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The impact of the digital economy on new industrial-agricultural and urban–rural relations

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The construction of new industrial-agricultural and urban–rural relations (IAUR) with coordinated development and shared prosperity is an inevitable requirement of the Chinese path to modernization. Based on the panel data of 275 prefecture-level cities and above in China from 2012 to 2023, we empirically verify the mechanism and spatial effects of the DE on the development of IAUR. The results show that: Firstly, the DE can effectively promote the development of IAUR, but there is a heterogeneous effect among cities with different geographic locations, administrative grades, and levels of development of the DE. Secondly, the promotional effect of DE on IAUR exhibits a non-linear pattern of increasing marginal returns, with digital financial inclusion (DFI) and the digital divide (DDI) serving as dual thresholds. Thirdly, the spatial spillover characteristics of the DE on the development of IAUR are obvious. Based on the above, policy recommendations are put forward, such as the widespread application of the DE, exploring differentiated development paths according to local conditions, and strengthening regional synergy and cooperation.

KEYWORDS

digital economy, digital inclusive finance, new industrial-agricultural and urban–rural relations, regional coordinated development, spatial spillover effect, digital divide

1 Introduction

The industrial-agricultural and urban–rural relations constitute vital components of China's modernization process. Although China has achieved significant progress in addressing issues related to agriculture and rural development, several structural challenges persist, such as the lack of coordinated growth across the three major industries, the persistent urban–rural income gap, and the uneven allocation of public resources (Ji et al., 2019). How to address these issues to achieve integrated industry development, mutual promotion among regions, and promote shared prosperity, remains a pressing and complex task. From the regional economics perspective, the balance between industrial-agricultural and urban–rural relations reflects broader concerns of inter-regional factor allocation and spatial structure optimization (Li et al., 2014). In this context, the DE, characterized by high permeability and expansive coverage, serves to dismantle institutional and spatio-temporal barriers. It encourages the smooth flow of production elements, promotes spatial restructuring, and alleviates regional disparities, thereby emerging as a pivotal driver in the evolution of IAUR (Guo et al., 2023; Qiao et al., 2025). Nevertheless, critical questions remain: How does the DE concretely influence the development of IAUR? Under what conditions can its enabling effects be fully realized? Furthermore, does the DE exert a spatial effect in transforming these

relations? In response to these questions, we investigate the impact of the DE on IAUR, with particular attention to potential threshold and spatial effects.

Academic research on industrial–agricultural and urban–rural relations has primarily focused on their theoretical connotations, historical evolution, and underlying mechanisms. Existing studies emphasize that socio-economic development exhibits distinct stage-specific characteristics (Cairncross, 1961; Qi et al., 2013), and that the evolution of industrial–agricultural and urban–rural relations in China has followed a clear developmental trajectory. Specifically, since the founding of the People's Republic of China, this relationship has evolved from a stage of "supporting industry with agriculture," to "promoting agriculture with industry," and ultimately to a stage of "mutual promotion between industry and agriculture" (Li et al., 2015). This transition reflects a broader shift in development priorities—from meeting basic subsistence needs and supplying industrial raw materials toward addressing structural weaknesses in agriculture and rural areas, balancing efficiency and equity, and promoting coordinated industrial–agricultural and urban–rural development (Li and Zhang, 2024; Shen et al., 2025).

Despite this growing body of theoretical research, empirical studies on industrial–agricultural and urban–rural relations remain relatively limited and fragmented. Most existing studies adopt either the urban–rural relationship or the industrial–agricultural linkage as the primary analytical focus, rather than examining them as an integrated system. In terms of indicator construction, scholars often employ the non-agricultural employment ratio and binary comparison coefficients to reflect population integration and economic convergence in studies of urban–rural integration (Chen et al., 2020; Wang et al., 2023). Similarly, indicators such as the total horsepower of agricultural machinery are commonly used to capture industrial interaction or industrial support to agriculture (Zeng and Chen, 2023; Zhan et al., 2023). Although recent research has begun to conceptualize industrial–agricultural and urban–rural relations as interconnected systems and to explore their coordinated development, the existing literature still pays insufficient attention to the quality and inclusiveness of such coordination, particularly from the perspective of common prosperity in urban–rural societies.

Against this background, an expanding strand of literature has turned to the DE as a potential new driver reshaping industrial–agricultural and urban–rural relations. Compared with the traditional real economy, the DE is characterized by rapid transmission, high permeability, and increasing marginal returns (Hao et al., 2023). These characteristics facilitate the release of digital dividends and enhance the complementary and mutually reinforcing advancement of industrial–agricultural and urban–rural relations (Zhang et al., 2025). At the theoretical level, the DE reduces temporal and spatial constraints through digital technologies and platform-based infrastructure (Nambisan et al., 2019), thereby promoting multidimensional integration. This integration manifests in economic integration through market and industrial linkages, social integration via the more equitable provision of public services and governance mechanisms, and spatial integration through improved transportation networks and optimized land use (Zhang et al., 2024). Collectively, these mechanisms help smooth urban–rural economic cycles and foster more harmonious industrial–agricultural and urban–rural development (Zhou et al., 2024).

Empirical studies further substantiate these theoretical arguments. From the perspective of income allocation, existing research finds that digital infrastructure development and the expansion of digital financial inclusion help narrow urban–rural income gaps by increasing residents' incomes and improving income distribution (Su et al., 2015; Hou et al., 2024; He et al., 2025). Other studies show that the digital economy promotes coordinated urban–rural development by enabling two-way flows of production factors (Chen et al., 2024), optimizing regional industrial structures (Wang and Li, 2024), and advancing the universality of public service provision (Wu et al., 2023). However, the literature also highlights important limitations and heterogeneity in the effects of the digital economy. Due to persistent urban bias and the digital divide, rural areas often receive fewer digital dividends than urban regions (Song et al., 2020; Liu and Zhou, 2023). Insufficient digital infrastructure in rural areas constrains entrepreneurial activity and non-farm employment, exacerbates productivity disparities (Salemink et al., 2017), and further widens the urban–rural economic gap (Gao et al., 2018). Moreover, several studies suggest that the impact of the digital economy on urban–rural income distribution and factor allocation may exhibit non-linear and stage-dependent characteristics, such as U-shaped or inverted U-shaped relationships (Jiang et al., 2022; Peng and Dan, 2023; Hu et al., 2023), or diminishing marginal returns in its contribution to integrated urban–rural development (Xiong et al., 2022).

In short, the previous literature presents several limitations that warrant further investigation. Firstly, research on the industrial-agricultural and urban–rural relations remains largely theoretical, with most studies emphasizing urban–rural mutual integration and communication. However, there is currently a lack of empirical analysis that specifically address the industrial-agricultural relations and urban–rural relations within a systematic context. Secondly, there is no unified analytical framework that effectively integrates the DE with IAUR, the threshold and spatial effects of this relationship also remain underexplored. Thirdly, while prior studies have proposed indicator systems that treat industrial-agricultural relations and urban–rural relations as interconnected subsystems, most fail to incorporate the central goal, "common prosperity." This study seeks to make several marginal contributions. Firstly, recognizing that mutual promotion and complementarity between industrial-agricultural and urban–rural are interdependent processes, and that common prosperity is a vital indicator of people's happiness. A multidimensional evaluation system is established to capture the development progress of IAUR across three dimensions: industrial-agricultural mutual promotion, urban–rural complementarity, and common prosperity. Secondly, in light of the current mismatches in factor allocation and spatial imbalances, the study investigates the impact of the DE on IAUR, further explores the threshold effects and spatial spillover effects. Thirdly, acknowledging the spatial heterogeneity of the DE, we examine how its uneven distribution influences industrial-agricultural and urban–rural development across regions. Based on these, it offers region-specific policy recommendations aimed at promoting differentiated development paths, thereby providing practical guidance for the advancement of both the DE and IAUR.

