

Article

Can China's New Infrastructure Promote Urban–Rural Integrated Development? Evidence from 31 Chinese Provinces

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Abstract: Whether and how new infrastructure (NI) promotes urban–rural integration (URI) remains crucial for addressing unbalanced urban–rural development. This study analyzes panel data from 31 provincial-level administrative regions in China (2013–2022) to construct an evaluation index system for URI, encompassing economic, social, ecological, spatial, and demographic dimensions. Using the entropy method, the study quantifies the development level of NI and investigates its differential effects on URI. The empirical findings demonstrate that NI exhibits a significant positive effect on URI, with the strongest impact manifested in economic and spatial dimensions. The influence on social, ecological, and demographic aspects, while positive, is comparatively modest. Regional disparities and innovation investment levels contribute to the heterogeneous impact of NI. Moreover, the study reveals that industrial structure advancement serves as the transmission mechanism through which NI drives URI. The promotional effect becomes more pronounced after crossing both the double threshold of industrial structure upgrading and the single threshold of industrial structure rationalization. Based on these findings, the following policy recommendations are proposed to optimize the new infrastructure investment structure, promote deep integration with industrial structural adjustments, and implement new infrastructure construction in accordance with local conditions.

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1. Introduction

Infrastructure constitutes the cornerstone of economic and social development, serving strategic, foundational, and leading functions. The correlation between the state of infrastructure and variations in regional development remains a central focus in economic discourse. Traditional infrastructure's impact on urban–rural gaps demonstrates complexity: while some studies indicate it facilitates trade, investment, and commerce through enhanced physical connectivity [1,2], thereby reducing regional differentiation [3], others suggest it promotes economic agglomeration [4,5], potentially widening urban–rural disparities. New infrastructure, as the evolutionary successor to traditional infrastructure, is characterized by information networks, technological innovation, and digital integration. Its unique capacity to transcend physical boundaries may transform conventional regional development patterns, potentially reshaping urban–rural development dynamics distinctly from traditional infrastructure [6,7].

Since 2020, China has systematically advanced new infrastructure development, achieving significant milestones. By 2022, China had established 2.312 million 5G base stations, accounting for more than 60% of the worldwide total, at a rate of 16.4 stations for

every 10,000 inhabitants. Regarding computing power infrastructure, the cumulative capacity of data center racks had reached 5.9 million standard racks, housing about 20 million servers, placing China in the second position globally in terms of computing power. Additionally, industrial internet platforms had integrated over 80 million industrial devices, providing services to more than 1.6 million industrial enterprises [8]. However, China's urban–rural development continues to face challenges including spatial disharmony, east–west regional disparities, and significant urban–rural income gaps [9–12]. Over time, China has experienced a process of urban–rural gaps widening, then fluctuating at high levels, and finally converging [12]. This unique context of rapid new infrastructure development, alongside persistent urban–rural gaps, makes China an ideal case study. The key questions to address are as follows: Can the new infrastructure promote integrated urban–rural development? What are the key mechanisms through which new infrastructure affects urban–rural integration development? Is there heterogeneity in these effects?

Academic discourse remains divided on new infrastructure's capacity to narrow urban–rural gaps. One perspective suggests that new infrastructure may exacerbate disparities, arguing it cannot enhance traditionally infrastructure-constrained industries like agriculture [13] or serve as an immediate economic stimulus [14]. It might enhance urban productivity due to the movement of labor and the presence of agglomeration benefits [5], accelerating urban development [15–17], while the digital divide could amplify urban–rural innovation gaps [18]. Conversely, alternative research indicates that new infrastructure investment introduces novel products and markets to rural areas, stimulates agricultural enterprise innovation, and enhances rural economic value [19]. Information infrastructure effectively mitigates rural income inequality [20,21] and helps bridge farmers' access gaps [22]. In fact, the innovative, interconnected, and shared characteristics of new infrastructure produce new impacts that traditional infrastructure does not have, such as from economic [23], social [24], spatial [25], demographic [26], and ecological [27,28] perspectives, potentially providing substantial support for urban–rural integration development. In terms of research methods, the entropy method, the analytic hierarchy process, the principal component weighting method, and the revised dynamic coordination coupling degree (CCD) model are commonly used for evaluating urban–rural integration and new infrastructure [29,30]. Existing studies have analyzed the impact on urban–rural integration from perspectives such as factor allocation, fiscal decentralization, and new urbanization [31,32], with multivariate regression models, spatial econometrics, and geographically weighted quantile regression (GTWR) serving as the primary analytical tools for these factors [33,34]. Based on the existing research, the following is true: First, current studies on the direct relationship between new infrastructure and urban–rural integration are not systematic and in-depth enough, mostly focusing on external direct factors of urban–rural integration while neglecting the analysis of internal relationships; Second, existing research fails to consider the regional differences in urban–rural integration development by capturing the characteristics of new infrastructure; Third, existing research lacks the study on the effect and mechanism of new infrastructure driving urban–rural integration development.

This research analyzes the effects and mechanisms of new infrastructure (NI) on urban–rural integration (URI) in China. The study's core components encompass the following: (1) Utilizing panel data from China's 31 provincial regions (2013–2022) to evaluate the influence of NI on the economic, social, ecological, spatial, and demographic facets of URI, with the objective of offering strategies for fostering high-quality integration; (2) Implementing robustness tests, such as instrumental variable approaches, the removal of outliers, and tail truncation, to validate the robustness of the results; (3) Exploring the varying impacts of regional distribution and investment in technological innovation on the nexus between NI and URI; (4) Investigating the mediating and threshold effects to delineate the intrinsic dynamics. Notably, indicators of industrial structure upgrading are employed as mediators to assess the direct effects of NI and as threshold indicators to examine the non-linear impacts on URI.

The marginal contributions of our findings are as follows: Firstly, this investigation expands upon the existing literature on the effects of traditional infrastructure on URI by integrating the influence of digital, intelligent, and network technologies; Secondly, it systematically examines the function of NI in advancing URI, transitioning from a one-directional urbanization approach to an emphasis on the mutual reliance and connectivity between urban and rural regions; Thirdly, it scrutinizes the impact mechanism of NI on URI through the lens of industrial structure, enhancing the theoretical underpinnings of URI and providing a conceptual framework for the formulation and implementation of future policy initiatives.

The article is structured as follows: Section 2 presents the literature review and hypotheses. Section 3 details model construction and variable description. Section 4 conducts empirical analysis, including regression results, robustness tests, and heterogeneity analyses. Section 5 concludes with policy recommendations.

2. Literature Review and Hypothesis

Building on the distinctive characteristics of informatization, intelligence, networking, and environmental sustainability, NI has substantially advanced URI by enhancing economic efficiency [35,36], promoting social equity [37], safeguarding the ecological environment [38], optimizing spatial configurations, and improving population structures. This has achieved balance and harmony between urban and rural areas across economic, social, ecological, spatial, and demographic dimensions [39]. Firstly, by improving the efficiency of information, logistics, capital, and technology flows, NI reduces transaction costs between urban and rural areas, strengthens market connections, fosters industrial coordination and resource sharing [40], and intensifies economic interactions between urban and rural economies. Secondly, NI bridges the social divide between urban and rural areas by providing equitable access to public services including education and healthcare [41,42], thus promoting social integration among urban and rural residents. Thirdly, the environmentally sustainable nature of NI contributes to enhancing the quality of urban and rural environments, promoting ecological protection and sustainable development [43,44], and achieving harmonious coexistence of urban and rural ecological environments. Fourthly, networked infrastructure optimizes the spatial distribution of urban and rural areas, facilitates the clustering and dispersion of economic activities, and promotes the optimization and integration of urban and rural spatial structures [45]. Fifthly, NI creates enhanced employment opportunities and educational resources for rural residents, facilitates population mobility and talent exchange, and promotes the optimization and integration of urban and rural population structures [26]. However, urban–rural social integration, ecological environment integration, and population integration involve more intangible factors such as social culture, ecological systems, and population dynamics. The integration of these fields requires a longer timeframe and more sophisticated institutional frameworks and social interactions [46]. Consequently, the direct impact of NI on economic and spatial integration is likely to be more immediate and substantial, whereas its influence on social, ecological, and population integration is relatively indirect and gradual. Based on these considerations, this paper proposes the following:

Hypothesis 1. *The NI has a promotional effect on URI.*

Hypothesis 2. *NI exerts a stronger influence on urban–rural economic and spatial integration compared to social, ecological, and population integration.*

The effectiveness of NI exhibits significant geographical variation [47]. The eastern region possesses advanced economic development, sophisticated transportation networks, and well-established industrial structures, with superior NI development in terms of both capital sources and investment scale. However, the marginal benefits of NI's impact on URI in this region remain uncertain. In contrast, the western region, despite its

infrastructure lag, presents considerable potential for NI development, lower industrial restructuring costs, and distinct late-mover advantages. The central region demonstrates varying levels of provincial development, with disparate alignment between NI demand and investment, making its contribution to URI less definitive. Additionally, NI development is fundamentally driven by innovations in next-generation information and communication technology. Scientific and technological investment serves as both the foundation and catalyst for NI, providing a theoretical framework for analyzing the heterogeneous effects of NI on URI [48]. From an economic perspective, provinces with substantial scientific and technological investment typically demonstrate more robust economic activities, diverse market opportunities, stronger capital attraction, efficient resource allocation, and superior innovation transformation capabilities. These regions successfully cultivate high-tech industries, facilitate traditional industry upgrading, and achieve industrial structure optimization. Consequently, scientific and technological investment emerges as a critical factor in understanding the varying impacts of NI on URI across different innovation-oriented regions [49]. Based on these considerations, this paper proposes the following:

Hypothesis 3. *Regional distribution patterns and innovation investment levels generate heterogeneous impacts of NI on URI.*

The key driver for the selection, adjustment, and upgrading of an industrial structure in a region lies in the changes of factor endowments [50]. The digital development and application of NI not only introduce new data production factors but also improve the combination of traditional production factors. This actively promotes the optimization and upgrading of urban and rural industrial structures and fosters a more coordinated, efficient, and sustainable urban–rural industrial ecosystem, thereby empowering the integrated development of urban and rural industries. On one hand, the transformation of traditional industries is mainly reflected in the application of digital information technology, which drives the evolution of traditional industries towards digitalization and intelligence, improving traditional production and organizational models [51]. For instance, in the agricultural sector, improving new agricultural infrastructure and developing smart agriculture help to establish a standardized agricultural production system [52], shifting rural areas from a single agricultural-based industrial structure to the integrated development of primary, secondary, and tertiary industries; in the industrial and service sectors, NI promotes the integration of producer services and manufacturing [53], accelerates the flow of capital and labor between industrial sectors, and achieves a high interconnectivity of people, machines, and objects, as well as the construction of full-factor chain, full-industry chain, and full-value chain, effectively integrating resources and optimizing the industrial structure from the aspects of factor flow and resource integration [54]. On the other hand, the digital advancement of industries can markedly improve industrial productivity and the efficiency of resource utilization. [55,56]. The application of digital technology also effectively improves the speed of resource flow and the upgrading of the industrial chain [57]. NI strengthens the linkage between upstream and downstream industries, optimizes the industrial chain layout, and thus increases the added value and competitiveness of the entire industry chain. In addition, investments in NI construction continuously give birth to new industries, new business formats, and new models. While achieving the advancement of industrial structure, it also increases local tax revenues [58], creates job opportunities [59], raises income levels [60], promotes the equalization of public services [61], and facilitates technology diffusion and market integration [62]. These mechanisms effectively enhance the mutual availability of urban and rural resources and the optimized allocation of production factors. This paper proposes the following:

Hypothesis 4. *NI promotes URI through the upgrading of industry structure.*

Industrial structure adjustment, encompassing both upgrading and rationalization, represents a complex and dynamic evolutionary process [63]. Throughout different stages of this evolution, the impact of NI on URI varies significantly [64]. During the initial phases of industrial structural adjustment and NI development, most agricultural entities possess limited digital technology capabilities, primarily relying on traditional production methods, resulting in weak integration with NI initiatives. Consequently, the promotional effect of NI on URI remains modest. With the relentless advancement of information networks and the gradual dissemination of information and communication technologies, the boundaries between economic activities across various sectors have become increasingly blurred. Additionally, the costs associated with utilizing NI, for instance the Internet of Things and big data centers, have seen a significant decline. On one hand, the extensive application of NI has enhanced the capabilities of digital technology, which in turn has boosted agricultural productivity and extended the industrial chain. This transition from traditional agriculture to high-value-added secondary and tertiary industries has imbued NI with the potential to drive industrial upgrading [14,65], resulting in a dynamic transformation of urban–rural integration processes. The marginal costs of interdepartmental linkages continue to decrease, while the benefits reaped by participants have increased exponentially. On the other hand, the development of NI has gradually driven the diversification and high value of rural industries [66], which not only increases rural employment opportunities and residents' income but also attracts urban capital and technology to flow to rural areas, as well as optimizing the allocation of urban and rural resources. Moreover, these effects will become more and more obvious with the improvement of the level of NI and the upgrading and rationalization of the industrial structure. This paper proposes the following:

Hypothesis 5. *NI exhibits non-linear effects on URI.*

3. Methodology

3.1. Model Design

3.1.1. Baseline Regression

To evaluate the impact of China's NI on URI, a linear regression model was formulated employing ordinary least squares (OLS) estimation (Equation (1)). To further dissect the influence of NI on the multifaceted dimensions of URI, a sub-dimensional OLS regression model (Equation (2)) was constructed. To mitigate the effects of heteroskedasticity, robust standard errors were employed in the regression analysis. The models are presented as follows:

$$y_{i,t} = \alpha_0 + \alpha_1 x_{i,t} + \sum \alpha Z_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad (1)$$

$$y_{i,t,j} = \alpha_{0,j} + \alpha_{1,j} x_{i,t} + \sum \alpha Z_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad (2)$$

In the model, y is the dependent variable, $x_{i,t}$ is the vector of explanatory variables, i and t represent the province and year, respectively, while j denotes the five dimensions of URI: $j = 1$ for economic integration, $j = 2$ for social integration, $j = 3$ for ecological integration, $j = 4$ for spatial integration, and $j = 5$ for population integration; Z_{it} represents control variables; μ_i , φ_t , and ε_{it} represent province fixed effects, time fixed effects, and the error term, respectively.

3.1.2. Mediation Model

Beyond the direct effect captured by Equation (1), to explore the potential mechanisms through which NI influences URI, we tested whether UIS acts as a mediator between the two variables, as previously discussed. The specific steps for this test are as follows: Based on the significance of coefficient α_1 in the linear regression model (1) of NI on URI, we constructed separate linear regression equations for NI on the mediator UIS and for both NI and UIS on URI. By examining the significance of regression coefficients β_1 , γ_1 , and γ_2 , we determined the presence of a mediating effect. The model is as follows:

$$M_{it} = \beta_0 + \beta_1 x_{i,t} + \sum \beta_3 Z_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad (3)$$

$$y_{i,t} = \gamma_0 + \gamma_1 x_{i,t} + \gamma_2 M_{it} + \sum \gamma_3 Z_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad (4)$$

Based on the aforementioned formula, the following steps are taken to test the mediating variable: First step, examine whether the $x_{i,t}$ has an impact on $y_{i,t}$. If the effect is significantly positive, it indicates a positive impact effect. Second step, analyze the relationship between $x_{i,t}$ and M_{it} . If β_1 meets expectations, proceed to the next test. Third step, if γ_2 is significant and γ_1 is less than α_1 or shows a significant decrease, it implies that introducing M_{it} has reduced the impact of $x_{i,t}$ on $y_{i,t}$. If γ_1 is not significant, it suggests that M_{it} plays a mediating role in the process of $x_{i,t}$ promoting $y_{i,t}$. On this basis, using $\beta_1 \gamma_2 / \alpha_1$, one can estimate the ratio of the indirect effect to the total effect of M_{it} .

3.1.3. Threshold Regression

In addition to the mediating effect model, the empirical test of the indirect conduction mechanism should also consider that UIS and RIS may also have an indirect effect on the nonlinear effect of MI-facilitated URI. Therefore, in order to avoid the arbitrariness of artificially dividing samples, the following threshold regression model is constructed on the basis of Equation (1):

$$y_{i,t} = \delta_0 + \delta_1 x_{i,t} \times I(\text{Thv}_{it} \leq \theta_1) + \delta_2 x_{i,t} \times I(\theta_1 < \text{Thv}_{it} \leq \theta_2) + \dots + \delta_n x_{i,t} \times I(\text{Thv}_{it} > \theta_n) + \sum \delta_3 Z_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad (5)$$

Among them, Thv_{it} represents the threshold variable. $I(\cdot)$ is an indicative function and the value of 0 if it does not meet the conditions in parentheses; if the condition in parentheses is matched, the value is 1.

3.2. Variable Selection

3.2.1. Dependent Variable

URI is a complex process that spans multiple dimensions, including urban–rural economic integration (Urei), urban–rural social integration (Ursoi), urban–rural ecological environment integration (Ureei), urban–rural spatial integration (Urspi), and urban–rural population integration (Urpi). Urei lays the material foundation for Ursoi, which in turn feeds back into sustained economic development. Ureei ensures the sustainability of the urban and rural environment, while Urspi provides the physical platform for economic and social activities. Urpi fosters balanced development across various fields through talent mobility. Overall, these dimensions are mutually supportive and constraining, jointly propelling the shift from urban–rural segregation to integration, realizing a comprehensive, coordinated, and sustainable development pattern [67,68]. To scientifically evaluate the URI, this paper constructs an indicator system with five dimensions: (1) Urei is the cornerstone of URI, encompassing the movement and allocation of production factors, as evidenced by income disparities, living standards, industrial shifts, and economic growth; (2) Ursoi signifies the fruits of integration, ensuring equitable access to public services like

healthcare, culture, and communication for all residents; (3) Ureei underscores the commitment to sustainable development, highlighting greening efforts, environmental stewardship, and ecological preservation; (4) Urspi characterizes the spatial dynamics, illustrating the interplay of transportation, land use, and information exchange; (5) Urpi portrays the demographic dimension, tracking population distribution, structure, and employment patterns, and facilitating a two-way flow of people. Subsequently, 18 indicators are meticulously selected to encapsulate the flow and distribution of urban–rural production factors, the equity of social and public service opportunities, the harmonious propulsion of circular and green development, population distribution, and information flow. This inclusive index framework is utilized to measure the level of URI in China.

Measurement methodologies such as the Entropy method, Analytic Hierarchy Process, Principal Component Analysis, and Factor Analysis are commonly used to evaluate development level of China's URI. Among these, the Entropy method, based on information entropy, is a robust multi-criterion decision tool for objective indicator weighting, facilitating optimal decision-making [69]. This paper employs the entropy method to compute the weight coefficients of the index system for China's URI. Following the normalization of the original data using MATLAB R2019a software, the entropy values are determined, and, subsequently, the weight coefficients are derived. The outcomes are presented in Table 1. The indicators at the indicator level are categorized into Positive Indicators and Negative Indicators, denoting the relationship between the selected indicators and the level of URI. For instance, a higher GDP per capita indicates a better level of URI, while a reduced disparity in the per capita disposable income between urban and rural areas signifies a higher level of URI. The rationale behind this is as follows:

Considering the differences in the units and dimensions of each index, it is necessary to convert the original data into the standardized processing of the measured values of dimensionless indicators so as to carry out comprehensive evaluation and analysis. The data are standardized to a range of ranges, and the range of values for each indicator is converted to between zero and one, as shown in Equations (6)–(10). The Positive Indicator is directly proportional to the level of URI, i.e., the higher the value, the better, while the Negative Indicator is inversely proportional to the level of URI, that is, the lower the value, the better.

$$\text{Positive Indicator: } x'_{ij} = (x_{ij} - x_{\min}) / (x_{\max} - x_{\min}) \quad (6)$$

$$\text{Negative Indicator: } x'_{ij} = (x_{\max} - x_{ij}) / (x_{\max} - x_{\min}) \quad (7)$$

Considering the need to avoid human factors interfering with the data, this paper chooses to use the entropy method to reduce the subjectivity given by the external environment. Here is how:

Calculate the weight of the i th subject indicator value under the j th indicator:

$$p_{ij} = x'_{ij} / \sum_{i=1}^m x'_{ij} \quad (8)$$

Calculate the entropy of the j th evaluation index:

$$e_j = -1 / \ln m \sum_{i=1}^m p_{ij} \ln p_{ij} \quad (9)$$

Calculate the weight of the evaluation index j :

$$w_j = (1 - e_j) / \sum_{j=1}^n (1 - e_j) \quad (10)$$

The use of the Entropy method to measure URI can help government departments and decision-makers to understand the level of URI more comprehensively and objectively and help formulate targeted policies and measures to promote URI in a more sustainable and balanced direction.

Table 1. Indicators and weights of URI.

Primary Indicator	Secondary Indicator	Tertiary Indicators	Indicator Type	Weight
Urban–rural integration development (URI)	Urban–rural economic integration	Ratio of per capita disposable income between urban to rural areas (%)	–	0.015
		Engel coefficient (%)	–	0.005
		Ratio of the added value of the secondary and tertiary industries to the added value of the primary industry (%)	+	0.274
		GDP per capita (RMB/person)	+	0.049
	Urban–rural social integration	Number of institutional beds in hospitals (units)	+	0.048
		Public library collection (10,000 volumes)	+	0.059
		Number of mobile phone subscribers (10,000 households)	+	0.051
	Urban–rural ecological environment integration	Green coverage rate of built-up area (%)	+	0.003
		Sewage treatment rate (%)	+	0.002
		Forest cover (%)	+	0.044
		Park green space per capita (sq m)	+	0.013
	Urban–rural spatial integration	Mobile phone subscribers (10,000 households)	+	0.051
		Private car ownership per capita (units/person)	+	0.081
		Proportion of built-up area (%)	+	0.165
	Urban–rural population integration	Transportation network density (mileage/total area)	+	0.043
		Urbanization rate (%)	+	0.012
		Proportion of employees in the primary sector (%)	–	0.017
		Ratio of urban to rural population (%)	+	0.069

3.2.2. Explanatory Variable

Building upon the National Development and Reform Commission’s elucidation of the concept of NI, this paper categorizes the evaluation index system for NI into three categories: information-based infrastructure, integrated infrastructure, and innovative infrastructure. Drawing upon the extant literature [33,35,37], 17 indicators are selected to construct the index system for China’s new infrastructure development level, as detailed in Table 2. The data undergo the same normalization process as previously described, with the Entropy method utilized to determine the index weights. The comprehensive score is then derived through linear weighting.

Table 2. Indicators and weights of the NI.

Primary Indicator	Secondary Indicator	Tertiary Indicators	Quaternary Indicators	Indicator Type	Weight
New infrastructure development (NI)	Information infrastructure	Internet infrastructure	IPv4 address density (pcs/person)	+	0.125
			Internet domain name density (per person)	+	0.092
			Internet broadband access port density (pcs/person)	+	0.018
		Communications infrastructure	Fiber optic cable line density (km/km ²)	+	0.084
			Mobile phone base station density (pcs/km ²)	+	0.100
		New technology infrastructure	Number of computers used per 100 people (units)	+	0.023
			Proportion of enterprises with e-commerce transaction activities (%)	+	0.015
	Converged infrastructure	Intelligent transportation infrastructure	Railway operating mileage density (km/10,000 km ²)	+	0.046
			Mileage density of high-speed highways (km/10,000 km ²)	+	0.064
		Smart weather infrastructure	Automatic weather station density (units/10,000 km ²)	+	0.042

Innovative infrastructure	Smart home infrastructure	Proportion of cable radio and television subscribers to total households (%)	+	0.027
		Proportion of digital TV subscribers to total households (%)	+	0.025
	E-commerce infrastructure	Number of companies with R&D activities (units)	+	0.121
		Number of enterprises with R&D institutions (units)	+	0.105
	Scientific and educational infrastructure	Density of R&D institutions (per million population)	+	0.048
		Density of regular institutions of higher learning (institutions) (per million students)	+	0.016
	Innovation infrastructure for high-tech industries	Density of high-tech enterprises (per million people)	+	0.050

3.2.3. Mediating Variables and Threshold Variables

Upgrading of industrial structure (UIS) refers to the process or trend of the transformation of industrial structure from low level to high level, which is the change of economic construction situation and the transformation of economic development mode. With information technology and intelligent manufacturing, modern agriculture, manufacturing and service industries are integrated and developed in the industrial chain. In this paper, advanced industrial structure (AIS) is selected as the proxy variable for UIS and as the mediating variable and threshold variable. Drawing upon the specific characteristics of AIS, this paper utilizes the UIS index to quantify the evolution of China's industrial structure. The index is measured by examining the proportion of the three primary industry types within the total output value.

$$AIS_{it} = \frac{Y_{1it}}{Y_{it}} \times 1 + \frac{Y_{2it}}{Y_{it}} \times 2 + \frac{Y_{3it}}{Y_{it}} \times 3 \quad (11)$$

Among them, Y_{it} represents the regional GDP of province i in year t , and $\frac{Y_{1it}}{Y_{it}}$, $\frac{Y_{2it}}{Y_{it}}$ and $\frac{Y_{3it}}{Y_{it}}$ represent the ratio of the added value of the primary, secondary, and tertiary industries to the regional GDP of province i in year t , respectively.

Rationalization of industrial structure (RIS) refers to maintaining an appropriate proportion and organic connection between industries and achieving a virtuous cycle under certain production technology conditions. In this paper, the RIS is selected as the threshold variable. The Theil index is employed to assess the level of rationalization in the industrial structure across various provinces. It effectively measures the structural discrepancies between output values and employment figures across various industries, as well as the varying economic statuses within each industry.

$$TL_{it} = \frac{Y_{1it}}{Y_{it}} \times \ln\left(\frac{Y_{1it}}{L_{1it}} / \frac{Y_{it}}{L_{it}}\right) + \frac{Y_{2it}}{Y_{it}} \times \ln\left(\frac{Y_{2it}}{L_{2it}} / \frac{Y_{it}}{L_{it}}\right) + \frac{Y_{3it}}{Y_{it}} \times \ln\left(\frac{Y_{3it}}{L_{3it}} / \frac{Y_{it}}{L_{it}}\right) \quad (12)$$

Among them, TL is Theil index, Y is the same as Equation (11), which indicates the number of people employed in province i in year t , and L_{1it} , L_{2it} , and L_{3it} represent the number of people employed in the primary, secondary, and tertiary industries in province i in period t , respectively. When the calculated Theil index is equal to 0, it means that the economy is in equilibrium, that is, the development of various industries is relatively balanced; conversely, it indicates that over- or under-development of certain industries has led to economic imbalances.

3.2.4. Control Variables

To prevent the distortion of regression outcomes by other variables, the study introduced four control variables. The first control variable is the economic development level

($\ln gdp$), gauged by the regional GDP per capita. The second is the level of external openness (Ope), assessed by the ratio of the total value of imports and exports to the GDP; the third is the degree of population density ($\ln Dop$). To a certain extent, population density has improved the negative impact of social population aging, improved the quality structure of labor force, upgraded consumption and supply, and promoted the quality of economic development, which is measured by the logarithm of the population per square kilometer. Fourth, the intensity of investment in innovation (Iii) can promote social production, improve economic efficiency, and narrow regional gaps, which is measured by the intensity of R&D investment.

3.3. Data Sources and Descriptive Statistics

The sample data utilized in this study comprise panel data from 31 provinces, municipalities, and autonomous regions across the Chinese mainland for the period from 2013 to 2022 (excluding data from Hong Kong, Macao, and Taiwan due to unavailability), including Beijing, Tianjin, Hebei Province, Shanxi Province, Inner Mongolia Autonomous Region, Liaoning Province, Jilin Province, Heilongjiang Province, Shanghai, Jiangsu Province, Zhejiang Province, Anhui Province, Fujian Province, Jiangxi Province, Shandong Province, Henan Province, Hubei Province, Hunan Province, Guangdong Province, Guangxi Zhuang Autonomous Region, Hainan Province, Chongqing, Sichuan Province, Guizhou Province, Yunnan Province, Tibet Autonomous Region, Shaanxi Province, Gansu Province, Qinghai Province, Ningxia Hui Autonomous Region, and Xinjiang Uygur Autonomous Region. The data were primarily sourced from the China Statistical Yearbook (2014–2023), the China Urban and Rural Statistical Yearbook (2014–2023), the China Science and Technology Statistical Yearbook (2014–2023), the provincial (autonomous region and municipal) statistical yearbooks (2014–2023), and the EPS data platform at <https://www.epsnet.com.cn/index.html#/Index>. Any missing data points were addressed through mean imputation and regression imputation. The descriptive statistics for each variable are provided in Table 3.

Table 3. Descriptive statistics.

Variable	Obs	Mean	Std	Min	Max
URI	310	0.185	0.105	0.025	0.639
Urei	310	0.040	0.050	0.005	0.328
Ursoi	310	0.042	0.028	0.000	0.138
Ureei	310	0.030	0.013	0.007	0.056
Urspi	310	0.043	0.031	0.002	0.210
Uрпи	310	0.029	0.018	0.005	0.097
NI	310	0.096	0.081	0.022	0.444
$\ln gdp$	310	9.892	0.976	6.704	11.769
Ope	310	0.321	0.978	0.001	16.372
$\ln Dop$	310	7.907	0.391	6.965	8.620
Iii	310	1.792	1.180	0.190	6.830
AIS	310	2.400	0.122	2.177	2.836
TL	310	0.174	0.129	0.001	0.700

4. Results

4.1. Baseline Regression Results

4.1.1. Double Fixed-Effect Regression

Table 4 reports the results of regression Equation (1). To examine the issue of multicollinearity in the model, we calculated the correlation coefficients for the explanatory variables and found that most correlations were less than 0.3, with only the correlation

coefficient between URI and the Iii reaching 0.8. Furthermore, we investigated the Variance Inflation Factor (VIF) and found that all values were less than 5, indicating that multicollinearity is not a serious issue.

Columns (1) and (2) report the regression results with and without control variables, respectively. The results indicate that NI has a significant positive impact on URI. For panel data models, the Hausman test results reject the random-effects model at the 1% significance level, indicating that there is a correlation between the explanatory variables and the unobserved individual effects. Therefore, using a fixed-effects model is more appropriate for our data analysis. To eliminate individual heterogeneity across provinces, we establish a two-way fixed-effects model (5). For comparison, the table presents the fixed-effects models (3) and (4) estimated with within-group deviations. The estimated coefficient for NI is positive and passes the 1% significance test, indicating that NI can significantly promote URI. This provides preliminary evidence to support Hypothesis 1. As a panel regression method, such results do not rule out the possibility of autocorrelation between groups in the data. Consequently, it is imperative to check for autocorrelation in the outcomes of the fixed-effects model previously discussed. For this purpose, the Wooldridge test is employed to detect any autocorrelation problems. The Wooldridge test results in a P-value of 0.203, which allows us to fail to reject the null hypothesis, suggesting that within-group autocorrelation is not present.

Table 4. Overall regression results.

	(1)	(2)	(3)	(4)	(5)
NI	1.098 *** (0.066)	0.718 *** (0.122)	0.900 *** (0.249)	0.888 *** (0.228)	0.924 *** (0.254)
lngdp		0.026 *** (0.003)	0.043 *** (0.006)	0.043 *** (0.007)	0.045 *** (0.007)
Ope		−0.004 (0.003)	−0.002 (0.002)	−0.002 (0.002)	−0.002 (0.002)
lnDop		0.020 ** (0.009)	−0.006 (0.009)	−0.010 (0.009)	−0.010 (0.010)
Iii		0.023 *** (0.006)	−0.003 (0.011)	−0.017 (0.018)	−0.016 (0.015)
_cons	0.080 *** (0.005)	−0.334 *** (0.054)	−0.257 *** (0.083)	−0.145 (0.117)	−0.228 ** (0.107)
Province	NO	NO	NO	YES	YES
Year	NO	NO	YES	NO	YES
N	310	310	310	310	310
R ²	0.713	0.813	0.773	0.749	0.723

Robust standard errors in parentheses. ** $p < 0.05$, *** $p < 0.01$.

4.1.2. Dimensional Regression

The influence of NI on URI across economic, social, ecological, spatial, and population dimensions is further scrutinized, with the results tabulated in Table 5(1)–(5). The analysis reveals that the impact of NI on urban–rural ecological integration and urban–rural population integration is positive, indicating that NI aids in narrowing the disparities between urban and rural areas across various dimensions, thus fostering a more balanced development, as corroborated by Hypothesis 2. However, the effects of NI on urban–rural economic integration and urban–rural spatial integration surpassed the 1% significance threshold, with impact coefficients of 0.681 and 0.207, respectively. These coefficients were larger than those observed for urban–rural social integration, urban–rural ecological integration, and urban–rural population integration. This suggests that NI effectively enhances economic interactions and spatial optimizations between urban and rural

areas, strengthens the economic ties between urban and rural regions, blurs the geographical divide between them, and facilitates the sharing of resources and services. In the Urei, NI enhances production efficiency and innovation capabilities through investment-driven, technology diffusion, and market expansion effects. In the Urspi, it strengthens urban–rural physical connections, optimizes spatial layouts, and guides the rational distribution of population and economic activities by improving infrastructure connectivity. While NI positively influences social, ecological, and population integration, it may require complementary measures such as the equitable distribution of educational and healthcare resources and the enforcement of environmental protection policies due to factors like social security, ecological restoration cycles, and household registration policies.

Table 5. Dimensional regression results.

	(1)	(2)	(3)	(4)	(5)
NI	0.681 *** (0.188)	0.021 (0.030)	0.005 (0.004)	0.207 ** (0.092)	0.011 (0.009)
Ingdp	0.008 *** (0.003)	0.017 *** (0.003)	0.001 (0.000)	0.018 *** (0.004)	0.001 ** (0.000)
Ope	−0.004 *** (0.001)	−0.001 (0.001)	−0.000 (0.000)	0.004 *** (0.001)	0.000 (0.000)
lnDop	−0.006 (0.007)	−0.003 (0.003)	−0.000 (0.001)	−0.002 (0.004)	0.002 * (0.001)
Iii	−0.006 (0.013)	0.001 (0.003)	0.001 (0.001)	−0.012 * (0.006)	0.000 (0.001)
_cons	−0.022 (0.096)	−0.135 *** (0.034)	0.023 *** (0.006)	−0.087 (0.054)	0.052 *** (0.009)
Province	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES
N	310	310	310	310	310
R ²	0.574	0.763	0.687	0.568	0.818

Robust standard in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2. Endogeneity and Robustness Checks

4.2.1. Endogeneity Test

The p -value of Hausman's test was 0.007, indicating that the benchmark regression model had endogeneity problems. To address this potential bias, instrumental variable (IV) methods were employed to ensure that the estimates are free from omitted variable biases or bi-directional causality. Therefore, drawing on the setting method of Nunn and Qian (2014) [70], the number of post offices per million people in 1984 was chosen as a tool variable for NI. This choice is based on the notion that the development of NI is intertwined with the evolution of traditional communication technology. As a key component of traditional communication, the post office can provide insights into a region's communication capacity and information dissemination efficiency, thereby reflecting the level of information transmission infrastructure in the past. Consequently, it may correlate with the current state of communication infrastructure construction, such as 5G base stations and broadband networks. Moreover, the continuity between the early postal system and modern communications infrastructure might have influenced the latter's development. For instance, the location and number of early post offices might have influenced the placement of later telecommunications base stations. The study's balanced panel data necessitated the selection of time-series data that could be interacted with the cross-sectional data to suit the panel data structure. In practice, the interaction term of the number of post offices per million people in 1984 (cross-sectional data) and the national information technology service income (time-series data) from the previous year was constructed as the IV

for NI. Subsequently, a two-stage least squares (2SLS) regression was conducted. The results, presented in column (1) of Table 6, indicate that the instrumental variable's regression coefficient is positive and statistically significant at the 1% level, reinforcing the notion that NI is positively associated with URI and that the benchmark results are relatively stable. The selected instrumental variables passed the weak instrument test (F-statistic 13.031) and the under-identification test (Anderson LM statistic 12.666), which rejects the weak instrument and the unidentifiable hypotheses, respectively. This suggests that the instrumental variable selection is reasonable and effective. Consequently, the instrumental variable regression results also corroborate the robustness of the impact of NI on URI.

Table 6. Endogeneity and robustness test.

	(1)	(2)	(3)
NI	0.986 ** (0.492)	0.885 *** (0.278)	0.913 *** (0.232)
lngdp	0.0445 *** (0.00423)	0.046 *** (0.006)	0.063 *** (0.009)
Ope	−0.00199 (0.00384)	−0.002 (0.002)	0.060 * (0.030)
lnDop	−0.0107 (0.00907)	−0.008 (0.009)	−0.013 (0.009)
Iii	−0.0186 (0.0200)	−0.035 * (0.017)	−0.016 (0.014)
_cons	−0.220 ** (0.0897)	−0.240 ** (0.090)	−0.398 *** (0.105)
Province	YES	YES	YES
Year	YES	YES	YES
N	310	270	310
R ²	0.516	0.864	0.760

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2.2. Exclusion of Municipalities

Considering the unique economic development level and urban–rural administrative system of the four municipalities directly governed by the central government—Beijing, Tianjin, Shanghai, and Chongqing—which set them apart from other provinces and make them susceptible to being identified as outliers, the data from these municipalities was excluded from the overall sample. This exclusion was made to prevent the regression results from being distorted by the special characteristics of these regions. Subsequently, the regression model was re-estimated, and the findings are presented in column (2) of Table 6. The results once again confirm the stability of the previous conclusions. After removing the sample data from the municipalities directly under the central government, the coefficient value for NI remains significantly positive. However, it is notably lower than that observed in the benchmark regression. This suggests a substantial disparity in the level of NI between these municipalities and the rest of the provinces, underscoring the need to address the issue of a “digital divide” to prevent a further widening of the urban–rural development gap between different regions.

4.2.3. Tail Reduction

To mitigate the potential impact of extreme values on the research outcomes, the relevant data for the variables employed in the study were subjected to a 1% tail trimming process. This involved removing the top 1% and bottom 1% of the data distribution for each variable. Subsequently, the regression analysis was re-conducted, and the results are

presented in column (3) of Table 6. The analysis reveals that there is no substantial discrepancy between the sign and statistical significance of the regression coefficient for NI in the trimmed sample and the benchmark regression results. This indicates that the benchmark regression findings are robust and reliable.

4.3. Heterogeneity Analysis

4.3.1. Regional Heterogeneity

Given the extensive geographical expanse of China, there are pronounced disparities in the foundational development of the digital economy, digital expertise, and capital investment across various regions. Consequently, the influence of development on URI may exhibit variability across these regions. To elucidate this heterogeneity, the study's comprehensive dataset was stratified into four administrative divisions according to the classification system employed by the National Bureau of Statistics: the eastern, central, western, and northeastern regions. Subsequently, the differential impact of NI on URI within these distinct regional contexts was examined, with the corresponding regression outcomes detailed in Table 7(1)–(4). The regression analysis revealed that the coefficients for NI on URI in the western and northeastern regions are 1.246 and 1.157, respectively, both of which are statistically significant at the 1% level, indicating a robust positive correlation. In the eastern region, the coefficient is 0.515, also positive and statistically significant at the 10% level. Conversely, the central region exhibited a negative coefficient for NI on URI, which did not reach statistical significance. This discrepancy may be attributed to the varying levels of existing infrastructure within the regions. The western and northeastern regions, with comparatively underdeveloped infrastructure, may experience a more pronounced marginal effect from NI. The eastern region, on the other hand, boasts a relatively mature infrastructure base, which may diminish the marginal benefits of new infrastructure investments. Furthermore, the eastern region's pre-eminence in information technology services implies that the incremental impact of NI may be relatively limited. Additionally, the high degree of marketization and intense competition in the eastern region may pose significant challenges for new entrants in the infrastructure sector, such as high land and labor costs, which could mitigate the economic returns of these investments. In the central region, the uneven development among the provinces suggests that while some provinces may have established a certain foundation in certain areas, others may be less developed. This imbalance could lead to divergent effects of NI within the region, resulting in an overall ambiguous impact on URI.

Table 7. Heterogeneity analysis.

	(1)	(2)	(3)	(4)	(5)	(6)
NI	0.515 *	−0.074	1.246 ***	1.157 ***	1.155 ***	0.648 **
	(0.300)	(0.432)	(0.036)	(0.125)	(0.098)	(0.322)
_cons	0.105	−0.438 **	0.000	−0.530 ***	−0.413 ***	0.270
	(0.524)	(0.194)	(.)	(0.130)	(0.089)	(0.208)
Province	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
N	100	60	120	30	182	128

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3.2. Heterogeneity of Investment in Scientific and Technological Innovation

To assess the heterogeneity of the impact of NI on URI across provinces with varying levels of technological innovation investment, this study employed the median research and development (R&D) investment intensity as an indicator of regional technological innovation investment. The median R&D investment intensity was set at 1.79, with provinces exhibiting an R&D investment intensity below this threshold categorized as having

low technological innovation investment and those above the threshold categorized as having high technological innovation investment. The regression results are presented in Table 7(5) and (6), respectively. The findings indicate that the regression coefficients for NI on URI are statistically significant at the 1% level in both low and high technological innovation investment groups, further corroborating Hypothesis 1. Additionally, in the context of new infrastructure construction, the regression coefficient for URI is higher in provinces with low technological innovation investment compared to those with high technological innovation investment. This phenomenon can be attributed to several factors. Firstly, in provinces with low technological innovation investment, NI can more effectively address deficiencies in existing technology and infrastructure, thereby yielding higher marginal benefits. Secondly, these provinces may be in the nascent stages of development, and NI can expedite technological progress and industrial upgrading, fostering a catch-up effect and accelerating the convergence with the development levels of more advanced provinces. Thirdly, in provinces with low technological innovation investment, NI can more effectively complement existing infrastructure, leading to greater synergies. In summary, the impact of NI on URI is heterogeneous across different regional distributions and provinces, validating Hypothesis 3.

4.4. Mechanism Analysis

4.4.1. Mediation Analysis

To ascertain the existence of this transmission mechanism, the study delves into the mechanisms through which NI influences URI, as encapsulated in Equations (3) and (4). The regression outcomes are presented in Table 8. In column (1) of Table 8, the regression coefficient for NI is statistically significant and positive, suggesting that its total effect on URI is positive. Column (2) reveals a significant positive coefficient for NI, indicating that NI can enhance the level of UIS. The coefficients for NI and the UIS index in column (3) are also significantly positive. However, the regression coefficient in column (3) is lower than that in column (1), indicating that UIS serves as a partial mediating variable between NI and URI. The mediating effect is quantified at 0.302, accounting for 42.02% of the total effect. The confidence intervals for the mediating effect are (0.194, 0.424) and the p-value is less than 0.01, indicating that the UIS effectively explains the relationship between NI and URI. This finding suggests that NI has a substantial positive impact on URI by promoting UIS, thereby validating Hypothesis 4.

Table 8. Mediation analysis.

	OLS	Mediation	
	URI (1)	AIS (2)	URI (3)
NI	0.924 *** (0.254)	0.643 * (0.347)	0.700 *** (0.131)
lngdp	0.045 *** (0.007)	0.022 * (0.013)	0.037 *** (0.004)
Ope	−0.002 (0.002)	−0.008 ** (0.004)	0.001 (0.001)
lnDop	−0.010 (0.010)	−0.029 (0.026)	0.000 (0.006)
lri	−0.016 (0.015)	−0.037 (0.026)	−0.004 (0.010)
AIS			0.348 *** (0.082)
_cons	−0.228 ** (0.107)	2.346 *** (0.252)	−1.045 *** (0.197)

Province	YES	YES	YES
Year	YES	YES	YES
N	310	310	310
R ²	0.723	0.608	0.837
Sobel		0.302 ***	
Mediator Effect/Total Effect = 42.02%			

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4.2. Threshold Effect

Before estimating the threshold model, a panel threshold existence test was conducted based on Hansen's (1999) method [71]. After 300 bootstrap resamples, the results indicated that the RIS threshold variable significantly passed the single threshold test but failed the double and triple threshold tests, while the UIS passed the double threshold test. Subsequently, regression models with the corresponding number of thresholds were set, yielding the results presented in Table 9. Column (1) of Table 9 illustrates the regression results when UIS is utilized as a threshold variable. Below the threshold value of 2.552, the impact coefficient for NI on URI is 0.313. As the threshold value falls between 2.552 and 2.739, the impact coefficient increases to 1.134, achieving significance at the 1% level. Above the threshold value of 2.739, the impact coefficient decreases to 0.764. This pattern suggests that at lower levels of UIS, the potential of NI is not fully realized, and its promotion of URI is limited. In the intermediate stage of UIS, the industrial structure reaches a level that is more supportive of NI, thereby enhancing the effectiveness of URI. Beyond this threshold, the marginal benefits of NI diminish, possibly due to the already advanced nature of the industrial structure, where further infrastructure enhancements contribute less to URI. Column (2) of Table 9 demonstrates the regression results when RIS is employed as a threshold variable. Below the threshold value of 0.457, the regression coefficient for NI on URI is 0.663. Above the threshold value of 0.457, the coefficient increases to 1.155. This indicates that in regions with an irrational industrial structure, while NI can still contribute to URI, its effect is comparatively muted. In areas with a more rational industrial structure, the impact of NI on URI is more pronounced. A rational industrial structure signifies a very complementary relationship among industries, thereby facilitating the integration of urban and rural economies and societies. In summary, as UIS and RIS surpass their respective thresholds, the role of NI in fostering URI becomes increasingly pronounced, substantiating Hypothesis 5.

Table 9. Regression results of panel threshold models.

		AIS	TL
		(1)	(2)
Threshold estimator	θ_1	2.552	0.457
	θ_2	2.739	
NI×I(Adj _{it} ≤ θ_1)		0.313 ** (0.118)	0.663 *** (0.181)
NI×I(θ_1 < Thv _{it} ≤ θ_2)		1.134 *** (0.106)	1.155 *** (0.069)
NI×I(Thv _{it} > θ_3)		0.764 *** (0.046)	
lngdp		0.046 *** (0.005)	0.044 *** (0.006)
Ope		0.002 (0.001)	0.000 (0.002)
lnDop		−0.018 ** (0.008)	−0.013 (0.009)

l _{ii}	0.025 *** (0.009)	−0.002 (0.015)
_cons	−0.223 *** (0.078)	−0.207 ** (0.096)
N	310	310
R ²	0.892	0.786

Robust standard errors in parentheses. ** $p < 0.05$, *** $p < 0.01$.

5. Conclusions and Recommendations

5.1. Conclusions

This study examines the impact of China's NI on URI using panel data from 31 provincial-level administrative regions (2013–2022), employing double fixed-effects, mediating effects, and threshold regression methods. The findings demonstrate that NI has significantly advanced URI. The research validity is confirmed through empirical analyses across five dimensions of integration—economic, social, ecological, spatial, and demographic—utilizing individual time fixed-effects and various robustness tests, including endogenous instrumental variables, outlier elimination, and tail truncation. The results indicate that NI positively influences URI, with pronounced effects on economic and spatial integration compared to social, ecological, and demographic dimensions. These findings highlight the potential of infrastructure construction that is based on new technologies—such as information technology, network technology, and intelligent technology—in bridging the urban–rural gap. This construction provides support for the connection, flow of information, and movement of people between urban and rural areas, which is crucial for the sustainable and equitable management of resources.

The impact exhibits regional heterogeneity based on geographical distribution and scientific-technological investment levels. Eastern, western, and northeastern regions show more substantial effects, highlighting the significance of geographical location and innovation capacity in leveraging NI benefits. These regions demonstrate considerable potential for industrial transformation, while the central region shows varying effects due to uneven provincial development levels.

Mechanism analysis reveals that NI promotes URI through industrial structure advancement. The impact intensifies significantly as UIS and RIS from low to high levels. Beyond certain thresholds, while the effect moderates, it remains above initial levels.

These findings not only clarify the intrinsic mechanisms by which NI influences URI, providing a new explanatory framework and analytical perspective for URI theory, but also discuss how to improve the livability and sustainability of urban and rural areas within the NI framework that integrates information technology, network technology, and smart technology. Additionally, they offer valuable insights for nations pursuing URI in the face of urbanization and digitalization challenges. More importantly, understanding the mechanisms of impact and regional differences is of significant importance to policymakers and practitioners who are interested in leveraging smart technologies and new infrastructure to promote more balanced and sustainable urban–rural development and to offer potential contributions to the existing practices of smart technology integration and regional integration.

However, several limitations warrant acknowledgment. First, while examining the overall impact and five dimensions of integration, the study does not separately analyze the three components of NI: information, convergence, and innovation infrastructure. Second, the mechanism analysis focuses primarily on industrial structure dynamics, potentially overlooking other influential factors such as infrastructure interconnectivity, regional digital development, and public service equalization. Third, the provincial-level data may not fully capture urban–rural disparities and inter-provincial variations in NI. The relatively recent emergence of NI concepts also limits time-series data availability.

Future research directions include the following: (1) refined dimensional analysis exploring the impact of NI's three components on five integration dimensions; (2) expanded mechanism research investigating policy support, capital investment, factor allocation, synergy, and distribution perspectives; (3) advanced methodological approaches combining county-level quantitative analysis with case studies and integrating theoretical modeling with computer simulation techniques for deeper insights into NI's impact on URI.

5.2. Policy Recommendations

URI serves as a fundamental mechanism for transcending the urban–rural divide. NI, centered on information technology, has emerged as a crucial catalyst for enhancing agricultural productivity, increasing farmers' incomes, and advancing agricultural sector modernization. Furthermore, it strengthens rural infrastructure, facilitating URI and contributing to high-quality economic development. Drawing on our research outcomes, we put forth a set of strategic policy recommendations.

The first consideration involves the rational optimization of new infrastructure investment. Given that NI significantly contributes to URI, particularly in economic and spatial integration, it is imperative to advance new urbanization strategies with counties as primary nodes. This involves prioritizing infrastructure investments at the county level, particularly in transportation and information technology networks. Attention should be directed towards building effective transport channels, such as intercity expressways, fiber optic networks, and 5G facilities, to reduce the time and geographical divides between urban and rural communities. Modify the investment composition of NI to align with regional characteristics. In the eastern coastal zones, prioritize investment in sophisticated manufacturing and IT industries to stimulate industrial progress and technological breakthroughs. For the central and western territories, prioritize the enhancement of the transportation grid, incorporating the development of highways and railways, to bolster economic linkages and demographic movement across regions. In the northeastern territories, escalate funding in new energy and eco-friendly sectors to aid in economic transformation and to ensure sustainable development.

The second strategic direction focuses on promoting the deep integration of NI with industrial structure adjustment. Our research indicates that NI facilitates URI through UIS, with effectiveness significantly influenced by regional industrial structure advancement and rationalization. Policymakers should tailor NI to specific regional industrial characteristics, maintaining real-time monitoring of UIS to optimize infrastructure investment allocation. This is particularly relevant for the central region, where industrial structures vary significantly across provinces, necessitating differentiated development strategies and adaptive policy adjustments aligned with evolving developmental needs. Additionally, inspired by the successful integration of industrial parks and transportation networks in Suzhou Industrial Park and the thriving Yiwu International Trade City in Zhejiang, we should strategically position industrial parks, logistics hubs, and R&D centers to attract businesses and cultivate industrial clusters. This strategy will foster the harmonized growth of the agricultural, manufacturing, and service sectors in rural regions.

The third strategic focus involves the adaptive layout of new infrastructure construction based on local conditions. Given the regional variations in impact and innovation investment levels, different approaches are necessary for different regions. In the western and northeastern regions, it is vital to persist in scaling up investments in new infrastructure, maximizing the incremental advantages it offers, swiftly bridging infrastructure deficits, and advancing equitable URI and regional economic progress. While the incremental returns of new infrastructure on URI in the eastern region are comparatively less, it remains important to refine the existing infrastructure, improve service levels, and investigate innovative models that incorporate market dynamics to combat intense market rivalry and elevated operational expenses. For the central region, considering its internal development variations, it is critical to enhance provincial-level planning and devise targeted strategies for individual provinces to guarantee that new infrastructure effectively

promotes URI. For provinces with low innovation investment, increased support for new infrastructure construction is crucial to bridge technological gaps and accelerate industrial upgrading, fostering catch-up development with more advanced regions. These differentiated strategies aim to maximize the effectiveness of NI in promoting high-quality URI.

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