

Article

How Can the Digital Economy Promote Rural Industrial Revitalization? Evidence from Production Networks

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Abstract

The digital economy has become an emerging driver of rural industrial revitalization. Based on an input-output model and a production-network framework, this study first constructs time-series input-output tables for the digital economy and urban-rural industries from 2002 to 2021. It then identifies key recipient nodes, urban-rural disparity paths, and priority optimization paths of digital value flows. The results show that urban-rural disparities in digital empowerment have narrowed, but the digital divide between urban and rural industries remains substantial. The direct integration of the digital economy into rural industries is still limited, whereas urban-rural industrial integration plays an important mediating role. At the same time, the urban-rural disparity paths in digitally enabled rural industrial revitalization are mainly concentrated in rural capital allocation, asset services, circulation systems, basic agricultural production, and agricultural science and technology services. The counterfactual simulations show that prioritizing the direct embedding of the digital economy into rural manufacturing, agricultural value chains, and public-service sectors, while improving coordinated transmission between urban and rural industries, can strengthen the overall empowerment effect. These findings provide empirical support for more precise and targeted policies to promote rural industrial revitalization through the digital economy.

Keywords: digital economy; rural industrial revitalization; production network; input-output model; industrial linkage

1. Introduction

Comprehensively advancing rural revitalization and realizing agricultural and rural modernization constitute an essential foundation for Chinese modernization. As an important component of comprehensive rural revitalization, rural industrial revitalization does not merely mean expanding the scale of agricultural output. Rather, by relying on agricultural and rural resources, the industrial foundation of county-level economies, and urban-rural industrial linkages, it seeks to enhance the value-creation capacity and sustainable development capacity of the rural industrial system through agricultural modernization, the upgrading of agriculture-related manufacturing and services, the extension of rural industrial chains, the cultivation of new industries and business forms, and the upgrading of value chains. In recent years, rural industrial revitalization has achieved remarkable progress in safeguarding food security, improving the level of agricultural mechanization, promoting the deep processing of agricultural products, and fostering more equal public services and urban-rural integration, while also stimulating the development of new industries and business forms such as specialty agriculture, rural leisure tourism,



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and rural e-commerce [1]. However, rural industries still face structural constraints that make it difficult to meet the requirements of agricultural and rural modernization and high-quality economic development [2].

Meanwhile, the digital economy has been developing rapidly in recent years. The enabling and general-purpose characteristics of digital technologies have made them a new source of momentum for improving the quality and efficiency of traditional industries and a driving force for industrial transformation and upgrading, thereby providing strong support for building a modern industrial system. China launched the Digital Rural Development Strategy as early as 2018, and the 2023 Key Tasks for Digital Village Development explicitly proposed empowering rural industrial development through digitalization, while also setting out key tasks such as strengthening the foundations for rural digital development, promoting smart agriculture, and deepening inclusive digital services in rural areas. Subsequently, policy efforts on digital village development have continued to deepen. In 2024, the key tasks for digital village development further emphasized empowering agricultural and rural modernization through information technology, with the aim of promoting high-quality and sustainable agricultural development, improving production efficiency, and enhancing rural livelihoods. In addition, the National Smart Agriculture Action Plan (2024–2028) proposes accelerating the digital transformation of the entire agricultural value chain and advancing smart agriculture, thereby providing a clearer policy framework for digitally driven rural industrial revitalization. Therefore, strengthening digital empowerment is an important way to address current constraints on rural industrial development and to provide new momentum for rural industrial revitalization. Scientifically measuring the effects of digitally enabled rural industrial revitalization, identifying the pathways of digital empowerment, and achieving precise and targeted industrial policy intervention are necessary prerequisites for attaining these goals.

Existing studies have examined how the digital economy promotes rural industrial revitalization from different perspectives. First, theoretical mechanism analyses suggest that the digital economy plays an important role in advancing the digitalization, intensive development, diversification, integration, and greening of rural industries through such mechanisms as the optimized allocation of production factors, changes in production modes, improvements in industrial efficiency, adjustments in industrial structure, and industrial integration and innovation [2–6]. Second, studies on practical pathways argue that the digital economy mainly promotes rural industrial revitalization through two pathways, namely the “Agriculture+” and “Digital+” pathways. The former refers to improving agricultural productivity and promoting high-quality agricultural development through means such as the digitalization of the entire agricultural value chain and smart agriculture [7–9]. The latter mainly refers to the penetration of the digital economy into other rural industrial chains, thereby giving rise to new industries, new business forms, and new business models, such as “digital media + rural cultural industries” and “digital finance + rural e-commerce” [10,11]. Empirical evidence based on household survey data further shows that digital infrastructure and the use of digital services in the rural digital economy can influence farmers’ innovation willingness, entrepreneurial behavior, and perceived outcomes, thereby promoting rural industrial revitalization [12]. Third, empirical tests of enabling effects show that some scholars, by constructing econometric models, have verified the positive role of digital inclusive finance in promoting rural industrial development, and have found nonlinear double-threshold effects and spatial spillover characteristics [13–15]. Mediation analyses further reveal a transmission path from digital economy development to urban-rural integrated development and then to rural industrial revitalization [16]. Digital inclusive finance has also been shown to promote rural household consumption through the mediating role of rural revitalization, suggesting

that digital financial empowerment can further diffuse through channels such as rural industries, income, and consumption [17]. In addition, the rural digital economy has been shown to facilitate the development of new-type urbanization through mechanisms such as improvements in rural human capital, agricultural economic growth, and the upgrading of rural industrial structure, which further supports the indirect role of the digital economy in promoting rural industrial revitalization from the perspective of urban–rural linkages and structural transformation [18].

While the above studies have affirmed the importance of the digital economy for rural industrial revitalization, they have mainly focused on general theoretical mechanisms at the macro level or on the enabling effects of a single industry, such as digital inclusive finance, and have paid relatively little attention to this issue from the perspective of production networks. This overlooks the diffusion and cascading effects generated by digital outputs used as intermediate inputs within complex industrial linkages. Moreover, digital technologies penetrate and integrate across industries at different speeds, while urban and rural industries differ in industrial structure and dependence on industrial-chain linkages. Quantitative analysis at the industry level is therefore more conducive to revealing the heterogeneity of both the magnitude and the pathways through which the digital economy promotes rural industrial revitalization. Therefore, the core question of this study is: how are digital-economy-related inputs embedded in urban-rural production networks, and through which industrial linkage pathways are they transmitted to rural industries? Centered on this question, this study aims to provide more targeted and differentiated empirical insights for enabling the digital economy to better serve rural revitalization.

Compared with the existing literature, this study makes three main contributions. First, in terms of research perspective, it analyzes how the digital economy influences and promotes rural industrial revitalization from the perspective of production networks. By leveraging the inherent strengths of the input-output model in handling multiple inter-industry linkages and heterogeneity, this study offers a more comprehensive and multidimensional depiction of the differentiated linkages among different industrial chains in the process connecting digital economy development and rural industrial revitalization. This compensates for the limitations of existing studies that mainly focus on a specific theoretical mechanism or a particular industry, provides a cross-sectoral systemic perspective, and complements the existing econometric literature. Second, in terms of analytical framework, the study integrates multiple quantitative methods under a production-network perspective. Specifically, the input-output model is used to measure the effects of digital empowerment on rural industrial revitalization, complex network analysis is employed to identify the key sectors and urban-rural disparity paths in this process, and a dynamic simulation framework is further constructed to optimize the improvement paths for digitally enabled rural industrial revitalization, thereby offering a new approach to maximizing empowerment effects. Third, in terms of data, this study attempts to compile time-series input-output tables for the digital economy and urban-rural industries. By constructing a multi-source heterogeneous dataset that includes economic census data, macro-accounting data, enterprise operating data, and geolocation information, the study decomposes official input-output tables into digital economy sectors, classifies urban and rural industrial sectors, and fills in missing years of data, thereby generating a 53-sector time-series input-output table for China's digital economy and urban-rural industries from 2002 to 2021, which constitutes the empirical foundation of this study.

2. Research Framework and Data Foundation

2.1. Analytical Framework for the Digital Economy Empowering Rural Industrial Revitalization

From the perspective of production networks, the existing economic structure and the input-output linkages among sectors constitute the practical foundation on which the digital economy exerts its influence. The entry of digital products and services into the rural industrial system is not a simple process of technological diffusion detached from the existing division of labor; rather, it relies on intersectoral input-output relationships to generate value transmission across different links of industrial chains. This study mainly focuses on the forward linkages (Some studies also measure the effects of digital empowerment from both forward and backward linkage perspectives. Backward linkages refer to the expansion of digital economy sectors themselves, that is, digital industrialization, which increases their consumption of products from upstream sectors and thereby promotes the development of upstream industries.) from digital sectors to rural industrial sectors, that is, rural industrial sectors, as downstream sectors, are the users of digital products and services.

Based on the above understanding, and in conjunction with the research design presented in the following sections, this study summarizes the analytical framework of the digital economy empowering rural industrial revitalization into five interlinked stages, as shown in Figure 1: “digital economy input–industrial transmission–measurement of digital empowerment effects–analysis of measurement results–identification and optimization of empowerment pathways.” First, in the stage of digital economy input, the digital economy consists of digital product manufacturing, digital technology applications, digital product services, and digital factor-driven industries, which enter the urban-rural industrial system in the form of inputs of digital products and services. Second, in the stage of industrial transmission, digital empowerment affects rural industries through both direct and indirect transmission paths, with the latter reflecting a cascading empowerment process in which the digital economy continues to diffuse from urban industries to rural industries.

In the stage of measuring digital empowerment effects, this study constructs indicators from two dimensions according to the underlying mechanism: the level of digital integration and the level of digital transformation. The former reflects the breadth and depth with which digital products and services, as intermediate inputs, are embedded in the production system of rural industries, whereas the latter reflects the extent to which rural industries use the products and services provided by digital sectors to produce final outputs and achieve value added. These two dimensions correspond respectively to the process dimension and the outcome dimension of digital empowerment, and together constitute the core representation of the extent to which the digital economy promotes rural industrial revitalization.

In the stage of analyzing the measurement results, this study further examines three aspects: urban-rural differences and overall evolution, industry heterogeneity, and the degree of support for the goals of rural revitalization, so as to reveal the temporal variation, industrial distribution, and how digital-empowerment effects correspond to different rural-revitalization goals. Measuring the effects of digital empowerment solely through the input-output model is still insufficient to uncover the mechanisms operating under specific patterns of industrial linkages and key transmission paths. Therefore, after completing the measurement of effects and the analysis of results, this study further turns to the identification and optimization of empowerment pathways. Specifically, it first constructs a core-path network of digital empowerment, then analyzes the characteristics of key paths, on this basis identifies the priority areas and urban-rural disparity paths in digitally enabled rural industrial revitalization, and finally employs counterfactual analysis to identify the optimal improvement paths for enhancing the effects of digital empowerment on rural

industrial revitalization. In this way, digitally enabled rural industrial revitalization is understood as a progressive process driven by industrial linkages that can be measured, identified, and optimized.

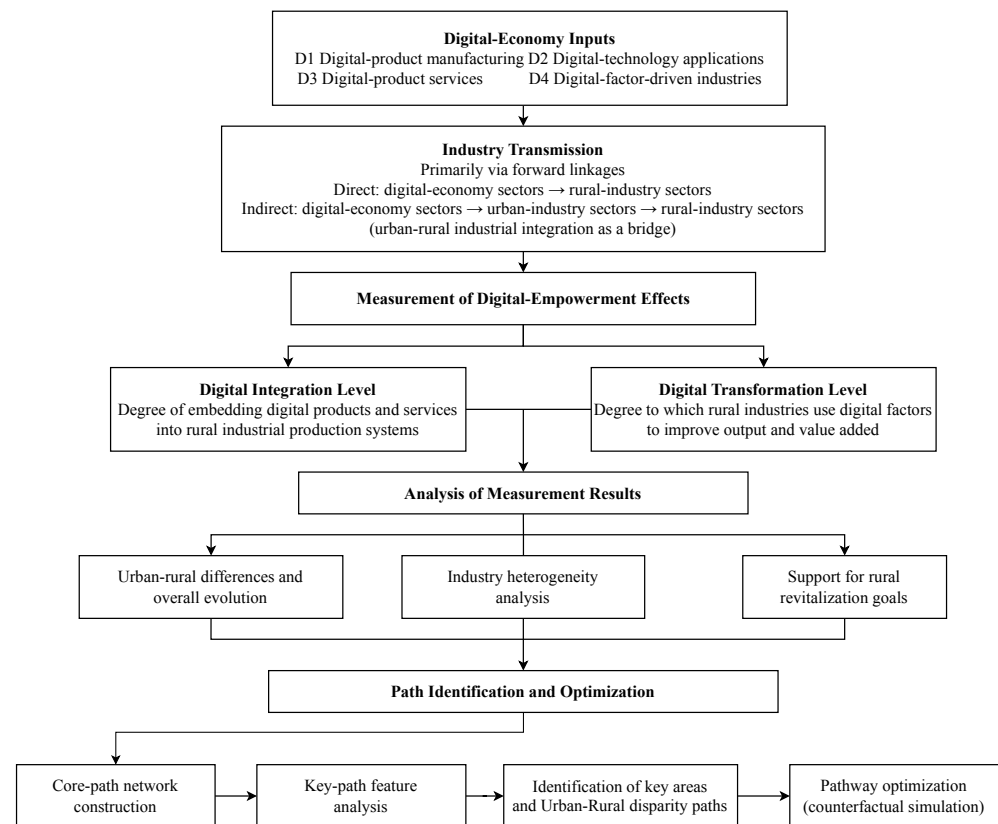


Figure 1. Theoretical framework of digital-economy empowerment for rural industrial revitalization.

2.2. Compilation of the Time-Series Input-Output Table for the Digital Economy and Urban-Rural Industries

Separating digital-economy sectors and urban/rural industrial sectors within the input-output table (IOT) and obtaining continuous time-series data are prerequisites for the subsequent analysis. The key steps in compiling the above time-series input-output table for the digital economy and urban-rural industries are as follows. First, the scope of the digital economy is defined, and the digital-economy split coefficient is estimated. Second, the urban-rural sectoral split coefficient is estimated, and the non-digital economy sectors are divided into urban and rural components. Third, IOTs for the missing interval years are estimated in order to complete the full time series. Fourth, robustness tests are conducted for the compiled tables.

2.2.1. Delineation of the Scope of the Digital Economy

Although some studies include both the digital industrialization and the digital transformation of industries within the scope of the digital economy, from the perspective of input-output analysis, digital economy industries must produce digital outputs, including digital products and digital services, whereas the intermediate use of digital outputs by other industries falls within the category of digital empowerment. Therefore, this study focuses on the core industries of the digital economy, that is, the digital industrialization component, while the intermediate use of digital outputs by other sectors is treated as digital empowerment. The sectoral scope is defined consistently with the Statistical Classification of Digital Economy and Its Core Industries (2021) (hereinafter referred to as the

Classification). The correspondence between the Classification and the official IOTs is shown in Table 1.

Table 1. Scope of the Digital Economy and Corresponding Official IOT Sectors.

	Core Digital Economy Industries in the Classification	Corresponding Official IOT Product Sectors (2020 Example)
D1–Digital Product Manufacturing	Computer Manufacturing	Computers
	Communication and Radar Equipment Manufacturing	Communication Equipment Broadcasting and Television Equipment,
	Digital Media Equipment Manufacturing	Radar and Supporting Equipment Audio-Visual Equipment
	Electronic Components and Equipment Manufacturing	
	Other Digital Product Manufacturing	Other Electronic Equipment
D2–Digital Technology Applications	Telecommunications	Telecommunications
	Broadcasting, Television and Satellite Transmission Services	Broadcasting, Television and Satellite Transmission Services
	Internet-Related Services	Internet and Related Services
	Software Development	Software Services
D3–Digital Product Services	Information Technology Services	Information Technology Services
	Wholesale and Retail of Digital Products	Wholesale and Retail *
	Leasing and Repair of Digital Products	Leasing and Other Services *
D4–Digital Factor-Driven Industries	Digital Content and Media	News and Publishing * Broadcasting Television Film and Audio-Video Recording Production *

Note: IOT sectors marked with “*” include only partial digital-economy core activities and therefore require further separation.

As shown in Table 1, the digital product manufacturing sector and the digital technology applications sector correspond exactly to the product sectors in the IOTs. However, for three sectors classified under digital product services and digital factor-driven industries—namely wholesale and retail, leasing and other services, and news publishing—the non-digital economy components still need to be separated out. In the absence of directly available value-added data for the relevant sectors, this study uses operating revenue, which is closely related to value-added accounting in the service sector, as an approximate measure [19]. The digital-economy split coefficient, denoted by α , is defined as the share of the main business revenue of all digital-economy sub-sectors within sector i , as shown in Equation (1):

$$\alpha_{i,t} = \frac{\sum_{j \in \text{Digital}_i} \text{Inc}_{j,t}}{\text{Inc}_{i,t}}, \quad (i = 1, 2, 3; t = 2002, \dots, 2021) \quad (1)$$

where Inc denotes main business revenue; Digital_i is the set of digital-economy sub-sectors belonging to sector i ; i and j index sectors and sub-sectors, respectively; and t indexes time. The estimation results are reported in Table 2. Overall, the shares of digital-economy sub-sectors exhibit an upward trend over time, indicating a continuous improvement in the level of digital industrialization.

Table 2. Digital-Economy Split Coefficients, 2002–2021 (%).

Year	Wholesale and Retail of Digital Products	Leasing and Repair of Digital Products	Digital Publishing
2002	2.29	1.39	1.04
2003	2.44	1.88	1.96
2004	2.58	2.36	2.88
2005	2.72	2.85	3.81
2006	2.86	3.33	4.73
2007	3.01	3.81	5.65
2008	3.15	4.30	6.63
2009	3.13	4.46	7.49
2010	3.12	4.63	8.28
2011	3.10	4.80	9.44
2012	3.08	4.96	11.63
2013	3.07	5.13	13.90
2014	3.27	5.22	16.96
2015	3.48	5.31	20.34
2016	3.69	5.40	24.25
2017	3.90	5.49	28.07
2018	4.10	5.59	30.83
2019	4.31	5.68	34.15
2020	4.52	5.77	41.26
2021	4.29	6.60	34.81

Note: Revenue data for digital publishing and the news and publishing sector are obtained from the Institute of Digital Publishing of the Chinese Academy of Press and Publication and the National Press and Publication Administration. Revenue data for the other sectors are obtained from the *China Economic Census Yearbook*. Missing data for non-census years are supplemented using piecewise linear interpolation.

2.2.2. Classification of Urban and Rural Industries

There is still no unified standard for classifying industries in the IOT into urban and rural categories. Early studies mostly adopted an a priori approach to defining the sectoral scope of rural industries, for example by identifying rural industries as agriculture or agriculture-related sectors such as food processing, textiles, and papermaking, while assigning most secondary and tertiary industries to urban industries [20,21]. However, with the extension of agriculture-related industrial chains and the emergence of new industries and business forms during the process of rural industrial revitalization, these early classifications are no longer well suited to current patterns of rural industrial development. The production and business activities of the same industry may be distributed across both urban and rural areas, and may participate in regional production networks through different types of firms. Starting from the urban-rural spatial distribution of industrial activities, this study further decomposes each industrial sector into its rural component and urban component. For ease of exposition, the rural component of an industry is referred to as a “rural industry,” while its urban component is referred to as an “urban industry.” Specifically, rural industries refer to the economic activities of a given industry carried by firms located in rural areas, whereas urban industries refer to the economic activities of that industry carried by firms located in urban areas. To characterize the relative spatial distribution of industrial activities between urban and rural areas, this study further constructs an urban-rural sectoral split coefficient [22,23], and uses it to decompose the original industrial sectors along the urban-rural spatial dimension.

Because macro-level data cannot reflect the urban-rural distribution of industries, the calculation must rely on micro-level enterprise operating information and geolocation data. First, the basic industrial and commercial registration information of enterprises was obtained from the National Enterprise Credit Information Publicity System, including enter-

prise name, industry classification, date of establishment, registered capital, and registered address. After removing abnormal observations and samples with missing information, (The screening criteria are as follows: the enterprise status must be active; registered capital must be non-missing and greater than zero; and the fields for date of establishment and registered address must be non-missing.) more than 22 million valid enterprise samples were ultimately retained. Second, based on enterprise names and registered addresses, the Baidu Maps point-of-interest (POI) API was used to obtain longitude and latitude data, which were then converted into structured four-level administrative addresses consisting of province, city, county (district/banner), and township (town/subdistrict), so as to determine the urban or rural affiliation of each enterprise. (In accordance with the Provisions on Statistical Delineation of Urban and Rural Areas, this study classifies an enterprise as rural if its fourth-level address (i.e., township, town, or subdistrict) corresponds to a township rather than a town or subdistrict, or if the detailed address—defined as the remaining part after removing all structured four-level address information—contains the name of a village.) Finally, the proportion of rural enterprises in the total number of sample enterprises within each industry was calculated. To account for differences in firm size, registered capital was used as a weight, and the urban–rural sectoral split coefficient is defined as follows:

$$\beta_{i,t} = \frac{\sum_{j \in R} I(s_j \leq t) C_{i,j}}{\sum_{j=1}^n I(s_j \leq t) C_{i,j}}, \quad i = 1, \dots, 24; t = 2002, \dots, 2021 \quad (2)$$

where β denotes the urban–rural sectoral split coefficient; C denotes the registered capital of an enterprise; n is the number of enterprises; s denotes the date of establishment; and R represents the set of rural enterprises. The subscripts i , j , and t denote the industry index, enterprise index, and time index, respectively. $I(s_j \leq t)$ is an indicator function, meaning that when calculating the urban–rural sectoral split coefficient at time t , only enterprise samples that had been established and remained active by time t are included. Using this method, the urban–rural sectoral split coefficients for 25 industries were obtained for each year. Owing to space limitations, Table 3 reports the results for only selected years.

As shown in Table 3, the share of rural industries in the national economy exhibits an overall upward trend. Resource-based industries, including mining, food and tobacco processing, and textiles, account for a relatively large share and have grown rapidly, indicating the continuous improvement of related deep-processing industrial chains. The development of the rural tertiary sector generally lags behind that of the secondary sector; however, the shares of industries such as education, healthcare, and social security have increased rapidly, suggesting stronger grassroots rural institutions and a marked improvement in governance capacity. By contrast, the shares of finance and real estate, warehousing and logistics, wholesale and retail, accommodation and catering, and culture and entertainment have remained persistently low, with relatively slow development, reflecting pronounced characteristics of insufficient and uneven development.

Industry 22 (education) also showed a marked increase in its urban–rural separation coefficient, rising from 5.14% in 2015 to 25.65% in 2017 and remaining at a relatively high level in 2018 and 2020. This change may be related to the 2016 revision of the Law on the Promotion of Private Education, the subsequent policies encouraging social forces to provide education, the expansion of inclusive preschool resources, and policy support for rural education. These policies improved the institutional environment for registering education providers and for social capital entry, while strengthening expectations for education service provision in counties, townships, and rural areas. Because education institutions usually have relatively strong persistence after establishment, newly registered entities continue to enter the stock sample. This may explain why the education sector displays a stepwise increase in the rural share of registered capital.

Table 3. Urban–Rural Sectoral Split Coefficients by Industry in Selected Years (%).

Industry	2002	2005	2007	2010	2012	2015	2017	2018	2020
0—Agriculture, Forestry, Animal Husbandry and Fishery	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
1—Mining	6.19	10.28	12.79	15.42	17.47	21.34	21.80	22.34	22.45
2—Food and Tobacco Processing	11.15	13.33	14.94	17.30	23.46	31.81	34.12	33.93	33.98
3—Textiles	22.13	23.12	19.81	21.34	30.73	34.22	33.94	33.96	33.99
4—Other Light Industrial Products	19.79	21.52	24.63	29.39	33.26	45.21	44.55	44.26	43.88
5—Chemical Raw Materials and Products	8.59	10.66	11.61	14.38	15.79	17.22	17.93	18.24	18.80
6—Mineral and Metal Products	38.52	34.40	33.85	36.10	37.33	39.73	39.15	39.10	38.90
7—General and Special Equipment	10.70	13.47	17.84	19.19	19.96	21.29	22.50	22.87	23.47
8—Transportation Equipment	5.30	6.61	7.29	7.02	7.41	9.30	10.26	10.85	11.78
9—Electrical Machinery and Equipment	13.77	15.78	16.87	17.19	18.09	21.79	22.34	22.55	23.24
10—Other Manufacturing	11.04	12.53	14.33	17.61	21.54	31.68	32.70	32.79	26.46
11—Production and Supply of Electricity, Heat, Gas and Water	4.20	12.37	17.21	17.66	17.58	20.65	20.25	20.16	19.75
12—Construction	6.46	7.05	7.54	8.57	9.56	10.71	11.77	12.28	12.06
13—Wholesale and Retail	3.91	4.93	5.50	6.75	7.43	8.98	9.70	9.88	10.38
14—Transportation, Storage and Postal Services	4.12	6.26	7.25	7.33	7.90	9.74	10.85	11.05	11.81
15—Accommodation and Catering	10.16	10.63	11.85	11.40	11.52	16.42	16.14	16.34	18.45
16—Finance	0.51	0.54	0.53	0.97	1.12	1.38	2.07	2.11	2.08
17—Real Estate	4.25	4.70	5.17	5.89	6.45	5.89	6.60	7.21	7.65
18—Leasing and Business Services	4.64	5.59	6.08	7.10	9.03	8.13	9.04	9.86	11.44
19—Scientific and Technical Services	3.71	5.59	6.35	6.82	7.85	9.79	9.85	10.09	11.07
20—Ecological and Environmental Management	6.79	11.55	12.28	12.83	13.98	16.40	16.63	13.91	16.35
21—Resident Services and Other Services	9.65	12.24	13.65	16.62	15.72	18.34	17.80	17.88	17.80
22—Education	5.68	9.52	7.57	8.88	8.97	5.14	25.65	27.64	25.76
23—Healthcare and Social Security	2.12	2.76	3.26	4.88	6.11	23.43	14.58	14.19	14.16
24—Culture, Sports and Entertainment	6.70	10.87	12.00	11.55	20.38	15.17	14.99	14.69	13.27
Average of Secondary Industries	13.15	15.09	16.56	18.43	21.01	25.41	25.94	26.11	25.73
Average of Tertiary Industries	5.19	7.10	7.62	8.42	9.71	11.57	12.83	12.90	13.35
Overall Average (Excluding Agriculture)	9.17	11.10	12.09	13.42	15.36	18.49	19.38	19.51	19.54

Note: Given the special importance of agriculture in rural revitalization, agriculture is fully assigned to rural areas; therefore, its urban–rural sectoral split coefficient is always 1.

The urban–rural sectoral split coefficients of some service industries exhibit temporary fluctuations. Industry 23, “Healthcare and Social Security,” reached 23.43% in 2015, substantially higher than the 6.11% observed in 2012, but then fell back to around 14%. Industry 24, “Culture, Sports, and Entertainment,” also reached a temporary peak of 20.38% in 2012 and then declined gradually. These peaks may be related to policy backgrounds during the corresponding periods, including the expansion of primary healthcare, elderly-care services, privately provided medical services, grassroots public cultural services, and sports facilities. (The relevant policy background mainly includes the 2014 *Opinions of the State Council on Establishing a Unified Basic Pension Insurance System for Urban and Rural Residents*, the 2015 *Outline of the National Healthcare Service System Plan (2015–2020)*, the 2015 *Several Policy Measures of the General Office of the State Council on Promoting the Accelerated Development of Privately Provided Medical Services*, and policies during the 12th Five-Year Plan period concerning the public cultural service system, rural cultural facilities, and public fitness facilities.) Because the urban–rural sectoral split coefficient in this study is weighted by enterprise registered capital, such local peaks are more likely to reflect the temporary concentration of rural-side entities or capital induced by policy implementation. They do not necessarily indicate sustained improvements in actual output, employment absorption, or public-service capacity in the corresponding industries. The urban–rural sectoral split coefficient can characterize the urban–rural allocation pattern under the registered-capital accounting framework, but it is sensitive to low-base industries, concentrated policy implementation, and the entry of a small number of large registered-capital entities. Overall, this

issue mainly affects the interpretation of local fluctuations in a few industries and years, and does not alter the long-term trend in urban–rural industrial shares reflected in Table 3.

2.2.3. Estimation of IOTs for the Missing Interval Years

Drawing on the basic methods used in the literature to construct time-series IOTs [23–26], this study first determines the row and column control totals for each sector in the missing interval years, including total output, total value added, total final use, and total intermediate input and intermediate use. It then estimates the three major matrices—intermediate flows, primary inputs, and final use—thereby obtaining the IOTs for the missing interval years.

When deriving the row and column control totals, gross output for agriculture, forestry, animal husbandry and fishery, industry, and construction can be taken from the gross output values reported in sources such as the *China Statistical Yearbook* and the *China Industrial Statistical Yearbook*, whereas gross output for services needs to be back-calculated from the value-added ratio. Total value added is estimated using GDP by the income approach together with sectoral value-added data, while total final use is estimated using GDP by the expenditure approach and its components. Owing to differences between the accounting classifications and the IOT classifications, and because the sectoral granularity of the accounting data is much coarser than that of the IOTs, it is necessary to make proportional adjustments to ensure consistency and to allocate values proportionally across sectors. The relevant proportions are then projected from benchmark years to the missing interval years through piecewise linear interpolation. Finally, based on the adjusted total output, total final use, and total value added for each sector, the total intermediate input and total intermediate use of each sector are obtained. The compilation procedure for the input-output tables for the missing interval years is shown in Figure 2.

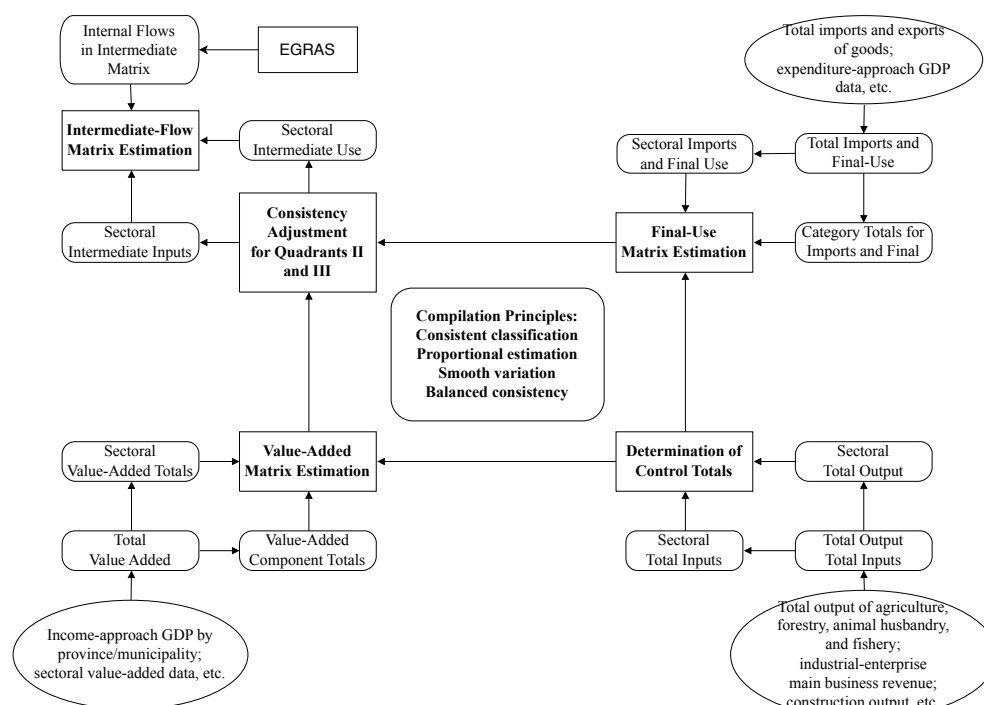


Figure 2. Flowchart for compiling input-output tables for the missing interval years.

After all row and column control totals have been obtained, the EGRAS method is applied block by block to estimate the three major matrices: intermediate flows, primary inputs, and final use. Its core function is to identify a target-year matrix when the row and column control totals for the target year are known but the detailed intersectoral flows

are unknown. Specifically, it uses the input-output structure of the adjacent benchmark year as the base and searches for a target-year matrix that both satisfies the row and column summation constraints for the target year and preserves, as far as possible, the techno-economic linkages in the base-year matrix. x_{ij}^0 denotes the known element in row i and column j of the base-year matrix, and the corresponding target-year element can be expressed as $\hat{x}_{ij} = c_{ij}x_{ij}^0$, where c_{ij} is the adjustment coefficient to be estimated, namely $c_{ij} = \hat{x}_{ij}/x_{ij}^0$. The coefficient c_{ij} reflects the magnitude of adjustment in this input-output relationship from the base year to the target year. When the interval between the base year and the target year is short, c_{ij} is generally close to 1, indicating a gradual adjustment in intersectoral technological linkages.

$$\min EGRAS = \sum_{i=1}^m \sum_{j=1}^n (c_{ij} - 1) \ln c_{ij} \quad (3)$$

$$\text{s.t.} \begin{cases} \sum_{j=1}^n c_{ij}x_{ij}^0 = u_i, & i = 1, \dots, m \\ \sum_{i=1}^m c_{ij}x_{ij}^0 = v_j, & j = 1, \dots, n \end{cases} \quad (4)$$

The nonlinear programming problem shown in Equations (3) and (4) specifies the objective function and constraints constructed according to this logic. The objective function measures the extent to which the adjustment coefficients deviate from 1. The closer c_{ij} is to 1, the smaller the objective-function value, indicating that the target-year matrix imposes a smaller perturbation on the structure of the base-year matrix. The constraints require that the adjusted matrix elements $\hat{x}_{ij} = c_{ij}x_{ij}^0$ sum to the target-year row control total u_i in the row direction and to the target-year column control total v_j in the column direction, respectively, where m and n denote the numbers of rows and columns of the matrix. Thus, the EGRAS method essentially obtains the input-output matrix for the missing interval year by making the minimum necessary adjustments to the base-year matrix while satisfying the aggregate balance conditions for the target year.

It should be noted that the EGRAS method estimates 25-sector input-output tables for the missing interval years, which provide the basis for the subsequent sectoral disaggregation. On this basis, this study further constructs the final input-output tables for the digital economy and urban-rural industries by following the sequence of “digital-economy separation followed by urban-rural industrial splitting.” First, based on the scope of the digital economy and the digital-economy split coefficients defined in Section 2.2.1, four categories of digital-economy sectors, namely digital product manufacturing, digital product services, digital technology applications, and digital factor-driven industries, are identified and separated from the 25-sector input-output tables. The remaining parts of the original sectors after deducting the digital-economy components are retained as non-digital-economy sectors. Subsequently, based on the urban-rural sectoral split coefficients estimated in Section 2.2.2, the non-digital-economy sectors are further divided into urban and rural components. Among them, agriculture, forestry, animal husbandry, and fishery are fully assigned to rural industrial sectors, while the remaining 24 non-digital-economy sectors are each split into a rural industrial sector and an urban industrial sector. In this way, this study ultimately obtains a 53-sector input-output table for the digital economy and urban-rural industries, consisting of four digital-economy sectors, 25 rural industries, and 24 urban industries.

2.2.4. Compilation Results and Robustness Tests

Following the procedures described above, this study compiles a 53-sector input-output table for China's digital economy and urban-rural industries covering the period 2002–2021. A simplified table structure is presented in Table 4. The digital economy comprises four sectors (D1–D4); rural industries comprise 25 sectors (R0–R24); and urban industries comprise 24 sectors (U1–U24). Owing to space limitations, the complete time-series input-output tables are provided in the Supplementary Materials File S1.

Table 4. Simplified Framework of the Digital-Economy and Urban–Rural Industry Input–Output Table.

		Intermediate Use				Final Use	Imports	Stat. Error	Total Output
		Digital Econ. (D1–D4)	Rural Ind. (R0–R24)	Urban Ind. (U1–U24)	Subtotal				
Intermediate Inputs	Digital Economy Rural Industries Urban Industries								
	Subtotal								
Primary Inputs (Value Added)									
Total Inputs									

Note: The sector names corresponding to the codes are the same as those listed in the left columns of Tables 1 and 3. Prefixes D, R, and U denote the digital economy, rural industries, and urban industries, respectively.

To assess the reliability of the compiled tables, this study first examines their numerical accuracy. Figure 3 reports the distribution of relative errors across industries over the years, where the relative error is defined as the percentage of statistical error in an industry's total output. In most years, the relative error for each industry is within 2%, with the maximum being approximately 6%. This indicates that the EGRAS algorithm used in this study has relatively high numerical precision. (For benchmark years, the official IOTs are directly processed through sectoral splitting and aggregation, and therefore no solution to the nonlinear programming problem in Equation (3) is required. Among them, the official IOTs for 2002, 2005, 2007, 2010, 2012, and 2015 contain non-zero statistical error columns, and these errors are also carried over into the IOTs for those years as well as the missing interval-year IOTs estimated using those years as benchmark years.)

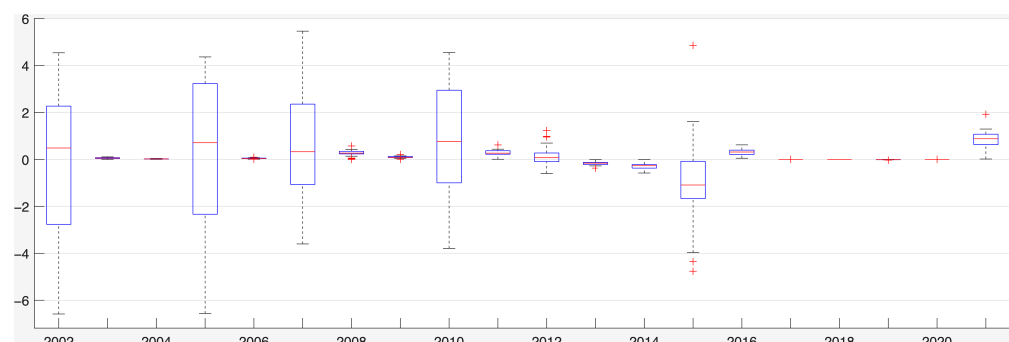


Figure 3. Distribution of relative errors by industry in the digital-economy and urban-rural input-output tables across years. *Note:* Boxes show interquartile ranges, red center lines show medians, whiskers show non-outlier ranges, and red crosses indicate outliers.

To assess the reliability of the compiled tables, this study then examines the reasonableness of the digital-economy split coefficients. This study further uses the compiled IOTs to calculate the share of digital economy value added in GDP, and compares the results with those reported in representative studies [19,27,28] or with estimates derived from macroeconomic indicators. The comparison results are shown in Figures 4 and 5.

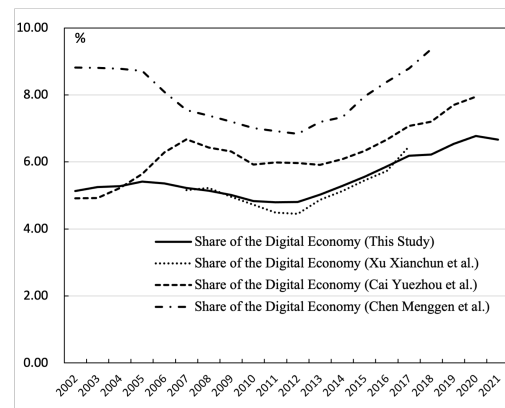


Figure 4. Share of digital-economy value added in GDP. *Note:* Comparison sources: Xu and Zhang [19], Cai and Niu [27], and Chen and Zhang [28].

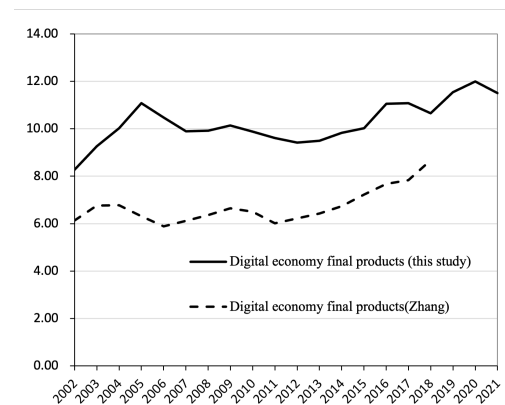


Figure 5. Share of digital-economy final products in GDP. *Note:* Comparison source: Zhang [29].

From the perspective of the reasonableness of the digital-economy split coefficients, the average share of digital-economy value added in GDP calculated in this study is 5.52% during 2002–2021, with a minimum of 4.80% and a maximum of 6.78%. Overall, it increased from 5.13% in 2002 to 6.67% in 2021. For the overlapping period of 2007–2017 with the results of Xu and Zhang [19], the series calculated in this study is highly consistent with their results, with a correlation coefficient of 0.976, an average difference of only 0.10 percentage points, and a mean absolute difference of 0.16 percentage points. Compared with Cai and Niu [27], the correlation coefficient between the two series during 2002–2020 is 0.776, and the estimates in this study are, on average, 0.81 percentage points lower. Compared with Chen and Zhang [28], the correlation coefficient during 2002–2018 is 0.748, and the estimates in this study are, on average, 2.63 percentage points lower. The latter two studies adopt broader measurement scopes, especially by including value added generated through the integration of digital technologies into traditional industries or their substitution for traditional production processes. It is therefore reasonable that their estimates are higher than those in this study. Overall, the estimates in this study are very close in magnitude to those in studies using a narrower measurement scope, and remain consistent in trend with those using broader measurement scopes.

As a supplementary test, this study further follows the final-product measurement approach of Zhang [29] and uses the IOTs compiled in this study to calculate the share of digital-economy final products in GDP. The results are then compared with the benchmark series reported by Zhang [29]. The results show that the estimate in this study increased from 8.28% in 2002 to 10.65% in 2018, while the benchmark series increased from 6.13% to 8.67%. Both series exhibit an upward trend, with stronger trend consistency after 2013. Considering that Zhang [29] mainly adopts a measurement scope covering ICT

manufacturing, ICT services, and digital content, whereas the digital-economy sectors in this study cover D1–D4 and therefore have a broader accounting scope, it is reasonable that the estimates in this study are higher in level than the benchmark series. Nevertheless, the two series are consistent in terms of trend direction and long-term magnitude of change.

To assess the reliability of the compiled tables, this study further examines the reasonableness of the urban-rural split coefficients. Figure 6 shows that, although no officially published rural GDP accounting data are available for a strict comparison, and although the nominal growth rate of county-area GDP used as a proxy differs to some extent in statistical scope from rural GDP (This study uses the GDP of each prefecture-level city reported in the *China City Statistical Yearbook* minus the GDP of the municipal districts under that prefecture-level city as a proxy for rural GDP, and then calculates the corresponding growth rate. Strictly speaking, the proxy refers to “county-area” regions, which include not only rural areas but also county seats, county-level cities, and designated towns.), the correlation coefficient between the two series is 0.527, with a p -value of 0.0204. After 2013, with the implementation of targeted poverty alleviation and rural revitalization policies, the growth rate of rural GDP began to exceed that of county-area GDP, leading to some divergence in their numerical levels. Nevertheless, the two series still exhibit similar trend patterns. The above robustness tests indicate that the compiled tables are reliable.

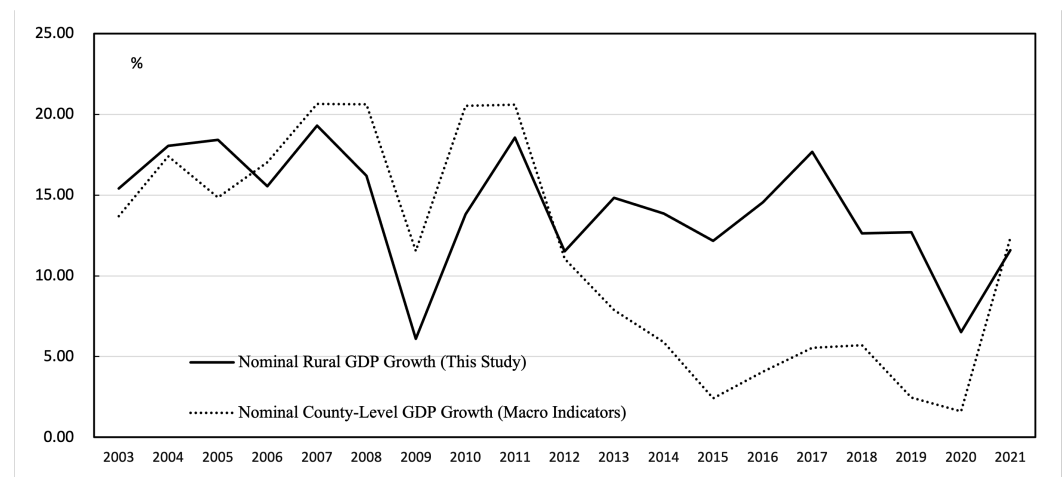


Figure 6. Nominal growth rate of rural GDP. Note: The comparison series is county-level GDP.

3. Measurement of Digital Empowerment Effects

3.1. Mechanisms of Digital Empowerment

The IOT describes the complex intermediate input-output relationships among sectors of the national economy. The inter-industry interconnection and mutual feedback formed on the basis of such input-output relationships constitute a production network. Moreover, the sectors in the IOT and the production linkages among them can be mapped onto the nodes and edges of a directed graph in complex network theory [29,30]. This enables us not only to assess the strength and direction of direct and indirect inter-industry linkages on the basis of the input-output model, but also to analyze and visualize, from the perspective of production networks, the general patterns of inter-industry interconnection and feedback effects, the main transmission paths, key intermediary nodes, and strategies for optimization and improvement [31].

In this study, the forward linkages from digital sectors to rural industrial sectors are specifically reflected in two aspects. First, in terms of the empowerment process, digital factors are widely used as intermediate inputs by rural industries and other related industries. Owing to their broad diffusion potential and substitution effects, they reduce

the excessive dependence of these industries on traditional production factors such as labor and natural endowments, thereby promoting further optimization of the production factor structure of rural industries. As a result, various digital products and services used as intermediate inputs become increasingly important to rural industries, which is manifested in a higher level of digital integration. Second, in terms of the empowerment outcome, rural industrial sectors incorporate digital factors such as data elements, digital technologies, and intelligent equipment into the production process, thereby promoting automation, digitalization, and smart upgrading in production. This transforms the traditional mode of production in rural industries and improves production efficiency. From the perspective of value formation, this means that the share of final output in rural industries generated on the basis of digital factors further increases, which is reflected in a higher level of digital transformation.

3.2. Design of Measurement Indicators

Based on the mechanism discussed above, this study constructs indicators from two dimensions—digital integration and digital transformation—to measure the effects of the digital economy in promoting rural industrial revitalization.

3.2.1. Level of Digital Integration

The total allocation coefficients from digital economy sectors to other sectors are used to measure the level of total digital integration. Total allocation coefficients are employed to capture complete forward inter-industry linkages, as shown in Equation (5).

$$S = (I - B)^{-1} - I = [s_{ij}]_{n \times n} \quad (5)$$

Here, B denotes the matrix of direct allocation coefficients; I is the $n \times n$ identity matrix; $G = (I - B)^{-1} = [g_{ij}]_{n \times n}$ is the Ghosh inverse matrix (the matrix of total supply coefficients); and S denotes the matrix of total allocation coefficients. The element s_{ij} in G reflects the extent to which the production of sector j depends on sector i . From the perspective of allocation circulation, the element s_{ij} in S represents the intermediate allocation from sector i to sector j net of the initial self-allocation in the production process of sector i ($j \neq i$) [32]. Therefore, s_{ij} is used to measure the degree of integration between sector i (the supplying sector) and sector j (the demanding sector).

Let D denote the set of digital economy sectors and R denote the set of rural industrial sectors. By selecting and aggregating the elements s_{ij} in S , the overall level of total digital integration in rural industries, γ^R , and the sector-specific level, γ_j^R , can be calculated, respectively, as shown in Equations (6) and (7). (Total integration takes into account both direct and indirect linkages. If only the direct linkages between the digital economy and rural industries are considered, the level of direct integration can be expressed accordingly, where b_{ij} denotes the element in the matrix of direct allocation coefficients.)

$$\gamma^R = \sum_{i \in D} \sum_{j \in R} s_{ij} \quad (6)$$

$$\gamma_j^R = \sum_{i \in D} s_{ij}, \quad j \in R \quad (7)$$

3.2.2. Level of Digital Transformation

The level of digital transformation is measured by the share of final-use output generated by rural industrial sectors using the products and services provided by digital sectors in the total final-use output of rural industries. From the perspective of production networks, the Ghosh input-output model can be used to estimate the amount of final-use

output generated by each industrial sector relying on the products and services provided by digital economy sectors. Let $\vec{Y}$ denote the row vector of value added, $\vec{F}$ the column vector of final-use output, and $\vec{f}$ the column vector of final-use-output ratios, where the representative element $f_j = F_j/Q_j$ denotes the proportion of sector j 's final-use output F_j in its total output Q_j . Then, the amount of final-use output generated by sector j relying on digital sector i , denoted by F_{ij}^D , can be expressed as follows:

$$F^D = E^D \text{diag}(\vec{Y}) (I - E \odot B)^{-1} \text{diag}(\vec{f}) = [F_{ij}^D]_{d \times n} \quad (8)$$

Here, “diag” denotes a diagonal matrix with the corresponding vector elements as diagonal entries, and the symbol “ $\odot$ ” denotes element-wise matrix multiplication. E^D is a $d \times n$ indicator matrix, where d is the number of digital sectors. Its elements are equal to 1 if and only if $i = j$, and 0 otherwise. Under the table structure adopted in this study (Table 4), the digital sectors are located in the first d positions among the n sectors ($d < n$); therefore, E^D is used to retain the digital economy part in the diagonal matrix of value added. E is an $n \times n$ indicator matrix. If both the row sector and the column sector corresponding to an element belong to digital sectors, that element is set to 0; otherwise, it is set to 1. Matrix E cuts off the internal linkages among digital sectors in the direct allocation matrix B , thereby avoiding double counting caused by the final-use output generated when digital sectors use products of their own sectors [29]. The representative element F_{ij}^D in matrix F^D measures the amount of final-use output of sector j generated in reliance on digital sector i . Accordingly, the component contribution of digital sector i to the digital transformation of sector j , denoted by η_{ij} , can be calculated as follows:

$$H = F^D \odot F^H = [\eta_{ij}]_{d \times n} = [F_{ij}^D / F_j]_{d \times n} \quad (9)$$

Here, F^H has the same dimensions as matrix F^D . In this matrix, all elements in column j are equal to the reciprocal of the final-use output of sector j , that is, $F_j^H = 1/F_j$. The column sum of matrix H , $\sum_{i=1}^d \eta_{ij}$, measures the level of digital transformation of sector j . By further restricting sector j to rural industries, the overall level of digital transformation in rural industries, δ^R , and the sector-specific level, δ_j^R , can be calculated as follows:

$$\delta^R = \sum_{i \in D} \sum_{j \in R} \eta_{ij} \quad (10)$$

$$\delta_j^R = \sum_{i \in D} \eta_{ij}, \quad j \in R \quad (11)$$

3.3. Analysis of Measurement Results

3.3.1. Urban-Rural Differences and Overall Evolution

Based on the digital-integration and digital-transformation formulas above, this study calculates the level of total digital integration, the share of direct digital integration, and the level of digital transformation for rural industries. For comparison, the corresponding indicators for urban industries are also measured, as shown in Figures 7 and 8.

The results show that, during the sample period, the digital integration level of rural industries increased overall, but the urban-rural gap remained pronounced. The complete digital integration level of rural industries rose from 0.73 in 2002 to 1.05 in 2021, indicating that production linkages between digital products and services and rural industries became increasingly strong. However, the digital integration level of urban industries was consistently much higher than that of rural industries. Although the urban-rural disparity narrowed from 3.40 in 2002 to 2.50 in 2021, rural digital integration in 2021 was still only 30.0% of the level observed in urban industries. These results indicate that

rural industries have been increasingly embedded in production linkages related to the digital economy, but the depth of this embedding remains substantially lower than that of urban industries.

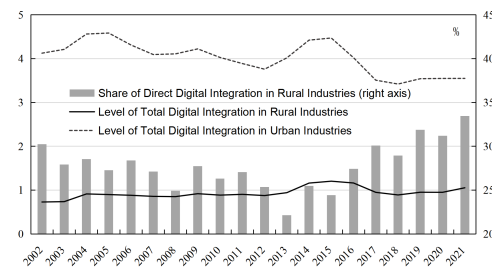


Figure 7. Urban-rural digital integration levels.

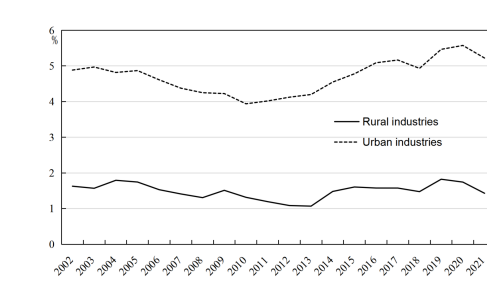


Figure 8. Levels of digital transformation in urban and rural industries.

In terms of the integration structure, the share of direct digital integration in rural industries was relatively low. During the sample period, direct digital integration accounted for around 25–30% of rural industries' digital integration. This indicates that a substantial share of rural industries' complete digital integration came from indirect linkages formed through other industries, rather than solely from direct input linkages between digital-economy sectors and rural industries. In other words, the digital economy has already become embedded in the rural industrial system through the production network, but direct integration still accounts for a limited share of overall digital integration. It is therefore necessary to further identify the transmission structure of digital value flows through specific industrial linkage paths.

The digital transformation level further supports this pattern. Compared with the digital integration level, the digital transformation level of rural industries remained in a low range for a long period, and the share of digitalized final products stayed at around 1–2%. This means that, although digital factors have entered the rural industrial system through the production network, their contribution to final-product formation and industrial output restructuring remains limited. The urban-rural gap in digital transformation did not improve in parallel with the narrowing gap in digital integration. Instead, it widened from 3.26 percentage points in 2002 to 3.79 percentage points in 2021. These results show that the main challenge in digitally enabling rural industries lies not only in the weaker intensity of digital linkages relative to urban industries, but also in the limited conversion of existing digital linkages into higher-level digital production capacity.

3.3.2. Industry Heterogeneity Analysis

A further sectoral analysis, as shown in Figures 9 and 10, indicates that the effects of digital empowerment on rural industrial revitalization exhibit pronounced temporal variation and industry heterogeneity. First, the level of digital integration is relatively high in the primary and secondary sectors of rural industries, such as mineral and metal products (R6), agriculture, forestry, animal husbandry, and fishery (R0), general and special

equipment (R7), chemical raw materials and products (R5), and textiles (R3), whereas it is relatively low in the tertiary sector, including finance (R16), ecological and environmental management (R20), real estate (R17), culture, sports, and entertainment (R24), and resident services and other services (R21). Second, digital transformation has progressed relatively rapidly in rural modern services and equipment manufacturing. For example, relatively high levels are observed in leasing and business services (R18), other manufacturing (R10), electrical machinery and equipment (R9), general and special equipment (R7), and finance (R16), whereas agriculture, forestry, animal husbandry, and fishery (R0), real estate (R17), food and tobacco (R2), accommodation and catering (R15), and mining (R1) remain relatively lagging behind. Finally, in terms of growth trends, the level of digital integration has increased rapidly in the production and supply of electricity, heat, gas, and water (R11), transportation equipment (R8), food and tobacco (R2), and healthcare and social security (R23), while the level of digital transformation has improved markedly in transportation, warehousing, and postal services (R14) and healthcare and social security (R23).