2 Theoretical analysis and research hypotheses

2.1 The role of the DE in driving the development of IAUR

The core objective of the IAUR is to progressively achieve industrial-agricultural integration and mutual promotion,

urban–rural coordination and mutual compensation, and ultimately the realization of urban–rural social coexistence and mutual prosperity (Liu, 2021). This objective encompasses not only the interaction of production factors but also reflects the spatial structuring of resource distribution and the equitable distribution of public services. Given the multidimensional nature of the DE, particularly its capacity to optimize industrial structures, transcend spatial constraints on factor flows, and enhance the universality of public services, we integrate it with IAUR into an analytical framework. The influential role of the DE is examined across three key dimensions, as illustrated in Figure 1.

Firstly, the DE influences the integration and mutual promotion of industrial-agricultural relations. It facilitates the convergence of industries by embedding digital capabilities into rural contexts. This integration gives rise to emerging formats, such as agricultural research, science popularization, and leisure agriculture, thus enabling the horizontal expansion of the agricultural industry chain (Lu and Li, 2024). Simultaneously, digital technologies enable deeper vertical integration, enhancing the flow from upstream production to midstream processing, downstream logistics and branding, contributing to the value enhancement of agricultural products and overall industry upgrading (Zhang et al., 2023). Furthermore, the DE promotes the outward expansion of non-agricultural industries into rural areas. By dismantling traditional industrial boundaries and fostering mechanisms for shared urban–rural resource utilization, the DE enables the reallocation of surplus agricultural labor, rural land and ecological assets, freed by digital technological applications. This supports the shift of industries to rural areas, facilitating an efficient division of labor and promoting complementary industrial development (Shi et al., 2022).

Secondly, the DE contributes to the coordination and mutual compensation of urban–rural relations. It facilitates the free movement of populations. By dismantling information barriers, the DE enhances the efficiency of human capital allocation through better alignment of supply and demand in the labor market (Li et al., 2022). At the same time, the DE promotes the rational allocation of land resources and strengthens urban–rural transportation linkages. Digital technologies help overcome information asymmetries by establishing platforms for land transaction indicators, enabling more accurate assessments of land demand, and optimizing land use efficiency (Gao and He, 2024; Wang et al., 2025). In addition, the DE supports the establishment of modern transportation networks, which reduces the cost of information and goods exchange between regions. It also enhances the spatial spillover effects of central cities, thereby injecting new momentum into regional coordinated development (Liu et al., 2025).

Furthermore, the urban–rural social coexistence and mutual prosperity emphasizes the pursuit of an improved quality of life built upon a stable economic foundation (Chen et al., 2023). This is primarily reflected in the growing demand among urban and rural residents for non-material wellbeing, in terms of essential public services and ecological improvements. The application of internet and big data helps to bridge the gap in digital access and enhancing more efficient and equitable allocation of public resources (Hodge et al., 2017). In addition, the construction of digitally integrated communication platforms among various social actors reduces the spatial and temporal distances involved in information exchange, lowers energy consumption, and mitigates environmental pollution. Digital technologies also enable dynamic monitoring of environmental conditions, ensuring greener and more sustainable development of urban–rural ecosystems (Ma and Lin, 2023). Taken together, the DE contributes to the integration and mutual reinforcement of agricultural and non-agricultural sectors, enhances the coordination and complementarity of urban–rural resource distribution, and promotes urban–rural social common prosperity, providing strong impetus for the development of IAUR. Based on the above analysis, the following hypothesis is proposed:

> *H1*: The DE can effectively drive the development of IAUR.

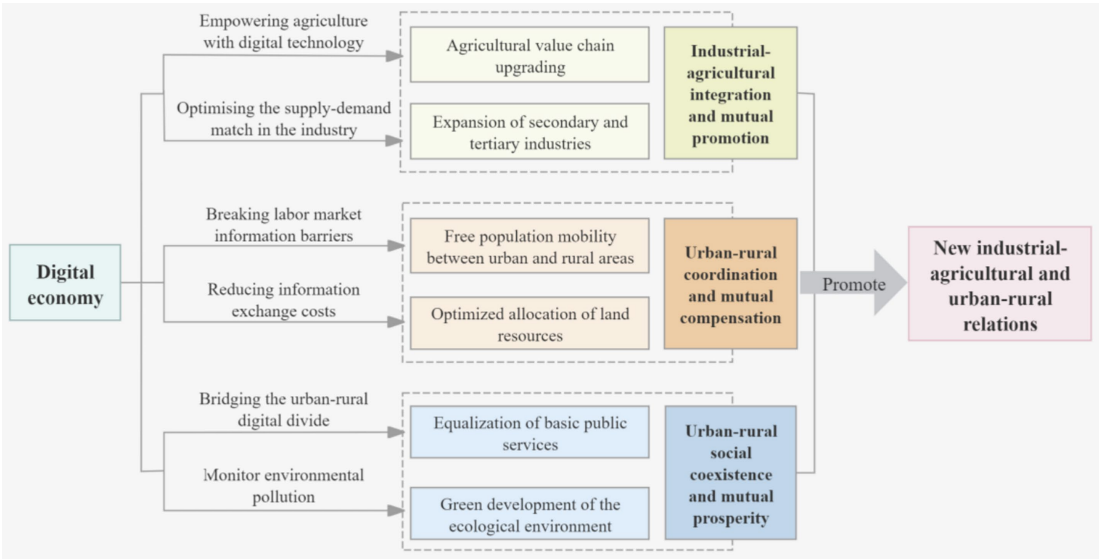

FIGURE 1
Theoretical logic of the DE affecting IAUR.

2.2 Threshold effects of the impact of the DE on IAUR

According to the network scale effects and externalities emphasized by Metcalfe's Law (Swann, 2002), the impact of the DE on IAUR is unlikely to follow a simple linear pattern. As the development environment evolves, this relationship may exhibit non-linear characteristics (Liu and Liu, 2024). With the continuous expansion of the DE and improvements in the level of DFI, the DE has increasingly become a key driver of industrial-agricultural integration, urban–rural resource coordination, and the common prosperity of residents (Li and Ma, 2021; Luo, 2024). However, the effects of this influence may also vary across stages of development, suggesting the presence of threshold effects.

DFI serves as a critical enabling condition for the DE to support the IAUR, because participation in digital economic activities depends, to a significant extent, on the financial capacity of economic agents. DFI lowers the cost of financial services through technological innovation, broadens service coverage, and provides more accessible financial products to rural populations (Jiang, 2024). The digital transformation of rural areas facilitated through digital platforms, creates interconnected financial networks, strengthening economic linkages between urban and rural regions (Wu and Li, 2024). Notably, in the early stages of DFI, improvements in financial services may exert limited or even negative effects on the DE's capacity to drive rural development. However, as DFI matures and rural economic activity becomes more dynamic, the DE begins to release greater dividends. Consequently, its role in advancing IAUR is becoming increasingly critical.

The DDI may also generate significant threshold effects in the process by which the DE promotes IAUR. DDI reflects disparities between urban and rural areas in terms of the completeness of digital infrastructure, accessibility to digital technologies, and capabilities in digital application (Mao et al., 2025). During phases characterized by weak digital foundations and low network coverage in rural regions, rural economic entities struggle to effectively integrate into digital markets. Consequently, the dividends generated by digital technologies remain underutilized, thereby limiting the relative impact of DE on advancing IAUR (Liu et al., 2025). As the urban and rural DDI narrows, conditions in rural areas, including network coverage, digital skills, and reliance on e-commerce platforms, continue to improve. The network effects of DE are gradually strengthened, facilitating the two-way flow and efficient allocation of urban and rural resources and production factors, thereby amplifying the role of DE in promoting IAUR (Lu et al., 2025). Consequently, the impact of DE on IAUR may exhibit distinct phase-specific variations as the DDI continues to decline. Based on the above analysis, the following hypothesis is proposed:

> *H2*: The impact of the DE on the development of IAUR is characterized by non-linearity, with DFI and DDI playing threshold roles.

2.3 Spatial effects of the impact of the DE on IAUR

According to new economic geography theory, there exists a strong spatial correlation among regions, whereby the economic activities of neighboring areas generate spatial spillover effects that significantly contribute to local economic development (Behrens and Thisse, 2007). The development of the DE exhibits a clustering effect, as talent and technology tend to concentrate geographically, forming regional "DE highlands." As a novel economic form that transcends temporal and spatial boundaries, the DE not only influences local development but also exerts spillover effects on adjacent regions through diffusion mechanisms, thereby facilitating interregional economic interaction (Zhang and Zhang, 2024). By enabling efficient and rapid matching of factor resources across different spatial domains according to supply and demand, the DE accelerates the integration of resources across regions and strengthens interregional connectivity (Peng et al., 2024). In the context of developing IAUR, the DE broadens the space for the flow of elements, the influence of DE highlands extends to neighboring regions, thereby restructuring industrial-agricultural and urban–rural dynamics at a broader spatial scale. Moreover, the development of IAUR exhibits spatial dependence and is influenced by the digital environment of surrounding areas. Through institutional convergence and behavioral imitation, regions can indirectly benefit from the digital resources of neighboring areas, thus fostering the coordinated development of local IAUR (Zhao and Jiao, 2022). Based on the above analysis, the following hypothesis is proposed:

> *H3*: The DE promotes the development of IAUR in spatially connected regions through spatial spillover effects.

3 Research design

3.1 Research methodology

In order to study the impact of DE on the development of IAUR, we construct the following benchmark regression model:

$$IAUR_{i,t} = \alpha_0 + \alpha_1 DED_{i,t} + \alpha_2 X_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t}, \quad (1)$$

where $IAUR_{i,t}$ and $DED_{i,t}$ represent the level of IAUR for city i in year t and its DE level; $X_{i,t}$ is a vector of control variables accounting for other influencing factors; α_1 and α_2 represent the fitting coefficients of each variable; μ_i and δ_t represent the city and the year fixed effects, respectively; and $\varepsilon_{i,t}$ represents the random error term.

Considering the potential non-linear relationship between DE and the evolution of IAUR, we further investigate this relationship using a panel threshold model. DFI and DDI are employed as threshold variables. The threshold model is constructed as follows:

$$\begin{aligned} IAUR_{i,t} = {} & \eta_0 + \eta_1 DED_{i,t} \cdot \mathrm{I}(q_{i,t} \le \gamma_1) + \eta_2 DED_{i,t} \cdot \mathrm{I}(\gamma_1 < q_{i,t} \le \gamma_2) \\ & + \cdots + \eta_{n+1} DED_{i,t} \cdot \mathrm{I}(q_{i,t} > \gamma_n) + \lambda X_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (2)$$

where I(·) represents the indicator function, I = 1 when the condition in brackets is true, and I = 0 otherwise; $q_{i,t}$ represents the threshold variable, and $\gamma_1 \sim \gamma_n$ is the threshold value to be estimated.

When analyzing the impact of the DE on IAUR, it is also important to take into account the externalities generated by spatially

correlated regions. We adopt the spatial–temporal double fixed spatial Durbin model (SDM):

$$IAUR_{i,t} = \beta_0 + \rho \mathbf{W} \cdot IAUR_{i,t} + \beta_1 DED_{i,t} + \varphi_1 \mathbf{W} \cdot DED_{i,t} + \beta_2 X_{i,t} + \varphi_2 \mathbf{W} \cdot X_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t}, \quad (3)$$

where $\mathbf{W}$ represents the spatial weight matrix, $\mathbf{W} \cdot IAUR_{i,t}$ $\mathbf{W} \cdot DED_{i,t}$ represent the spatial lag term of IAUR and DE.

3.2 Indicator selection

3.2.1 Explained variable: IAUR

In accordance with the conceptual framework of IAUR, this study constructs a multidimensional index system to evaluate the development level of IAUR at the city level (Table 1). IAUR is understood not merely as a set of sectoral or spatial linkages, but as a goal-oriented relational system that integrates structural coordination with inclusive development outcomes. Accordingly, the index system comprises three interrelated dimensions.

First, the degree of industrial–agricultural mutual promotion captures the intensity and quality of factor flows and value-chain integration across primary, secondary, and tertiary sectors, reflecting the economic foundation of IAUR. Second, the degree of urban–rural mutual compensation reflects spatial and demographic coordination, focusing on population mobility, and income linkages between urban and rural areas. These two dimensions together constitute the structural and functional mechanisms through which IAUR operates. Third, the degree of mutual prosperity represents the normative orientation and developmental objective of IAUR in the Chinese context. Rather than being treated solely as an ex-post outcome, common prosperity is conceptualized as an integral dimension that shapes the sustainability and inclusiveness of industrial–agricultural and urban–rural interactions. This dimension is operationalized through indicators capturing balanced economic performance, equitable access to basic public services, social security coverage, and ecological sustainability, which jointly reflect the quality and depth of coordinated development.

To ensure objectivity in indicator aggregation, the entropy weight method is employed to derive comprehensive IAUR development scores across cities.

3.2.2 Core explanatory variable: DE

The DE encompasses a range of economic activities that involve the investment in and deployment of digital technologies and data elements to boost efficiency and optimize economic structures (Tan et al., 2024). Based on this definition and constrained by city-level data availability, we construct an indicator system as shown in Table 2 comprising three dimensions: digital infrastructure, digital elements and technologies inputs, and DE penetration. These indicators collectively reflect the full development pathway of the DE, from foundational infrastructure to practical application and eventual empowerment of broader economic systems. To objectively assign weights to the selected indicators, the entropy weight method is employed, enabling the construction of a composite DE development index.

3.2.3 Control variables

To consider potential factors that may influence the development of IAUR and to enhance the accuracy of empirical analysis, we incorporate several control variables: (1) Government intervention (*Govint*), measured by the ratio of local public budget expenditures to GDP; (2) business environment (*Envir*), proxied by the share of actual foreign direct investment in GDP; (3) financial development (*Fina*), captured by the ratio of the year-end balance of loans from financial institutions to GDP; (4) openness to foreign trade (*Open*), measured by the proportion of total import and export trade in GDP. To mitigate the effects of scale differences and skewed distributions, all control variables are log-transformed after adding one.

3.3 Data sources and descriptive statistics of variables

Based on data availability, we conduct an empirical analysis using panel data from 275 prefecture-level cities in China, covering the period from 2012 to 2023. With the exception of the China Digital Inclusive Finance Index compiled by the Digital Finance Research Center of Peking University, all other raw data are sourced from the China Urban Statistical Yearbook, relevant provincial and municipal statistical yearbooks, and the statistical bulletins on national economic and social development. Where necessary, missing values have been addressed using interpolation methods. Descriptive statistics for all variables used in the analysis are presented in Table 3.

4 Empirical analysis

4.1 Characteristics of spatial and temporal evolution

To visually illustrate the spatial evolution of the development level of IAUR as well as DE across China's prefecture-level cities, we select the years 2012, 2015, 2019, and 2023 as representative time points. Using ArcGIS software, spatial distribution maps are generated for both the development of IAUR (Figure 2) and DE (Figure 3). The spatial pattern of IAUR reveals a clear east–west divide, with higher development levels concentrated in eastern coastal cities and comparatively lower levels in middle and western regions. Over time, the overall development of IAUR has improved nationwide. The spatial agglomeration effect has weakened, and regional disparities have narrowed, reflecting a significant diffusion of development from east to west. This trend aligns with the objectives of China's regional coordinated development policy.

The spatial distribution of the DE also exhibits a clear gradient pattern of "East-Central-West." High-development areas have gradually expanded from the eastern coastal region and North China into the central and western regions. Notably, unlike findings in some earlier studies, the northeastern region also demonstrates a high level of DE concentration. Overall, the DE shows a dynamic evolutionary trend: while the development level in most cities has steadily increased, a minority of cities have experienced fluctuations or temporary declines. Spatial differentiation remains evident, indicating persistent regional differences exist in DE development.

TABLE 1 Construction of the index system for the development of IAUR.

Primary indicators	Secondary indicators	Tertiary indicators	Description of indicators	unit
Development index of IAUR	The degree of industrial-agricultural mutual promotion	Integration of primary and secondary industries	Degree of coupled coordination between primary and secondary sectors	–
		Integration of primary and tertiary industries	Ratio of the output value of agricultural support services to the total output of the primary sector	%
		Integration of agricultural and non-agricultural industries	Value added by secondary and tertiary sectors/ that of the primary sector	–
	The degree of urban–rural mutual compensation	Rate of population urbanization	Urban resident/total resident population	%
		Rate of land urbanization	Urban built-up land/administrative area land	%
		Ratio of income in urban and rural areas	Urban/rural disposable income per capita	–
	The degree of mutual prosperity	GDP per capita	–	Yuan
		Ratio of pupils to teachers in basic education	Number of teachers/pupils in primary and basic secondary schools	–
		Percentage of expenditure on education	Education expenditure/budget expenditure	%
		Number of hospital beds	Number of hospital and health center beds/total population	Number per 10,000 people
		Doctors' population	Number of doctors/totals population	Number per 10,000 people
		Unemployment insurance participation rate	Individuals enrolled in unemployment insurance/total participants	%
		Medical insurance participation rate	Individuals enrolled in basic medical insurance/ total participants	%
		Non-hazardous domestic waste disposal rate		%

TABLE 2 Construction of DE development index indicator system.

Primary indicators	Secondary indicators	Tertiary indicators
Development index of DE	Level of digital infrastructure	Internet users per 100 persons
		Percentage of staff in digital technology services
	Input of digital elements and technologies	Per capita telecommunications service volume
	Degree of DE penetration	Mobile phone subscribers per 100 persons
		China Digital Inclusive Finance Index

To further explore the dynamic evolution of IAUR and DE, this study uses the Kernel density estimation method to clarify its distribution location, shape and ductility trend, shown in Figure 4. In terms of the distribution location, the rightward shift of the kernel density curve over the sample period, suggesting that the development level of IAUR and DE at the nationwide level tends to increase overall during the period from 2012 to 2023. In terms of distribution shape, the main peak of the curve of IAUR shows a "rising-declining" trend, and the width of the peak does not change obviously, that is, the absolute difference in the development of IAUR among cities first narrows and then widens; whereas the height of the DE curve decreases markedly and the width becomes wider, suggesting that the difference in the development of the DE gradually expands and the degree of agglomeration decreases, and the spatial diffusion effect of the DE becomes more and more significant. In terms of ductility trend, the curves of IAUR and DE in China are both trailing on the right and gradually lengthening, which means that the cities' development gap is gradually expanding, and the development trend is diffuse and balanced.

4.2 Benchmark regression

The benchmark regression results based on Equation (1) are presented in Table 4. Columns (1) and (3) report the estimates without and with control variables, respectively. The coefficients of the core explanatory variable (0.0503 and 0.0424), both significant at the 1% level, indicate that a 1% increase in the level of the DE is associated with approximately a 0.04–0.05% improvement in IAUR. This magnitude suggests that the DE not only has statistical significance but also exerts a meaningful economic impact, reflecting its growing role in reducing factor misallocation, enhancing industrial–agricultural linkages, and narrowing urban–rural gaps. These findings

TABLE 3 Descriptive statistics of variables.

Variable name	Notation	Observations	Mean	Standard deviation	Minimum value	Maximum values
Development index of IAUR	*IAUR*	3,300	1.289	0.046	1.145	1.575
Development index of DE	*DED*	3,300	0.099	0.051	0.022	0.680
Government intervention	*Govint*	3,300	2.965	0.398	1.684	4.528
Business environment	*Envir*	3,300	0.477	0.535	0.000	2.504
Financial development	*Fina*	3,300	0.536	0.119	0.058	1.889
Openness to foreign trade	*Open*	3,300	2.251	1.138	0.001	5.900

are broadly consistent with existing studies showing that the DE promotes rural revitalization, industrial integration, and regional coordination (Lin et al., 2024; Wang et al., 2025).

4.3 Dimensional analysis

To further examine the differentiated effects of DE on each dimension of URID, we replace the dependent variable in Equation (1) with three sub-dimensions: industrial-agricultural mutual promotion, urban–rural mutual compensation, and mutual prosperity. The regression results are presented in Table 5.

As shown in Table 5, the DE significantly promotes the integration and mutual promotion of agricultural and non-agricultural industries, as well as the mutual prosperity of urban and rural societies. However, its effect on the coordination and mutual compensation of urban–rural factor allocation does not appear to be statistically significant during the sample period.

At the current stage of developing IAUR, industrial prosperity remains the foundation for coordinated regional development. The integration and mutual promotion of industry and agriculture serve as the central mechanism driving the transformation of these relations. Meanwhile, the widespread availability of basic public services and improvements in the ecological environment reflect the growing non-material pursuit of the population for a higher quality of life. Consequently, the DE demonstrates a more pronounced positive impact on industrial-agricultural mutual promotion and urban–rural social mutual prosperity.

4.4 Robustness tests

To validate the robustness of the benchmark regression results, this paper employs three complementary methods: (1) the core explanatory variable is replaced with the DFI index. The motivation for this replacement is that the urban–rural disparity in DE development is largely due to the underdeveloped rural infrastructure, and the capacity for endogenous economic growth among rural residents remains comparatively weak. As a key driver of rural economic revitalization, DFI serves as a meaningful proxy for assessing the breadth and effectiveness of the DE in urban and rural settings. (2) Key cities are eliminated, including 4 centrally administered municipalities, 15 sub-provincial cities, and provincial capitals. Given their relatively advanced levels of DE development and IAUR, these cities may potentially lead to an upward bias in the coefficients. (3) To address potential distortion from extreme values, the main variables are bilaterally winsorized at the 1st percentiles. This approach helps control for estimation errors resulting from extreme values. According to the results in Table 6, across all methods, the estimated coefficients of the core explanatory variable remain significantly positive, reaffirming the conclusion that DE exerts a robust positive impact on the development of IAUR.

To address potential endogeneity, we construct an instrumental variable (IV) by interacting the number of telephones in 1984 with the lagged share of employees in computer service and software. This design follows Ma and Zhu (2022) and is rational for two reasons. First, relevance: the historical penetration of telephones reflects early-stage information infrastructure, and its interaction with the evolving digital-service workforce strengthens its correlation with current DE development. Areas with a stronger historical communication base and higher digital-service potential are more likely to exhibit faster digital economy growth. Second, exogeneity: neither the number of telephones in 1984 nor the lagged digital-service workforce is expected to directly affect today's IAUR, except through their influence on the DE, thereby reducing concerns of reverse causality and omitted variables. The 2SLS results further show that the IV passes weak-instrument and identifiability tests, and the DE coefficient remains significantly positive, reinforcing the robustness of H1.

4.5 Heterogeneity analysis

To assess whether the effects of the DE on IAUR vary across regions, we conduct a regional heterogeneity analysis based on three dimensions: geographic location, administrative hierarchy, and development type.

4.5.1 Geographic location

To examine regional disparities in impact, the 275 prefecture-level cities are grouped into four categories based on geographic location: eastern, middle, western, and northeastern regions. The regression results by subgroup are reported in Table 7.

The findings reveal clear heterogeneity in the impact of the DE across different regions. The DE significantly promotes the development of IAUR in both the eastern and middle regions, with the marginal effect being particularly strong in the western region. One possible explanation is that the eastern region already possesses advanced digital infrastructure, higher digital literacy among residents, and a well-functioning market economy. These conditions enable the DE to be effectively embedded within the real economy,

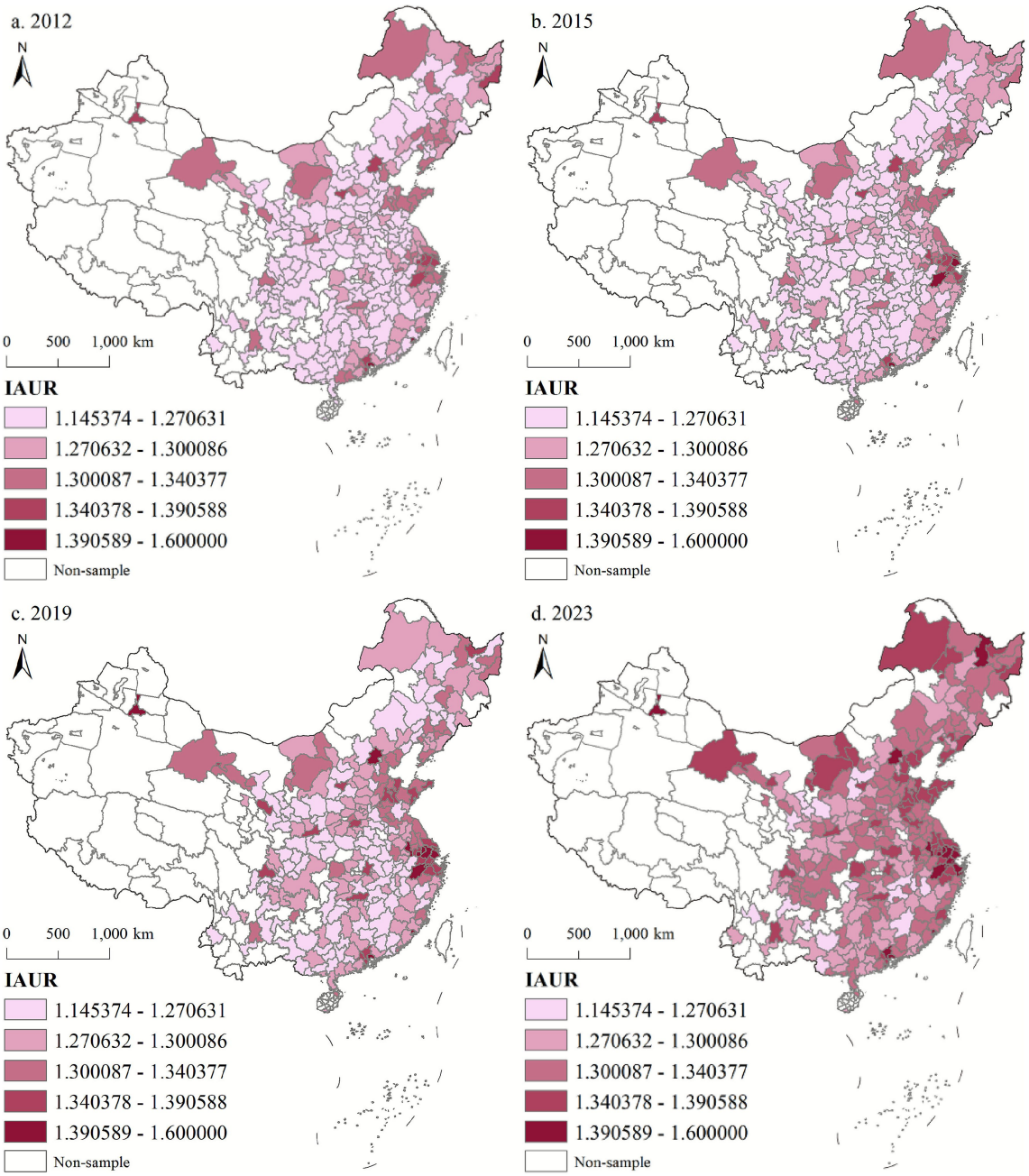

FIGURE 2
Spatial distribution of the level of IAUR development in Chinese cities (2012, 2015, 2019, 2023).

thereby accelerating the transformation of IAUR. In the middle region, where traditional industries remain dominant, digital technologies help to compensate for deficiencies. This results in greater marginal gains and a more pronounced synergistic effect of the DE on IAUR.

In contrast, the estimated coefficients for the western and northeastern regions, although positive, are not statistically significant, which means that the DE has yet to exert a strong developmental impact in these areas. In the western region, complex geographical conditions may hinder the diffusion of digital technologies. In the northeastern region, a reliance on traditional agriculture and heavy industry, coupled with ongoing population outflows, constrains development. Addressing these challenges will require accelerating the establishment of a modern industrial system that leverages local comparative advantages and fully harnesses the potential of DE.

4.5.2 Administrative hierarchy

According to China's administrative classification, the 275 prefecture-level cities are classified into two groups: central cities, which include administered municipalities, sub-provincial cities, and all provincial capitals; and peripheral cities, comprising all other prefecture-level cities. This classification allows for a comparative analysis of the differential impact of the DE on IAUR across administrative hierarchies.

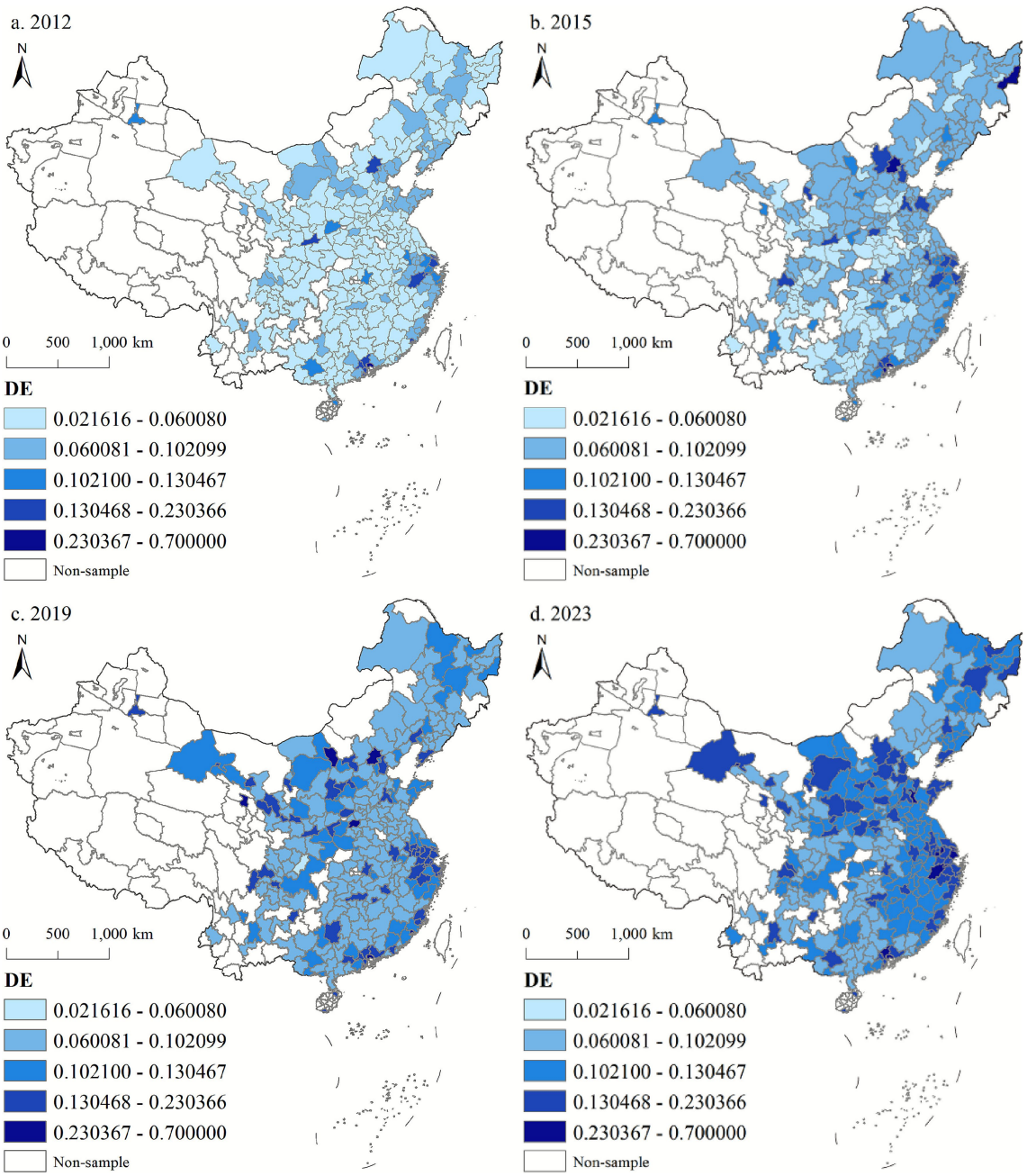

FIGURE 3
Spatial distribution of the level of DE development in Chinese cities (2012, 2015, 2019, 2023).

The findings in Table 8 indicate that the DE has a promotional effect on IAUR in both central and peripheral cities. However, the effect is more pronounced in central cities. This may be attributed to the fact that central cities benefit from stronger policy support, more concentrated human and technological resources, and enhanced factor agglomeration effects. These conditions amplify the scale effects of the DE, thereby accelerating its integration into real economic systems and promoting IAUR. By contrast, while peripheral cities also benefit from DE, their industrial structure, factor agglomeration, and investment in digital infrastructure generally lag behind those of central cities. Furthermore, they face persistent bottlenecks in policy access, talent attraction, and the provision of public services. Consequently, the efficiency with which the DE promotes IAUR is, to some extent, diminished. In contrast, while the DE also positively influences peripheral cities, its impact is relatively weaker. This suggests that there remains considerable untapped potential in these areas.

4.5.3 DE development level

To investigate the heterogeneity in the effect of the DE across cities with different development levels, we classify the 275 cities into two groups based on their 2023 DE development index scores. Cities with scores above the mean are classified as high-development cities, while those below the mean are classified as low-development cities. The grouped regression results are presented in Table 9.

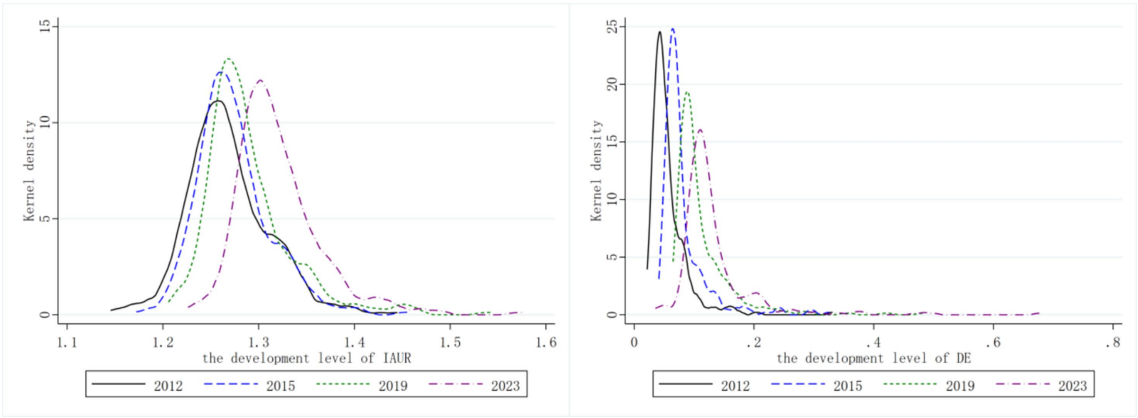

FIGURE 4
Kernel density of the development level of IUAR and DE in Chinese cities.

TABLE 4 Benchmark regression results.

Variables	(1)	(2)	(3)	(4)
	FE	RE	FE	RE
DED	0.0503*** (3.2972)	0.0890*** (4.6795)	0.0424*** (2.8166)	0.0769*** (3.8611)
Govint			−0.0181*** (−6.2647)	−0.0239*** (−8.9864)
Envir			0.0030 (0.4728)	0.0056 (0.8773)
Fina			0.0003 (0.2249)	0.0012 (1.0098)
Open			−0.0004 (−0.3826)	0.0036*** (3.3522)
Constant	1.2652*** (891.9602)	1.2630*** (473.9609)	1.3166*** (135.0286)	1.3198*** (147.0749)
City	YES	NO	YES	NO
Year	YES	NO	YES	NO
Hausman	$chi^2(2) = 366.37$		$chi^2(6) = 353.27$	
Test	0.0000		0.0000	
Obs	3,300	3,300	3,300	3,300
R^2	0.692	0.690	0.706	0.700

***, ** and * indicate significance at the 1, 5 and 10% levels, respectively; *t*-statistics in parentheses. Posterior tables are the same.

The findings reveal that the DE exerts a positive impact on IAUR in both high-development and low-development cities. The marginal effect is slightly greater in cities with lower levels of DE development. The possible explanation is that in these low-development cities, traditional economic structures are generally less integrated with digital technologies. As a result, the initial introduction of the DE mainly manifested itself in improvements to digital infrastructure, which can yield immediate and substantial gains in production efficiency, reduce information exchange costs, and enhance the connectivity of urban and rural resource flows. These transformations allow the DE to generate a more pronounced catalytic effect on IAUR in low-development cities.

TABLE 5 Dimensional regression results.

Variables	(1)	(2)	(3)
	Industrial-agricultural mutual promotion	Urban–rural mutual compensation	Mutual prosperity
DED	0.0118** (2.0577)	0.0045 (1.2529)	0.0261** (2.1409)
Control	YES	YES	YES
Constant	0.2731*** (51.0558)	0.2704*** (80.4032)	0.7732*** (97.3215)
City	YES	YES	YES
Year	YES	YES	YES
Obs	3,300	3,300	3,300
R^2	0.057	0.737	0.599

5 Extension analysis

5.1 Analysis of threshold effects

To investigate whether the impact of the DE on IAUR exhibits non-linear characteristics, DFI and DDI are selected as threshold variables to construct the threshold effect model as shown in Equation (2). Based on 300 bootstrap replications, the threshold test results presented in Table 10 indicate that both the single and double thresholds for DFI and DDI are significant at the 1% level. The estimated first and second threshold values for DFI are 140.760 and 247.520, respectively. For DDI, the first threshold value is 0.4099, and the second is 2.8981.

The results in Columns (1) of Table 11 indicate that, when the DFI score is below 140.760, the DE exerts a negative effect on IAUR. This suggests that in the early stage of DFI, the high cost of digital access in rural areas, combined with a risk-averse allocation of limited digital financial resources toward more developed urban regions, prevents rural economic agents from effectively participating in the DE. As a result, the urban–rural element misallocation may be exacerbated. When the DFI score falls between 140.760 and 247.520,

TABLE 6 Robustness and endogeneity tests results.

Variables	(1)	(2)	(3)	(4)	
	Replacement of core explanatory variables	Exclusion of important cities	Winsor	IV	
				Phase I	Phase II
DED	0.0001* (1.7911)	0.0298* (1.7011)	0.0524** (2.5099)		0.7549*** (5.1100)
IV				0.0919** (2.0390)	
Control	YES	YES	YES	YES	YES
Constant	1.3066*** (106.6960)	1.3089*** (133.2453)	1.3165*** (132.6718)	0.0175* (1.7797)	1.2991*** (164.0142)
City	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES
Kleibergen–Paap rk LM					21.028 [0.000]
Cragg–Donald Wald *F*					151.761 {16.38}
Obs	3,300	2,904	3,300	2,676	2,676
R^2	0.704	0.711	0.705		0.547

p-values for non-identifiable tests are in middle brackets, and Stock Yogo thresholds at the 10% level for tests of weak IV are in large brackets.

TABLE 7 Heterogeneity analysis by geographical location.

Variables	(1)	(2)	(3)	(4)
	Eastern regions	Middle regions	Western regions	Northeastern regions
DED	0.0391** (2.4722)	0.0948** (2.4670)	0.0281 (1.3183)	0.0332 (0.4828)
Control	YES	YES	YES	YES
Constant	1.3626*** (50.4140)	1.2761*** (66.3559)	1.2890*** (82.4979)	1.3562*** (58.9270)
City	YES	YES	YES	YES
Year	YES	YES	YES	YES
Obs	1,020	936	936	408
R^2	0.719	0.762	0.731	0.651

TABLE 8 Heterogeneity analysis by city administrative hierarchy.

Variables	(1)	(2)
	Central cities	Peripheral cities
DED	0.0528** (2.1283)	0.0298* (1.7011)
Control	YES	YES
Constant	1.3688*** (36.9741)	1.3089*** (133.2453)
City	YES	YES
Year	YES	YES
Obs	396	2,904
R^2	0.734	0.711

the effect of the DE on IAUR is statistically insignificant. Although DFI improves coverage during this phase, the marginal return on digital investment remains low, and a critical mass has yet to be reached to generate scale effects. Only when the DFI score exceeds 247.520 does the DE show a significantly positive effect on IAUR. At this stage, each one-unit increase in the DE index is associated with a 0.189-unit increase in the level of IAUR. This indicates the emergence of network externalities, where the DE begins to unlock its potential, substantially enhancing its marginal contribution to IAUR.

The results in Column (2) of Table 11 present regression estimates using DDI as the threshold variable. DDI is negatively defined by a composite index constructed through principal component analysis, incorporating the proportion of administrative villages with broadband internet access and the number of Taobao villages. This index captures both the extent of digital infrastructure coverage and the degree of digital application in rural areas. The findings reveal that the DE exerts a pronounced non-linear influence on IAUR across different stages of the DDI. Below the first threshold value, DE has a significantly positive effect on IAUR, with a coefficient of 0.2277, significant at the 1% level. This suggests that DE maintains a positive impact even under conditions of weak digital infrastructure and limited rural e-commerce adoption. As the DDI narrows beyond the first threshold, the estimated coefficient increases further to 0.2814, indicating an enhanced promotional effect. With rising broadband coverage in rural areas and the emergence of e-commerce industries such as Taobao Villages, the scale effects of DE progressively accumulate, resulting in a more pronounced boost to IAUR. When the DDI exceeds the second threshold, which corresponds to the most advanced stage of digital infrastructure development, the estimated promotional coefficient of DE increases to 0.3514. At this stage, rural areas possess relatively comprehensive digital infrastructure and mature capabilities in the application of digital technologies, enabling the full realization of DE's externalities. Its marginal effect on promoting IAUR becomes most significant. Based on this result, H2 is supported.

5.2 Analysis of spatial effects

This study calculates Moran's I for the DE and IAUR from 2012 to 2023 using an economic distance matrix. As reported in Table 12, Moran's I values for both IAUR and DE are significantly positive at the 1% level in all years, indicating strong spatial autocorrelation. This result is consistent with the theoretical arguments in Section 2.3, which emphasize regional clustering of digital development and spatial dependence in industrial–agricultural and urban–rural relations. The observed spatial clustering suggests that cities with similar levels of digital development and IAUR tend to agglomerate geographically, providing an empirical foundation for analyzing spatial spillover effects.

To determine the most appropriate spatial model, this study sequentially performs a series of diagnostic tests based on the economic distance matrix, including the LM-lag, Robust LM-lag, LM-error, and Robust LM-error tests. The results show that all four tests pass the significance threshold, providing initial evidence in support of employing a spatial Durbin model (SDM). Further, based on the results of the Hausman test and likelihood ratio (LR) test, we select a spatial–temporal double fixed effects SDM, and formally reject model simplifications into either the spatial autoregressive model (SAR) or the spatial error model (SEM). To validate the robustness of this model selection, the panel data are re-evaluated using the same set of diagnostic tests under a geographic distance matrix. The results are consistent, reaffirming the SDM as the most appropriate specification. Therefore, we adopt the SDM as shown in Equation (3) to explore the spatial effects of the DE on IAUR.

As shown in Table 13, regression results under both economic distance and geographic distance matrices indicate that the coefficients of the DE variable and the spatial autoregressive term are significantly positive. These findings suggest that improvements in the digital economy promote IAUR both locally and in spatially connected regions. From a theoretical perspective, this result supports the argument that the clustering of digital resources and the formation of regional "DE highlands" generate spillover effects that extend beyond administrative boundaries, thereby reshaping industrial–agricultural and urban–rural dynamics at a broader spatial scale.

To further clarify the underlying spatial mechanisms, the estimated coefficients are decomposed into direct, indirect, and total effects. The results show that both the direct and indirect effects of the digital economy on IAUR are significantly positive. The direct effect reflects the local mechanism emphasized in Section 2.3; whereby digital technologies enhance factor matching efficiency, reduce transaction costs, and facilitate industrial–agricultural integration within a region. The indirect effect captures the spatial spillover mechanism, indicating that digital development in one region positively affects IAUR in neighboring areas through channels such as factor mobility, digital diffusion, and institutional convergence. These empirical findings provide strong support for Hypothesis 3.

TABLE 9 Heterogeneity analysis by DE development level.

Variables	(1)	(2)
	High-development cities	Low-development cities
DED	0.0297** (2.0043)	0.0677** (2.0425)
Control	YES	YES
Constant	1.3633*** (59.4824)	1.3007*** (122.1669)
City	YES	YES
Year	YES	YES
Obs	972	2,328
R^2	0.705	0.718

6 Conclusion and discussion

Based on panel data from 275 Chinese prefecture-level cities spanning 2012 to 2023, we constructed measurement indicators for DE and IAUR, and characterized their spatial–temporal evolution. On this basis, we empirically analyze the impact and spatial effects of the DE on IAUR. The following conclusions are reached: firstly, both the DE and IAUR in China have shown rapid development over the study period, with significant spatial differentiation persisting. Secondly, the DE has a significant positive effect on IAUR. However, this effect exhibits regional heterogeneity: it is more evident in eastern and middle regions, in central cities with higher administrative status, and in cities with lower DE development level. Thirdly, the impact of DE on IAUR demonstrates a dynamic non-linear pattern characterized by increasing marginal effects, with DFI and DDI serving as dual thresholds. Specifically, once DFI exceeds the second threshold, the DE exerts a significantly positive promoting effect. Regardless of the level of DDI, the DE consistently produces positive outcomes; however, as DDI declines, these positive effects become increasingly pronounced. Fourthly, there is a clear spatial dependence between the DE and the development of IAUR. Not only does the DE significantly enhance local development, but it also generates positive spatial spillover effects, promoting the advancement of IAUR in neighboring cities.

The findings of this study offer important implications for policy design. Rather than uniformly expanding digital development, policies should emphasize the effective integration of digital technologies into industrial systems and urban–rural structures. Promoting digital

TABLE 10 Threshold interval test results.

Variables	Threshold	Threshold value	*F*-value	*P*-value	Critical value		
					10%	5%	1%
DFI	Single threshold	140.760	480.70	0.0000	78.3529	86.3636	104.7574
	Double threshold	247.520	162.48	0.0000	37.7934	42.9239	55.5793
DDI	Single threshold	0.4099	91.42	0.0000	30.1654	33.2739	42.3687
	Double threshold	2.8981	33.33	0.0033	18.0671	22.8542	30.3558

TABLE 11 Threshold effects regression results.

Variables	(1)	(2)
	DFI	*DDI*
$DED \cdot I(q \le \gamma_1)$	−0.0966** (−2.2228)	0.2277*** (7.7784)
$DED \cdot I(\gamma_1 < q \le \gamma_2)$	0.0474 (1.4934)	0.2814*** (9.1456)
$DED \cdot I(q > \gamma_2)$	0.1890*** (6.3265)	0.3514*** (12.0509)
Control	YES	YES
Obs	3,300	3,300
R^2	0.556	0.477

TABLE 12 Global Moran's *I* of the IAUR and DE, 2012–2023.

Year	IAUR		DE	
	Moran's *I*	*Z*-value	Moran's *I*	*Z*-value
2012	0.313***	10.603	0.259***	9.154
2013	0.362***	12.257	0.236***	8.259
2014	0.338***	11.444	0.258***	8.922
2015	0.375***	12.701	0.246***	8.534
2016	0.399***	13.509	0.268***	9.318
2017	0.394***	13.358	0.290***	10.146
2018	0.403***	13.646	0.271***	9.414
2019	0.393***	13.381	0.197***	6.926
2020	0.374***	12.738	0.259***	8.926
2021	0.374***	12.737	0.179***	6.39
2022	0.365***	12.439	0.280***	9.675
2023	0.343***	11.667	0.186***	6.645

applications that enhance production efficiency and extend value chains can facilitate deeper industrial integration and improve regional connectivity. At the same time, digital platforms can play an important role in improving access to public services, thereby contributing to better living conditions and advancing common prosperity.

Policy design should also account for regional heterogeneity in digital foundations and development stages. In regions with relatively weak digital development, priority should be given to strengthening digital infrastructure, improving digital literacy, and encouraging the adoption of digital technologies in both agricultural and non-agricultural sectors. Expanding access to digital financial services in these areas can help activate local economic potential. In more developed regions, policy efforts should shift toward addressing intra-regional disparities by narrowing the digital divide, optimizing urban–rural resource allocation, and fostering innovation capacity to support digital industrial upgrading.

Furthermore, greater emphasis should be placed on cross-regional coordination. Given the presence of spatial spillover effects, enhancing interregional cooperation can help diffuse digital innovations, promote policy alignment, and mitigate persistent spatial disparities. Leveraging technological advantages in more advanced regions while supporting adaptive development in less developed areas can contribute to more inclusive and balanced regional development.

TABLE 13 SDM regression results and effects decomposition.

Variables	(1)	(2)
	Economic distance matrix	Geographic distance matrix
DED	0.0409*** (0.000)	0.0391*** (0.000)
Control	YES	YES
Direct effect	0.0418*** (0.000)	0.0424*** (0.000)
Indirect effect	0.0458* (0.082)	0.8406* (0.089)
Aggregate effect	0.0876*** (0.002)	0.8829* (0.076)
rho	0.1047*** (0.003)	0.7294*** (0.000)
sigma2_e	0.0001*** (0.000)	0.0001*** (0.000)
Obs	3,300	3,300
R^2	0.167	0.371

p-values are in parentheses.

Despite these contributions, several limitations remain. Owing to data constraints, the indicators used to measure the digital economy and its sub-dimensions may not fully capture the rapid evolution of digital technologies or the diversity of application scenarios. