resources are essential to reduce the negative effects of over-concentration of data resources in cities. Finally, the institutional environment for urban-rural integration development should be optimized, and the marketization of data factor allocation should be improved to increase the efficiency of data resource circulation between urban and rural areas, promoting integrated urban-rural economic development. For regions with lower levels of urban-rural industrial integration, local governments should actively build a collaborative development ecosystem for urban and rural industries, guide quality enterprises to settle in rural areas, and promote the optimization and upgrading of rural industrial structures. For regions with higher levels of urban-rural industrial integration, efforts should be made to deepen the empowering role of data factors and promote urban-rural industrial integration toward higher-quality development.

Although this study reveals the inverted U-shaped impact of data factor flow on urban-rural industrial integration efficiency and explores the mediating effects of factor flow and configuration efficiency, as well as the moderating effects of digital technology and marketization, several limitations remain. First, due to data availability constraints, this study is based on provincial panel data. Future research can further utilize enterprise-level or county-level data to improve the precision of the data and enhance the applicability of the research conclusions. Second, this study primarily focuses on the impact of data factor flow on urban-rural factor flow and configuration efficiency, while potential influencing factors such as government digital governance, urban-rural consumption integration, and industrial structure upgrading remain to be explored. Moreover, the impact of data factor flow on urban-rural industrial integration may be further influenced by regional economic structures, industrial characteristics, and policy environments. Future research could combine more refined data, more advanced econometric methods, and more targeted policy experiments to deepen the understanding of how data factor flow promotes urban-rural industrial integration, providing more scientific policy support for the development of the digital economy and urban-rural integration.

References

Antonić, B., & Djukić, A. (2018). The phenomenon of shrinking illegal suburbs in Serbia: Can the concept of shrinking cities be useful for their upgrading?. *Habitat international*, *75*, 161-170.

Baffoe, G. (2019). Exploring the utility of Analytic Hierarchy Process (AHP) in ranking livelihood activities for effective and sustainable rural development interventions in developing countries. *Evaluation and program planning*, *72*, 197-204.

Bennett, K. J., Yuen, M., & Blanco-Silva, F. (2018). Geographic differences in recovery after the great recession. *Journal of Rural Studies*, *59*, 111-117.

Che, B. Q., Lu, Y. Q., & Wang, Y. (2017). Research on spatial form evolution of urban and rural integration development in Jiangsu province. *Resour. Environ. Yangtze Basin*, *26*, 1022-1031.

Chen, C., LeGates, R., Zhao, M., & Fang, C. (2018). The changing rural-urban divide in China's megacities. *Cities*, *81*, 81-90.

Chen, H., & Wang, X. (2019). Exploring the relationship between rural village characteristics and Chinese return migrants' participation in farming: Path dependence in rural employment. *Cities*, *88*, 136-143.

Chen, K., Long, H., Liao, L., Tu, S., & Li, T. (2020). Land use transitions and urban-rural integrated development: Theoretical framework and China's evidence. *Land use policy*, *92*, 104465.

Dai, H., Sun, T., Zhang, K., & Guo, W. (2015). Research on rural nonpoint source pollution in the process of urban-rural integration in the economically-developed area in China based on the improved STIRPAT model. *Sustainability*, *7*(1), 782-793.

Dong, K., Liu, Y., Wang, J., & Dong, X. (2024). Is the digital economy an effective tool for decreasing energy vulnerability? A global case. *Ecological Economics*, *216*, 108028.

Fang, C. (2022). On integrated urban and rural development. *Journal of Geographical Sciences*, *32*(8), 1411-1426.

He, B. J., Zhu, J., Zhao, D. X., Gou, Z. H., Qi, J. D., & Wang, J. (2019). Co-benefits approach: Opportunities for implementing sponge city and urban heat island mitigation. *Land use policy*, *86*, 147-157.

Herberholz, C., & Phuntsho, S. (2018). Social capital, outpatient care utilization and choice between different levels of health facilities in rural and urban areas of Bhutan. *Social Science & Medicine*, *211*, 102-113.

Hommes, L., & Boelens, R. (2017). Urbanizing rural waters: Rural-urban water transfers and the reconfiguration of hydrosocial territories in Lima. *Political Geography*, *57*, 71-80.

Javaid, M., Haleem, A., Singh, R. P., & Sinha, A. K. (2024). Digital economy to improve the culture of industry 4.0: A study on features, implementation and challenges. *Green Technologies and Sustainability*, 100083.

Ji, X., Ren, J., & Ulgiati, S. (2019). Towards urban-rural sustainable cooperation: Models and policy implication. *Journal of Cleaner Production*, *213*, 892-898.

Li, Y. (2012). Urban–rural interaction patterns and dynamic land use: Implications for urban–rural integration in China. *Regional Environmental Change*, *12*, 803-812.

Li, Y., Wang, X., Zhu, Q., & Zhao, H. (2014). Assessing the spatial and temporal differences in the impacts of factor allocation and urbanization on urban–rural income disparity in China, 2004–2010. *Habitat International*, *42*, 76-82.

Li, Y., Westlund, H., & Liu, Y. (2019). Why some rural areas decline while some others not: An overview of rural evolution in the world. *Journal of Rural Studies*, *68*, 135-143.

Liu, Y., Schen, C., & Li, Y. (2015). Differentiation regularity of urban-rural equalized development at prefecture-level city in China. *Journal of Geographical Sciences*, *25*, 1075-1088.

Long, F., Liu, J., & Zheng, L. (2022). The effects of public environmental concern on urban-rural environmental inequality: Evidence from Chinese industrial enterprises. *Sustainable Cities and Society*, *80*, 103787.

Lysgård, H. K. (2019). The assemblage of culture-led policies in small towns and rural communities. *Geoforum*, *101*, 10-17.

Ma, L., Cheng, W., & Qi, J. (2018). Coordinated evaluation and development model of oasis urbanization from the perspective of new urbanization: A case study in Shandan County of Hexi Corridor, China. *Sustainable cities and society*, *39*, 78-92.

Ma, L., Liu, S., Fang, F., Che, X., & Chen, M. (2020). Evaluation of urban-rural difference and integration based on quality of life. *Sustainable Cities and Society*, *54*, 101877.

Marans, R. W. (2015). Quality of urban life & environmental sustainability studies: Future linkage opportunities. *Habitat International*, *45*, 47-52.

Murdoch, J. (2000). Networks—a new paradigm of rural development?. *Journal of rural studies*, *16*(4), 407-419.

Peng, J., Liu, Y., Ma, J., & Zhao, S. (2018). A new approach for urban-rural fringe identification: Integrating impervious surface area and spatial continuous wavelet transform. *Landscape and Urban Planning*, *175*, 72-79.

Phillipson, J., Tiwasing, P., Gorton, M., Maioli, S., Newbery, R., & Turner, R. (2019). Shining a spotlight on small rural businesses: How does their performance compare with urban?. *Journal of Rural Studies*, *68*, 230-239.

Raihan, A. (2024). A review of the potential opportunities and challenges of the digital economy for sustainability. *Innovation and Green Development*, *3*(4), 100174.

Razin, E., & Hasson, S. (1994). Urban-rural boundary conflicts: the reshaping of Israel's rural map. *Journal of Rural Studies*, *10*(1), 47-59.

Salvati, L., & Carlucci, M. (2011). The economic and environmental performances of rural districts in Italy: Are competitiveness and sustainability compatible targets?. *Ecological Economics*, *70*(12), 2446-2453.

Shi, J. G., Xu, K., Si, H., Song, L., & Duan, K. (2021). Investigating intention and behaviour towards sorting household waste in Chinese rural and urban–rural integration areas. *Journal of Cleaner Production*, *298*, 126827.

Simwanda, M., & Murayama, Y. (2018). Spatiotemporal patterns of urban land use change in the rapidly growing city of Lusaka, Zambia: Implications for sustainable urban development. *Sustainable cities and society*, *39*, 262-274.

Xia, L., Baghaie, S., & Sajadi, S. M. (2024). The digital economy: Challenges and opportunities in the new era of technology and electronic communications. *Ain Shams Engineering Journal*, *15*(2), 102411.

Yan, J., Chen, H., & Xia, F. (2018). Toward improved land elements for urban–rural integration: A cell concept of an urban–rural mixed community. *Habitat International*, *77*, 110-120.

Yang, R., Zhang, J., Xu, Q., & Luo, X. (2020). Urban-rural spatial transformation process and influences from the perspective of land use: A case study of the Pearl River Delta Region. *Habitat International*, *104*, 102234.

Yang, Y., Bao, W., Wang, Y., & Liu, Y. (2021). Measurement of urban-rural integration level and its spatial differentiation in China in the new century. *Habitat International*, *117*, 102420.

Yin, J., Cao, X. J., Huang, X., & Cao, X. (2016). Applying the IPA–Kano model to examine environmental correlates of residential satisfaction: A case study of Xi'an. *Habitat International*, *53*, 461-472.

Zhang, R., Jiang, G., & Zhang, Q. (2019). Does urbanization always lead to rural hollowing? Assessing the spatio-temporal variations in this relationship at the county level in China 2000–2015. *Journal of Cleaner Production*, *220*, 9-22.

Zhang, R., Yuan, Y., Li, H., & Hu, X. (2022). Improving the framework for analyzing community resilience to understand rural revitalization pathways in China. *Journal of Rural Studies*, *94*, 287-294.

Author Introduction

First and Corresponding author, Donghong Li, Female, born in 1987, Ph.D. student in Global Business at Kyonggi University. Master's degree in Business from KyungHee University in 2022. Research interest in digital economy. Email: lidonghonghanguo@163.com