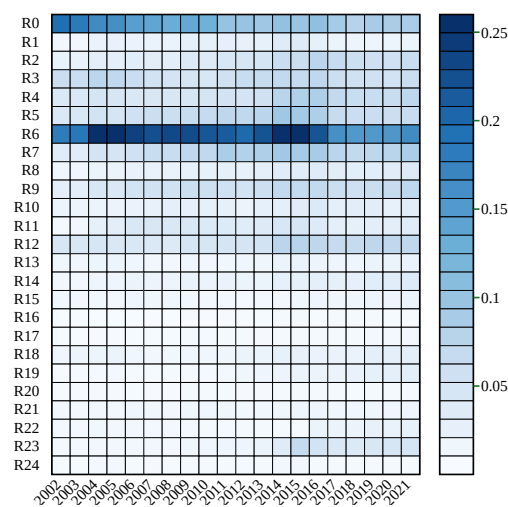


Figure 9. Heat map of digital integration levels in rural industries. *Note:* In the industry codes, “R” denotes rural industries, and the numbers correspond to the industry names listed in the left column of Table 3.

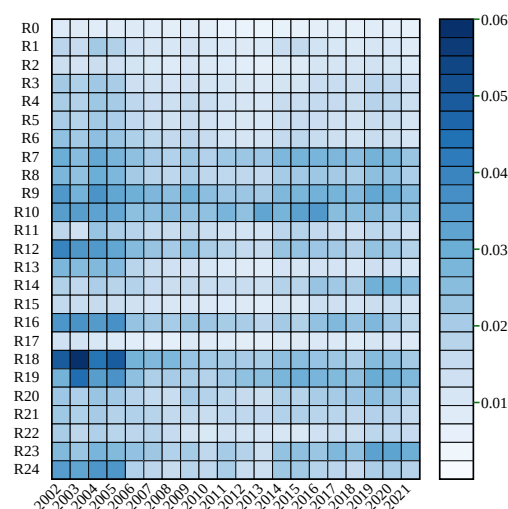


Figure 10. Heat map of digital transformation levels in rural industries.

3.3.3. Support for Rural Revitalization Goals

To further assess how the digital economy supports different rural revitalization goals, this study maps the 25 rural sectors in the input-output tables to the strategy’s five re-

quirements. These requirements are industrial prosperity, ecological livability, rural civility, effective governance, and affluent living [33]. Existing studies on rural revitalization evaluation usually construct multidimensional indicator systems around these five requirements. They further specify them as observable domains, including industrial development and industrial integration, ecological environment and living conditions, education and culture, governance and public services, and income, consumption, and quality of life [34–36]. Because input-output tables are organized by production sectors rather than policy indicators, this study follows these indicator domains and combines them with the dominant production or service function of each rural sector. The 25 rural sectors are assigned to the rural revitalization goal with which they are most closely associated in functional terms. Specifically, industrial prosperity includes R0–R10 and R13–R15, ecological livability includes R11–R12 and R20–R21, rural civility includes R19, R22, and R24, effective governance includes R23, and affluent living includes R16–R18. This mapping does not imply that each sector contributes exclusively to a single goal. Rather, it is used to avoid double counting in category-specific weighted averages. This study uses the value added of each rural sector as weights and aggregates sector-level digital empowerment measures by category, thereby measuring the support provided by the digital economy for different rural revitalization goals.

As shown in Figure 11, the support provided by the digital economy for different rural revitalization goals was not evenly distributed. It exhibited an overall pattern in which production-chain support was relatively strong, service-function support was relatively insufficient, and process-based embedding was not fully consistent with outcome-based conversion. From the perspective of the digital integration level, sectors with relatively strong support were concentrated in agriculture, forestry, animal husbandry, and fishery, mining, food and tobacco, chemical materials and products, mineral products and metals, and related fields. This indicates that the digital economy first supports rural revitalization through traditional industrial chains, including agricultural production, resource development, and agricultural product processing. The result further shows that the digital economy's support for industrial prosperity has a strong production-sector orientation.

From the perspective of the digital transformation level, differences across rural revitalization goals were more pronounced. Some infrastructure- and public-service-related sectors already showed certain digital transformation features, including the production and supply of electricity, heat, gas, and water, resident services, scientific and technical services, education, and health care and social security. This indicates that digital technologies provide practical support for improving rural infrastructure, public-service provision, and grassroots governance capacity. However, such support remained concentrated in a small number of functional sectors and had not expanded evenly across different types of rural industries.

By contrast, the digital empowerment level of sectors related to affluent living remained relatively low, especially in finance, real estate, leasing, and business services. These sectors are closely related to rural capital allocation, asset services, business organization, and market expansion. Their insufficient digital integration and digital transformation indicate that the digital economy still has considerable room to improve its support for rural income growth, business capability, and the cultivation of new business forms. Overall, the digital economy has already formed a certain foundation for supporting rural revitalization goals. However, its effects remain concentrated in traditional production chains and selected public-service sectors, while support for modern services, market organization, and income-enhancing activities remains relatively insufficient.

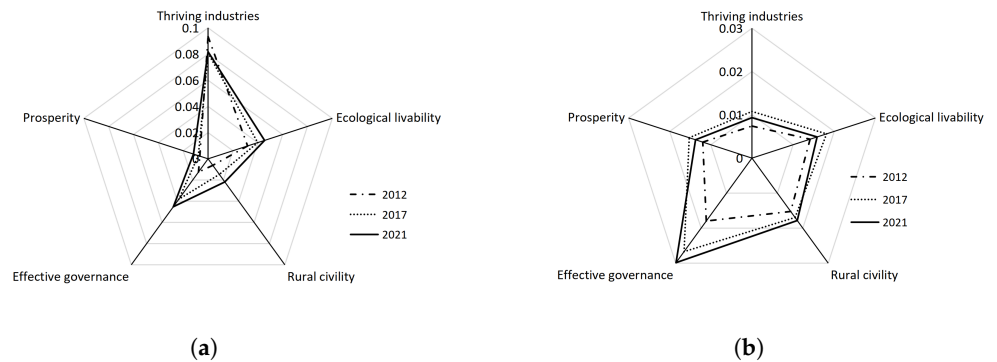


Figure 11. Support of the digital economy for different rural revitalization goals. *Note:* (a) Based on the level of digital integration; (b) based on the level of digital transformation.

4. Identification and Optimization of Empowerment Pathways

By leveraging the advantages of the input-output model in handling multiple inter-industry linkages, this study has analyzed the effects of digital empowerment on rural industrial revitalization. However, the input-output model can only calculate the aggregate effect of digital empowerment across all possible linkage paths on the basis of total allocation coefficients, and cannot reveal the empowerment effects associated with specific patterns of industrial linkages and particular transmission paths. Therefore, the following analysis examines production networks from the perspective of complex networks, characterizes the importance and distributional features of different industrial nodes.

4.1. Construction of the Core Path Network of Digital Empowerment

A complex network consists of two sets of attributes: nodes (V , vertices) and edges (E , edges). In the production network considered in this study, denoted by $G_{IOT} = (V, E)$, the sectors in the IOT constitute the nodes of the production network, where $V_{G_{IOT}} = \{D1, \dots, D4, R0, \dots, R24, U1, \dots, U24\}$. The input-output linkages constitute the edges of the production network. Since this study focuses on forward linkages, edge weights are defined by the direct allocation coefficients b_{ij} from sector i to sector j . Accordingly, the edge set can be expressed as $E(G_{IOT}) = \{\langle v_i, v_j, b_{ij} \rangle \mid v_i, v_j \in V_{G_{IOT}}\}$.

However, the above production network cannot be used directly. Because the IOT records all direct industrial linkages in great detail, the resulting production network is close to a fully connected network, as shown in Figure 12. This makes it difficult to identify key industrial linkages from the production network and also increases the complexity of subsequent analysis, making pruning necessary. Common network-pruning methods include the Minimum Spanning Tree (MST) (In the Minimum Spanning Tree algorithm, “minimum” refers to minimizing the sum of edge weights. When edge weights represent distance measures, minimizing edge weights implies identifying the shortest path. In economic analysis, however, edge weights may represent economic flows, which often need to be maximized rather than minimized, as is also the case in this study. For this reason, some studies refer to it as a “maximum spanning tree” algorithm. In such cases, the original edge weights need to be multiplied by -1 or transformed by taking their reciprocals so that the standard MST algorithm can still be applied.) algorithm and the threshold method. The threshold method is relatively subjective, and an excessively high threshold may destroy graph connectivity and fragment the network. The MST algorithm considers the importance of edges at the global level. Although it guarantees graph connectivity, it may delete edges that are not globally important but are highly important for the specific problem under study. This study is mainly concerned with specific economic flows and industrial linkages that originate from digital economy sectors and terminate

in rural industrial sectors. Because the level of digital integration in rural industries is significantly lower than that in urban industries, the corresponding edges tend to have lower global importance, which may cause the MST algorithm to remove certain important linkage patterns between the digital economy and rural industries, thereby undermining subsequent analysis.

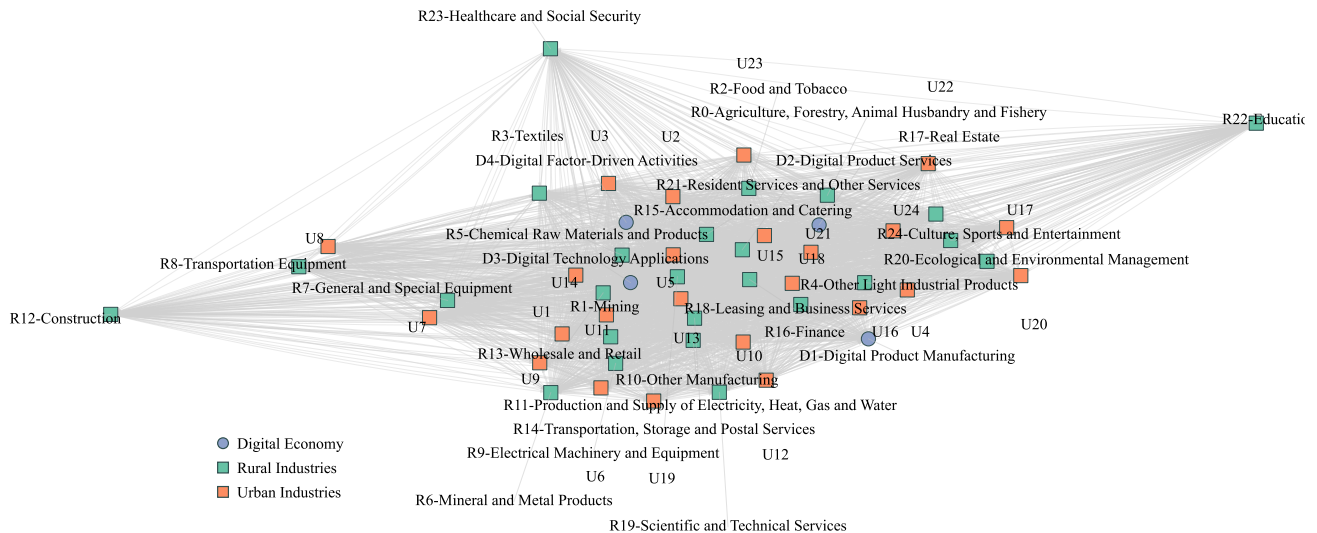


Figure 12. Production network directly derived from the intermediate flow matrix (2020).

Returning to input-output analysis itself, the reason why the total allocation coefficient captures the entire allocation flow between industries i and j is that it exhausts all direct and indirect paths from i to j , as shown in Equation (12):

$$s_{ij} = b_{ij} + \sum_{k \in V} b_{ik}b_{kj} + \sum_{s \in V} \sum_{k \in V} b_{is}b_{sk}b_{kj} + \sum_{t \in V} \sum_{s \in V} \sum_{k \in V} b_{it}b_{ts}b_{sk}b_{kj} + \dots \quad (12)$$

Because $0 \leq b_{ij} < 1$, the higher-order terms in the above equation, which represent long-chain indirect linkages, have only a negligible effect on s_{ij} , whereas the first term (the direct linkage b_{ij}) and the first few subsequent terms (short-chain indirect linkages) largely determine the value of s_{ij} . Accordingly, the network-pruning strategy adopted in this study is as follows: for any digital economy sector i and rural industry j , all nodes and edges involved in the direct linkage b_{ij} and in the strongest indirect linkage (i.e., the largest term other than b_{ij}) are retained. After exhausting all combinations of i and j , the nodes and edges that appear at least once in the above process together constitute the core path network of digital empowerment for rural industrial revitalization, denoted by $G'_{\text{IOT}} = (V', E')$.

The specific procedure is as follows. In Step 1, a mask matrix $M = [m_{ij}]_{n \times n} = 0$ with the same dimensions as matrix B is initialized. In Step 2, for a given pair of digital economy sector i and rural industry j , the corresponding element in the mask matrix is set to $m_{ij} = 1$ (direct linkage). In Step 3, the corresponding element in the direct allocation matrix is set to $b_{ij} = 0$, thereby temporarily removing the direct linkage between i and j . The modified direct allocation matrix is denoted by B_m . Using $-\ln(B_m)$ as the distance matrix, the shortest-path algorithm is applied to identify the shortest path between nodes i and j . This path is, in fact, also the strongest indirect linkage path between i and j . (The shortest-path algorithm searches for a continuous path from i to j , such as $i \rightarrow r \rightarrow s \rightarrow \dots \rightarrow t \rightarrow j$, and minimizes the total path distance, $w_{ir} + w_{rs} + \dots + w_{tj}$. In this study, the strongest linkage path is also a continuous path from i to j , but the objective is to maximize the product of

edge weights, $b_{ir}^m b_{rs}^m \cdots b_{tj}^m$. Taking the negative logarithm transforms this maximization problem into the minimization of $-\ln(b_{ir}^m) - \ln(b_{rs}^m) - \cdots - \ln(b_{tj}^m)$. Therefore, $-\ln(b^m)$ can be treated as the equivalent edge distance, and the shortest-path algorithm can be applied directly. A smaller direct allocation coefficient b^m corresponds to a larger equivalent distance between two industries.) Then, for each step along this path, the corresponding element in mask matrix M associated with the connected node pair is set to 1 (strongest indirect linkage). In Step 4, the corresponding element in the direct allocation matrix is restored to its original value, and the next combination of i and j is selected. By repeating Steps 2–4 until all combinations of digital economy sectors and rural industries have been exhausted, (The above procedure is implemented in R. The shortest-path problem between two nodes in the network is solved using the Floyd algorithm.) the edge-weight matrix of the digital empowerment network $G'_{\text{IOT}} = (V', E')$ is obtained as the element-wise product of the direct allocation matrix B and the mask matrix M , namely $B' = M \odot B$. The resulting core path network of digital empowerment for rural industrial revitalization (taking 2020 as an example) is shown in Figure 13, while the complete annual results are reported in Supplementary Materials File S2.

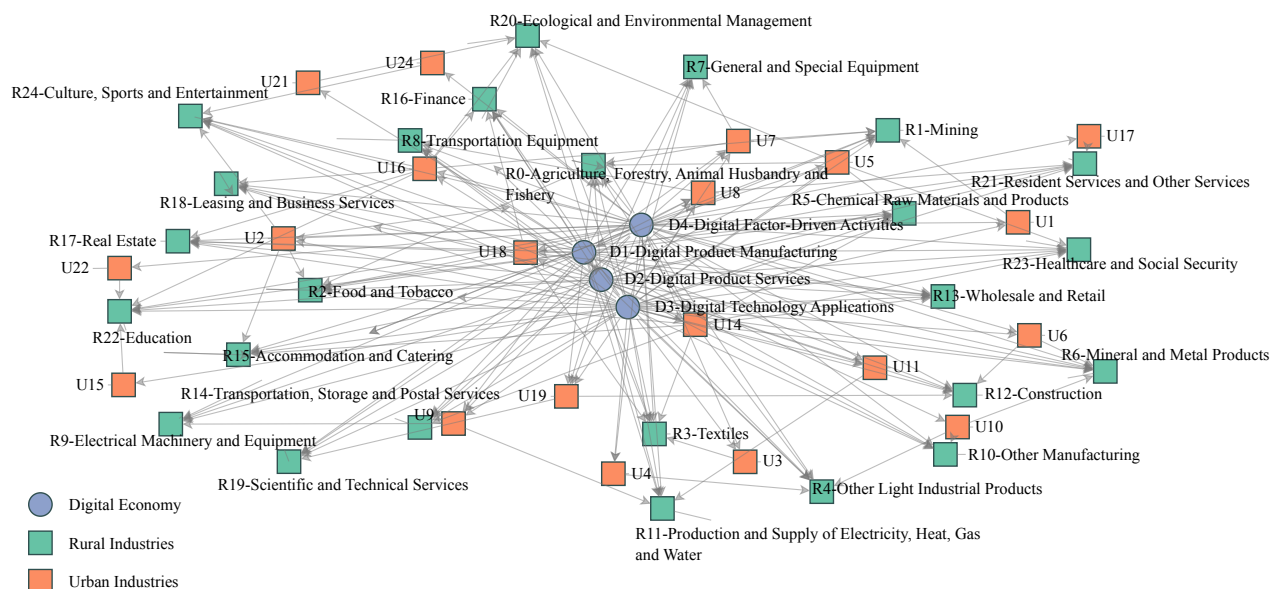


Figure 13. Core path network of digital empowerment for rural industrial revitalization (2020).

The network shown in Figure 13 exhibits a pronounced “core-periphery” structure. The above complex-network pruning process ignores certain linkages between nodes. For the purpose of robustness testing, it is therefore necessary to determine whether the pruned network retains the main characteristics of the original network and whether the degree of information loss remains acceptable. To this end, this study compares the largest eigenvalues of the direct allocation coefficient matrix (the edge-weight matrix) and the total allocation coefficient matrix (According to the construction process of B' described above, all diagonal elements of B' are equal to zero. When calculating the eigenvalues or the total allocation coefficient matrix S' , the diagonal elements of B' need to be restored to the corresponding diagonal elements in the original direct allocation coefficient matrix B , that is, $B' + \text{diag}(B)$.) before and after pruning. The proportion of information retained in the pruned network is expressed by Equations (13) and (14), where $\lambda_{\max}$ denotes the largest eigenvalue; matrices B and S denote the direct allocation coefficient matrix and the total allocation coefficient matrix, respectively; and k_1 and k_2 are the ratios of the largest

eigenvalues of the two types of networks before and after pruning, calculated on the basis of matrices B and S , respectively, that is, the proportions of information retained.

$$k_1 = \frac{\lambda_{\max}(B' + \text{diag}(B))}{\lambda_{\max}(B)} \quad (13)$$

$$k_2 = \frac{\lambda_{\max}([I - (B' + \text{diag}(B))]^{-1} - I)}{\lambda_{\max}((I - B)^{-1} - I)} = \frac{\lambda_{\max}(S')}{\lambda_{\max}(S)} \quad (14)$$

Table 5 reports the information loss after production-network pruning for each year. The results show that although the number of network edges is reduced to approximately 9% of the original network, the ratio of the largest eigenvalue of the direct allocation coefficient matrix between the pruned and original networks remains above 70%, reaching a maximum of 87%. The corresponding ratio for the total allocation coefficient matrix is slightly lower, but still exceeds 50% in most years and approaches 70% at its highest level. These results indicate that the pruned network retains most of the structural information of the original network, suggesting that the pruning procedure is appropriate.

Table 5. Information Loss from Production-Network Pruning, 2002–2021 (%).

Year	Network Scale (Number of Edges)			Max Eigenvalue of Direct Allocation Matrix			Max Eigenvalue of Total Allocation Matrix		
	New	Original	Comp.	New	Original	Retention (k1)	New	Original	Retention (k2)
2002	259	2789	9.29	0.4576	0.6268	73.01	0.8438	1.6798	50.23
2003	255	2789	9.14	0.4357	0.6478	67.26	0.7721	1.8393	41.98
2004	255	2789	9.14	0.4778	0.6742	70.87	0.9149	2.0695	44.21
2005	253	2789	9.07	0.4391	0.6731	65.24	0.7830	2.0592	38.02
2006	256	2799	9.15	0.4835	0.6806	71.04	0.9361	2.1307	43.93
2007	255	2799	9.11	0.5246	0.6871	76.35	1.1034	2.1955	50.26
2008	252	2799	9.00	0.5348	0.6909	77.41	1.1497	2.2352	51.43
2009	269	2799	9.61	0.4886	0.6801	71.83	0.9552	2.1263	44.92
2010	259	2799	9.25	0.4847	0.6919	70.05	0.9405	2.2460	41.87
2011	260	2802	9.28	0.5027	0.6844	73.45	1.0108	2.1683	46.62
2012	256	2802	9.14	0.5016	0.6765	74.14	1.0063	2.0911	48.12
2013	257	2802	9.17	0.5300	0.6928	76.51	1.1277	2.2548	50.01
2014	253	2802	9.03	0.5052	0.6985	72.33	1.0211	2.3163	44.08
2015	256	2802	9.14	0.4984	0.6933	71.88	0.9935	2.2609	43.94
2016	262	2809	9.33	0.5144	0.6902	74.52	1.0591	2.2278	47.54
2017	256	2809	9.11	0.5217	0.6447	80.91	1.0906	1.8147	60.10
2018	256	2809	9.11	0.5346	0.6404	83.49	1.1489	1.7808	64.52
2019	259	2809	9.22	0.5105	0.6316	80.82	1.0428	1.7146	60.82
2020	256	2809	9.11	0.5221	0.6352	82.20	1.0926	1.7412	62.75
2021	259	2809	9.22	0.5719	0.6574	86.99	1.3359	1.9192	69.60

On this basis, the core path network not only provides the structural foundation for the subsequent identification of key intermediary nodes, priority areas, and urban-rural disparity paths, but also offers a visual basis for further analyzing the main transmission characteristics of digital empowerment for rural industrial revitalization.

4.2. Analysis of Key-Path Characteristics

To provide a more intuitive presentation of the transmission directions and path distribution of digital value flows across different industries, the structural characteristics of the core path network are further analyzed below. The core paths of digital empowerment

for rural industrial revitalization are visualized as a Sankey diagram according to the magnitude of their edge weights b'_{ij} , and the results for 2020 are shown in Figure 14.

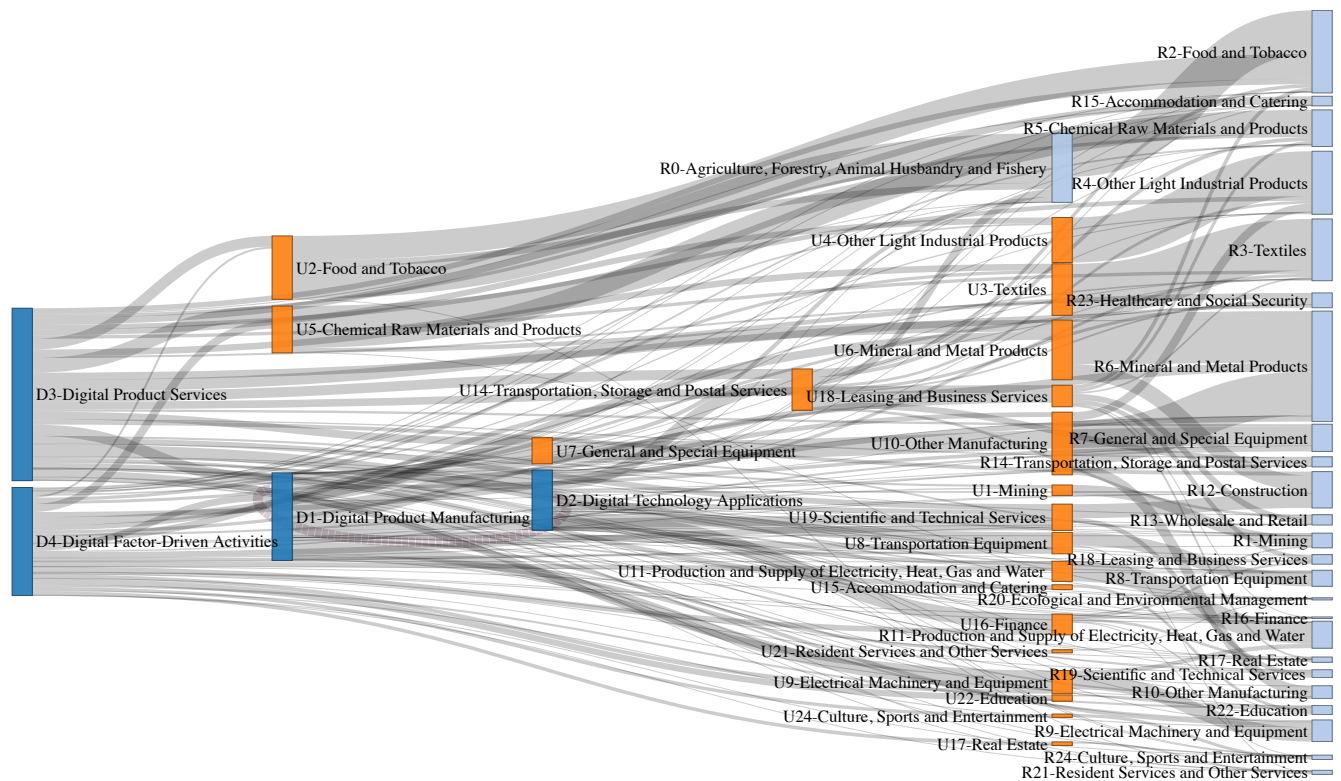


Figure 14. Sankey diagram of the digital empowerment path network (2020).

Figure 14 shows that the core paths through which the digital economy enables rural industrial revitalization exhibit a clear multi-level transmission structure. After digital value flows originate from digital-economy sectors, one part enters rural industries directly, whereas another part continues to diffuse downstream through sectors within the digital economy and several urban industries. At the path level, this result explains the limited share of direct integration reported in the preceding measurement results. Digital integration in rural industries is not formed through a single direct embedding process. Rather, it gradually emerges through multi-sector linkages in the production network.

From the source side of the paths, D3 digital product services and D4 digital-factor-driven sector are located on the left side of the Sankey diagram and serve as important starting points of digital value flows. D1 digital product manufacturing and D2 digital technology application occupy positions between digital-economy sectors and other industrial sectors. They both receive value flows within the digital economy and further allocate digital products, digital technologies, and related services to downstream industries. From the perspective of intermediate transmission, urban industrial sectors such as U2 food and tobacco, U3 textiles, U5 chemical materials and products, U6 mineral products and metals, U7 general and special-purpose equipment, U14 transportation, storage, and postal services, and U18 leasing and business services perform relatively prominent connecting functions. This indicates that urban manufacturing, circulation services, and business services are important intermediate channels through which digital value enters the rural industrial system.

From the receiving structure on the rural side, digital value flows mainly enter agricultural production chains, resource processing, and manufacturing-related sectors. The most visible recipient nodes include R0 agriculture, forestry, animal husbandry, and fishery, R2

food and tobacco, R3 textiles, R5 chemical materials and products, R6 mineral products and metals, and R7 general and special-purpose equipment. This shows that digital value flows are not evenly distributed on the rural side. Instead, they are concentrated first in traditional production and processing chains. Meanwhile, except for the relatively clear linkages between R0 agriculture, forestry, animal husbandry, and fishery and some processing sectors, most rural sectors appear mainly as terminal recipient nodes. The chains for further transmission and extension within the rural industrial system are relatively limited. Overall, the core path structure revealed by Figure 14 can be summarized as the coexistence of source-side driving by the digital economy, intermediate transmission through urban industries, and concentrated reception by rural industries.

4.3. Identification of Key Recipient Areas and Urban-Rural Disparity Paths

The preceding analysis of the core production network and the Sankey diagram shows the main transmission patterns through which the digital economy contributes to rural industrial revitalization. To further identify where digital value flows are absorbed in the network and where urban-rural disparities are concentrated, this subsection examines the core production network from both node and edge perspectives. It first uses network centrality measures to identify key recipient sectors, and then uses the ratio of rural to corresponding urban direct allocation coefficients to identify paths with large urban-rural disparities.

From a complex-network perspective, intersectoral input-output relationships are reflected not only in edge weights but also in the positions of nodes within the network. PageRank and HITS are widely used algorithms for identifying node importance [37,38]. This study uses PageRank and the Hub score from the HITS algorithm to evaluate the importance of nodes in the production network. PageRank emphasizes incoming linkages and is therefore suitable for identifying intermediate and terminal nodes that receive digital value flows. The Hub score emphasizes outgoing linkages and is therefore suitable for identifying intermediate nodes that further diffuse digital value downstream. Because the digital-economy sectors are defined as the initial nodes of digital value flows, this study focuses on intermediate and terminal nodes. The sectors whose indicator values fall in the top quartile are reported in Table 6.

Table 6. Identification Results of Priority Areas for Digital Empowerment (2020).

Intermediary Nodes					Terminal Nodes		
Code	Page Rank		Hub		Code	Page Rank	
	Value	Rank	Value	Rank		Value	Rank
D1	0.0174	4	0.4435	1	R2	0.0485	1
U14	0.0176	3	0.1563	3	R22	0.0399	2
U16	0.0177	2	0.1058	5	R6	0.0361	3
D2	0.0167	7	0.4408	2	R0	0.0306	4
U18	0.0155	10	0.1098	4	R11	0.0296	5
U7	0.0167	6	0.0452	8	R1	0.0290	6
R0	0.0306	1	0.0162	14			
U19	0.0174	5	0.0282	11			

Note: Prefixes D, R, and U in sector codes denote the digital economy, rural industries, and urban industries, respectively. Full sector names corresponding to the codes are reported in Table 3.

The intermediate-node results in Table 6 show that digital product manufacturing (D1), urban transportation, storage, and postal services (U14), and urban finance (U16) all have high PageRank and Hub scores. These sectors not only absorb digital value flows but also help transmit them to downstream sectors. Digital product manufacturing is a core

digital-economy sector and acts as an upstream source in both the development of digital industries and the digitalization of downstream industries. Urban transportation, storage, and postal services and urban finance perform key organizational functions for logistics, capital flows, and information flows. They therefore serve as important intermediate nodes through which digital value is transmitted from the urban industrial system to the rural industrial system. By contrast, agriculture, forestry, animal husbandry, and fishery (R0) and scientific and technical services (U19) have relatively high PageRank values but lower Hub rankings. This indicates that they receive relatively more digital factor inflows, but their ability to further diffuse digital value downstream remains limited.

The terminal-node results further show that digital value flows mainly enter agricultural value chains and resource-based sectors, especially food and tobacco (R2), mineral products and metals (R6), and agriculture, forestry, animal husbandry, and fishery (R0). Rural education (R22) and the production and supply of electricity, heat, gas, and water (R11), which are related to public services and infrastructure, also show some absorption effects. These results indicate that the digital economy does not affect all rural sectors evenly. Instead, its effects first concentrate in agricultural value chains, resource-based sectors, and selected public-service sectors. Table 6 therefore answers the question of which sectors mainly receive digital value flows, but it does not show whether the corresponding paths differ substantially from their urban counterparts.

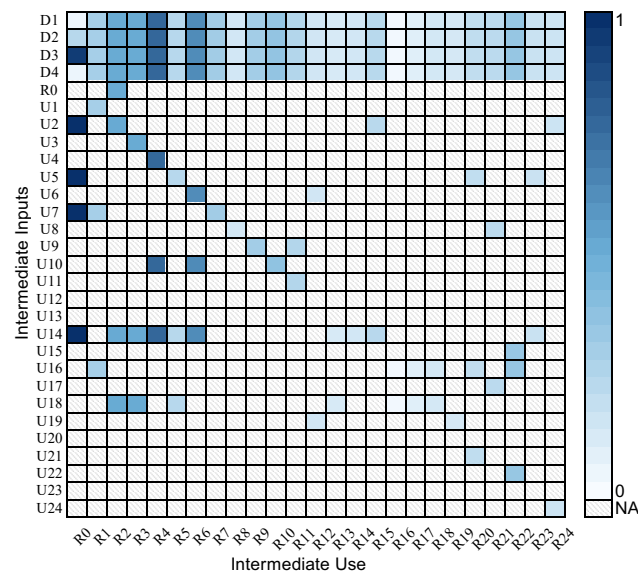
To identify structural differences between urban and rural industries, this study further compares the direct allocation coefficients of rural-related digital value paths with those of the corresponding urban industries. The ratio between the two coefficients is used to measure the degree of urban-rural disparity. Because urban industries generally have a higher level of digitalization than rural industries at the current stage [39–41], this ratio helps identify whether comparable industrial linkages remain relatively weak on the rural side. The calculation rules are reported in Table 7.

Table 7. Measurement of urban-rural disparities under different types of industrial linkages.

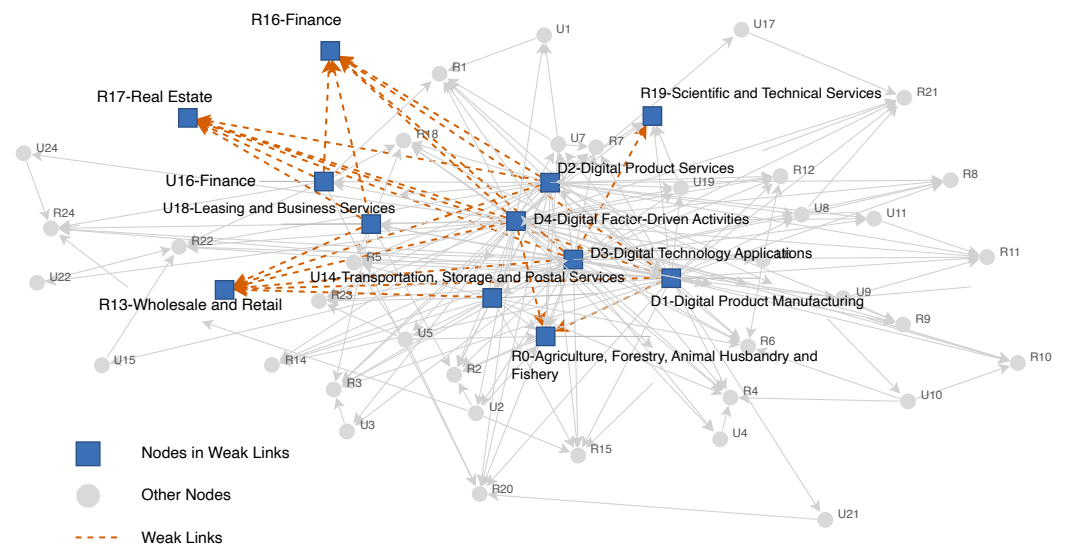
Industrial Linkage Type ($i \rightarrow j$)	Rural-Side Linkage Coefficient	Matched Urban-Side Benchmark Coefficient	Urban-Rural Disparity Ratio
Digital Economy (D_i)→Rural Industry (R_j)	$B'_{D_i \rightarrow R_j}$	$B_{D_i \rightarrow U_j}$	$B'_{D_i \rightarrow R_j} / B_{D_i \rightarrow U_j}$
Urban Industry (U_i)→Rural Industry (R_j)	$B'_{U_i \rightarrow R_j}$	$B_{U_i \rightarrow U_j}$	$B'_{U_i \rightarrow R_j} / B_{U_i \rightarrow U_j}$
Rural Industry (R_i)→Rural Industry (R_j)	$B'_{R_i \rightarrow R_j}$	$B_{U_i \rightarrow U_j}$	$B'_{R_i \rightarrow R_j} / B_{U_i \rightarrow U_j}$

Note: Because agriculture (R0) has no corresponding urban sector in the urban-rural sector classification, ratios involving direct paths from digital-economy sectors to R0 cannot be computed from a one-to-one rural-urban sector match. For a path $D_i \rightarrow R0$, the denominator is approximated by the mean direct allocation coefficient from the same digital-economy sector D_i to all urban industries $U_1, \dots, U_{24}$.

Using 2020 as an example, this study identifies, within the core path network, the industrial linkages whose urban-rural ratios are positive and at or below the 10th percentile as paths with large urban-rural disparities. (Across the rural-to-urban ratio heat maps of direct allocation coefficients from 2002 to 2021, this study identifies 3226 valid ratios. Only 13 ratios are greater than 1, accounting for approximately 0.403%.) These paths are marked with dashed lines in Figure 15.



(a) Heat map of the ratio of urban-rural direct allocation coefficients



(b) Positions of urban-rural disparity paths in the core production network

Figure 15. Identification of urban-rural disparity paths in digital empowerment (2020): (a) heat map of the ratio of urban-rural direct allocation coefficients; (b) positions of urban-rural disparity paths in the core production network. *Note:* Undefined ratios (N/A) in panel (a) arise because the core network retains only major industrial linkages and the edge-weight matrix is therefore sparse; these ratios are shown as shaded cells.

Figure 15b marks 21 key industrial linkages with large urban-rural disparities. Among them, 15 are direct linkages from digital-economy sectors to rural industries, and 6 are intermediate transmission paths from urban industries to rural industries. These dashed edges are not evenly distributed across the core production network. Instead, they are concentrated in two positions: the entry points where digital-economy sectors directly connect to rural industries, and the cross-urban-rural linkages through which urban industries transmit digital value to rural industries. The first pattern indicates that the connection intensity through which digital products, digital services, and data factors enter some rural sectors is markedly lower than that of the corresponding urban sectors. The second pattern indicates that even after digital value has diffused through urban industries, it still weakens in the final transmission segment into the rural industrial system.

In terms of node distribution, the dashed edges mainly point to rural finance (R16), rural real estate (R17), rural wholesale and retail trade (R13), agriculture, forestry, animal husbandry, and fishery (R0), and rural scientific and technical services (R19). The relatively large number of paths related to rural finance and rural real estate indicates substantial urban-rural disparities in the transmission of digital value from digital-economy sectors and urban modern services to rural capital allocation and asset services. The paths related to rural wholesale and retail trade connect not only digital-economy sectors but also urban transportation, storage, and postal services and urban leasing and business services. This suggests that the entry of digital value into the rural circulation system depends not only on digital-economy sectors themselves but also on supporting linkages in logistics and business services. Agriculture, forestry, animal husbandry, and fishery and rural scientific and technical services reflect relative insufficiencies in the entry of the digital economy into basic agricultural production and agricultural technology services.

4.4. Prioritized Optimization of Core Paths

The preceding section identifies key recipient sectors and urban-rural disparity paths, but disparity identification alone does not determine the priority order for path optimization. Even if several industrial linkages show large urban-rural disparities, it remains necessary to determine which linkage would generate a larger marginal effect if strengthened within the existing core production network. This study therefore constructs a counterfactual path-optimization experiment to identify priority paths for improving rural industries' complete digital integration level.

This study uses a marginal perturbation approach to characterize the meaning of path optimization. Instead of imposing an external target structure, the experiment applies a small marginal enhancement to candidate industrial linkages within the identified core production network and compares how different candidate paths improve rural industries' complete digital integration level. This design preserves the existing rural production-network structure, avoids reducing path optimization to a static gap comparison, and allows direct paths from digital-economy sectors to rural industries and intermediate paths transmitted through urban industries to be compared within the same framework. The resulting output is not a single disparity measure, but a set of priority paths with both ranking and network-interpretation value.

According to Equation (5), given the direct allocation coefficient matrix B , the Ghosh inverse matrix is

$$G(B) = (I - B)^{-1}, \quad (15)$$

and the complete allocation coefficient matrix is

$$S(B) = G(B) - I = (I - B)^{-1} - I. \quad (16)$$

The element $s_{ij}(B)$ in $S(B)$ represents the complete allocation relationship after excluding the one-unit initial self-allocation of sector i . Following the notation defined above, let D denote the set of digital-economy sectors, R the set of rural industries, and U the set of urban industries. Rural industries' complete digital integration level can then be expressed as the sum of complete allocation coefficients from digital-economy sectors to rural industries:

$$\gamma_R(B) = \sum_{i \in D} \sum_{j \in R} s_{ij}(B). \quad (17)$$

For comparability, this study retains the complete digital integration level of urban industries as the benchmark:

$$\pi(B) = \frac{\gamma_R(B)}{\gamma_U}. \quad (18)$$

Here, γ_U is obtained by summing the complete allocation coefficients from digital-economy sectors to urban industries under the benchmark state, and it remains fixed during the path-optimization process. Therefore, maximizing $\pi(B)$ is equivalent to maximizing $\gamma_R(B)$ for path selection. The optimization objective is to improve rural industries' complete digital integration level, while the relative level $\pi(B)$ is used only to report the position of rural industries' complete digital integration relative to the urban benchmark.

The iterative procedure starts from the direct allocation coefficient matrix of the pruned core production network, denoted by $B_0 = B'$. The candidate path set $\mathcal{E}$ includes all positive off-diagonal directed edges in the core production network, that is, all industrial linkages satisfying $b_{ij} > 0$ and $i \neq j$. Based on the 2020 data, there are 202 candidate paths. Suppose that the counterfactual direct allocation coefficient matrix at step k is B_k . For each unselected candidate path $e_q = (i, j) \in \mathcal{E}$, a temporary perturbation matrix $B_{k,q}^*$ is constructed as follows:

$$b_{ij,k,q}^* = b_{ij,k}(1 + \delta), \quad (19)$$

while all other elements remain unchanged. In the main experiment, $\delta = 2\%$, which means that the direct allocation coefficient of one unselected path is increased by 2% at each step. The complete allocation coefficient matrix is then recomputed according to Equation (5), and the perturbed rural complete digital integration level $\gamma_R(B_{k,q}^*)$ is calculated using Equation (17). At step k , the marginal improvement of path e_q is defined as the change in the level relative to the urban benchmark:

$$\Delta\pi_{k,q} = \pi(B_{k,q}^*) - \pi(B_k). \quad (20)$$

Because γ_U remains fixed during the optimization process, selecting the path that maximizes $\Delta\pi_{k,q}$ is equivalent to selecting the path that maximizes $\gamma_R(B_{k,q}^*) - \gamma_R(B_k)$. At each iteration, the path with the largest $\Delta\pi_{k,q}$ is selected as the priority path, and its 2% enhancement is retained in the next iteration. To avoid mechanical amplification of a small number of high-return paths, each path can be selected at most once in the main experiment. Repeating this procedure produces a sequential ranking of core paths for digital-economy-enabled rural industrial revitalization. For each step, this study reports the rural complete digital integration level, the level relative to the urban benchmark $\pi(B)$, the marginal improvement, and the cumulative improvement.

Figure 16 reports the counterfactual simulation results under the 2% proportional perturbation and non-repeated selection setting. Under the factual benchmark, the complete digital integration level of rural industries in 2020 was 0.4933, equivalent to 23.77% of the complete digital integration level of urban industries. As core paths were gradually enhanced at the margin, the rural complete digital integration level increased steadily. After the first 10 optimization steps, it rose to 0.4968, and the relative level increased to 23.94%. After the first 20 steps, the rural complete digital integration level reached 0.4985, and the relative level increased to 24.02%. After the first 30 steps, the relative level further increased to 24.08%. After all 202 candidate paths had been enhanced once, the rural complete digital integration level increased to 0.5057, and the relative level reached 24.37%, corresponding to a cumulative increase of 0.60 percentage points.

The increase in the relative level is moderate, which is consistent with the marginal-perturbation design. Because each step in the main experiment increases the direct allocation coefficient of only one candidate path by 2%, the purpose of the counterfactual simulation is not to estimate the overall effect of large-scale structural adjustment. Rather, it is to compare the marginal returns of different industrial linkages under a unified perturbation size. Figure 16 should therefore be interpreted as a priority ranking of core paths. The higher marginal improvements in the early steps show that a small number of paths

generate larger marginal returns under the same perturbation. The subsequent decline in marginal contributions indicates a clear priority order among candidate paths.

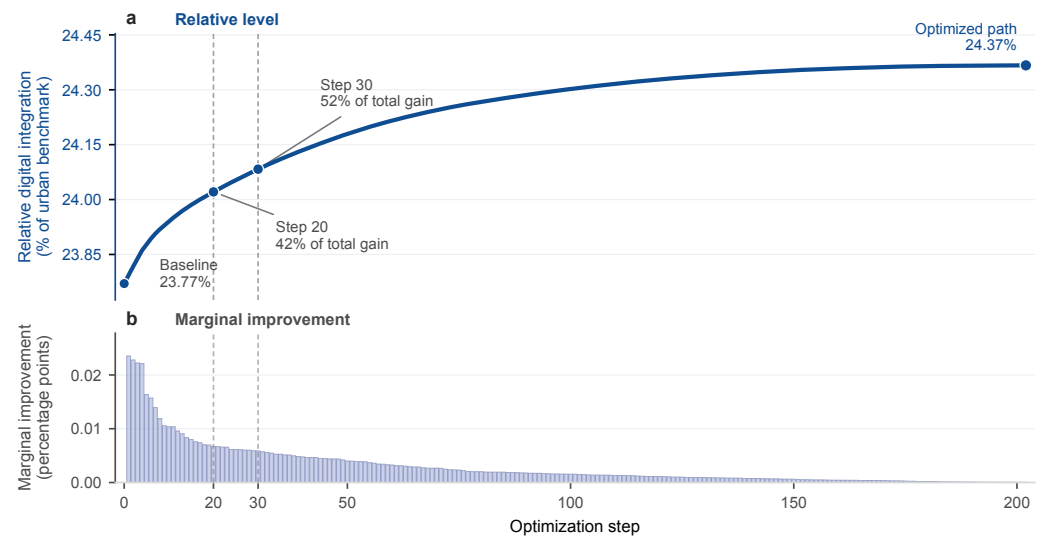


Figure 16. Counterfactual simulation of path optimization for digital empowerment in rural industrial revitalization. *Note:* (a) Rural-to-urban relative digital integration level across optimization steps; (b) marginal improvement at each optimization step. The candidate set was defined as all non-zero, off-diagonal edges in the pruned core network.

Table 8 further reports the 20 paths with the highest marginal returns. The first 12 steps are all direct paths from digital-economy sectors to rural industries, including D1→R9, D3→R0, D3→R6, D1→R7, D4→R6, D3→R2, and D3→R4. This indicates that, within the existing core network structure, the direct embedding of digital product manufacturing, digital product services, and digital-factor-driven sectors into rural equipment manufacturing, agriculture, mineral products, and food and tobacco generates relatively high marginal returns. After step 13, intermediate paths begin to enter the priority sequence, including U6→R6, D3→U5, D1→D2, U7→R7, D3→U6, and D3→U2. This pattern indicates that, after the high-return portion of direct rural paths has been selected, linkages within the digital economy, linkages between digital-economy sectors and urban industries, and cross-urban-rural transmission from urban industries to rural industries become important channels for further improving rural complete digital integration. Table 8 therefore does not merely list sectors. It reveals the sequential structure of core path optimization: marginal returns in the initial stage mainly arise from direct reinforcement of digital-economy linkages to rural industries, whereas later improvements rely more on coordinated transmission along the digital economy-urban industry-rural industry chain.

To test whether the identified path ranking depends on a particular perturbation size, this study further considers 0.5%, 1%, and 5% proportional perturbation scenarios and compares them with the 2% main scenario. The results are reported in Table 9. The results show that, under the 0.5%, 1%, and 5% proportional perturbations, the overlap rates of the top 10, top 20, and top 30 paths with the 2% main scenario are all 100%, and the rank correlations are also close to 1. This indicates that, under proportional marginal enhancement, the ranking of core paths is highly stable across perturbation sizes. The priority paths identified in the main experiment are therefore not driven by the specific choice of the 2% parameter.

Table 8. Path Identification Results for the Top 20 Steps in the Counterfactual Simulation (2020).

Step	Improved Digital Empowerment Path			Relative Level vs. Urban Benchmark	Marginal Improvement	Cumulative Improvement
	Upstream Industry	Downstream Industry	Link Type			
1	D1—Digital Product Manufacturing	R9—Electrical Machinery and Equipment	Direct	23.794	0.024	0.024
2	D3—Digital Product Services	R0—Agriculture, Forestry, Animal Husbandry and Fishery	Direct	23.817	0.023	0.046
3	D3—Digital Product Services	R6—Mineral and Metal Products	Direct	23.839	0.022	0.069
4	D1—Digital Product Manufacturing	R7—General and Special Equipment	Direct	23.861	0.022	0.091
5	D4—Digital Factor-Driven Industries	R6—Mineral and Metal Products	Direct	23.877	0.016	0.107
6	D3—Digital Product Services	R2—Food and Tobacco Processing	Direct	23.893	0.016	0.123
7	D3—Digital Product Services	R4—Other Light Industrial Products	Direct	23.907	0.014	0.137
8	D2—Digital Technology Applications	R23—Healthcare and Social Security	Direct	23.919	0.012	0.149
9	D1—Digital Product Manufacturing	R10—Other Manufacturing	Direct	23.930	0.011	0.159
10	D3—Digital Product Services	R3—Textiles	Direct	23.940	0.010	0.169
11	D3—Digital Product Services	R12—Construction	Direct	23.950	0.010	0.180
12	D3—Digital Product Services	R5—Chemical Raw Materials and Products	Direct	23.960	0.010	0.189
13	U6—Mineral and Metal Products	R6—Mineral and Metal Products	Intermediate Path	23.969	0.009	0.199
14	D4—Digital Factor-Driven Industries	R23—Healthcare and Social Security	Direct	23.977	0.008	0.207
15	D3—Digital Product Services	U5—Chemical Raw Materials and Products	Intermediate Path	23.985	0.008	0.215
16	D1—Digital Product Manufacturing	D2—Digital Technology Applications	Intermediate Path	23.993	0.008	0.222
17	D1—Digital Product Manufacturing	R19—Scientific and Technical Services	Direct	24.000	0.007	0.230
18	U7—General and Special Equipment	R7—General and Special Equipment	Intermediate Path	24.007	0.007	0.237
19	D3—Digital Product Services	U6—Mineral and Metal Products	Intermediate Path	24.014	0.007	0.244
20	D3—Digital Product Services	U2—Food and Tobacco Processing	Intermediate Path	24.021	0.007	0.251

Note: Prefixes D, R, and U in sector codes denote the digital economy, rural industries, and urban industries, respectively.

Table 9. Robustness tests for counterfactual path identification.

Scenario	Top-10 Path Overlap (%)	Top-20 Path Overlap (%)	Top-30 Path Overlap (%)	Cumulative Gain After 20 Steps (Percentage Points)
0.5% proportional perturbation	100.0	100.0	100.0	0.063
1% proportional perturbation	100.0	100.0	100.0	0.125
5% proportional perturbation	100.0	100.0	100.0	0.627
Absolute perturbation (+0.00010)	20.0	20.0	13.3	0.231
2% proportional perturbation, repeated selection allowed	10.0	5.0	3.3	0.572

Note: Path overlap is calculated relative to the main scenario, defined as 2% proportional perturbation with non-repeated selection. Cumulative gain reports the increase in the relative level after the first 20 optimization steps.

This study also considers an equal absolute perturbation scenario in which the same direct allocation coefficient increment, +0.00010, is applied to each candidate path. This value is approximately equal to 2% of the median candidate-edge coefficient and is used to provide a comparison with the 2% proportional perturbation scenario. The results show

substantial differences between the path rankings generated by equal absolute perturbations and proportional perturbations. The overlap rates for the top 10 and top 20 paths are both 20%, and the overlap rate for the top 30 paths is 13.3%. This difference indicates that the proportional perturbation identifies priority paths shaped jointly by existing linkage scale and network transmission efficiency, whereas the equal absolute perturbation places greater weight on the network leverage of each unit increase in edge weight. The proportional perturbation results are therefore more suitable for identifying priority paths under marginal reinforcement along the existing core production network. The equal absolute perturbation results are still informative because they show that some low-base but high-leverage paths may also have interpretive value when the focus is on transmission efficiency per unit increase in edge weight.

Finally, this study tests the effect of allowing the same path to be selected repeatedly. Under the 2% proportional perturbation with repeated selection, the model repeatedly selects D1→R9, causing the first 20 steps to be almost entirely dominated by a single path and mechanically amplifying the relative level. This result indicates that, without a restriction on repeated selection, the optimization outcome would mainly reflect the effect of continuously reinforcing one path, rather than identifying a set of priority paths with industrial coordination meaning. The main experiment therefore adopts the non-repeated selection rule, which avoids mechanical amplification of a few high-return paths and is better suited for identifying a core set of optimization paths for rural industrial revitalization.

In summary, the counterfactual path-optimization results in Section 4.4 show that the priority paths for improving rural industries' complete digital integration level are first concentrated in direct linkages from digital-economy sectors to rural industries, especially linkages between digital product manufacturing, digital product services, digital-factor-driven sectors, and rural manufacturing, agricultural value chains, and public-service sectors. As the optimization process proceeds, linkages within the digital economy, linkages between digital-economy sectors and urban industries, and intermediate transmission paths from urban industries to rural industries also enter the priority sequence. These results indicate that core path optimization should strengthen the direct embedding of the digital economy into rural industries while also improving the coordinated transmission of digital value through urban-rural industrial linkages.

5. Conclusions and Policy Implications

The preceding measurement results, network identification, and counterfactual simulations jointly show that the role of the digital economy in rural industrial revitalization is not a simple process of technological diffusion into rural areas. Rather, it is a systemic process in which digital factors become embedded in, transmitted through, received by, and ultimately converted into industrial capabilities along the urban-rural production network. Section 3 answered how far digital empowerment had progressed. Section 4 further answered through which paths digital value operates and which paths deserve priority reinforcement. Based on the preceding analysis, this study summarizes the main findings from three perspectives: digital empowerment effects, transmission through urban-rural industrial networks, and core path optimization. It then proposes corresponding policy implications.

First, the digital economy has been continuously embedded in the rural industrial system, but current empowerment is still moving from linkage formation toward capability conversion. The increase in the digital integration level of rural industries shows that digital products and services are entering the rural production network. However, the persistent urban-rural gap and the low digital transformation level indicate that digital factors have not yet been fully converted into changes in rural production methods, adjustments in

product structure, or improvements in value-creation capacity. Therefore, the key to digitally enabling rural industrial revitalization is not only to expand the scale of digital inputs, but also to improve the ability of rural industries to absorb, transform, and recreate digital factors internally.

Second, digitally enabled rural industrial revitalization is not an isolated process of technological diffusion within rural areas. It is a value-transmission process formed through urban-rural industrial division and production-network linkages. The intermediate transmission role of urban industries in digital value flows shows that the digitalization level of rural industries depends not only on digital conditions within rural areas, but also on whether logistics, finance, business services, manufacturing support, scientific and technical services, and other industrial linkages between urban and rural areas operate smoothly. Digital rural development should therefore not be understood only as sending digital technologies to rural areas. It should also be understood as reconnecting and reorganizing urban-rural industrial chains, supply chains, and service chains. Only by improving the transmission efficiency of digital value within urban-rural industrial networks can the digital economy be more fully converted into a practical driver of rural industrial revitalization.

Third, digital empowerment policies should not apply uniform support across all sectors. Instead, they should precisely strengthen key nodes and key linkages in the production network. Paths with large urban-rural disparities reveal relative shortcomings when digital value enters the rural industrial system, while the path-optimization results further show that different industrial linkages generate different marginal improvements. Policy attention should therefore shift from general digitalization support to industrial-linkage-based path governance. This means prioritizing the reinforcement of key linkages that contribute more strongly to rural digital integration, while improving the coordinated transmission conditions among the digital economy, urban industries, and rural industries.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/doi/s1>, Supplementary Materials File S1: Annual 53-Sector Input–Output Tables for the Digital Economy and Urban–Rural Industries, 2002–2021; Supplementary Materials File S2: Annual Core-Path Networks of Digital Empowerment for the Revitalization of Rural Industries, 2002–2021.

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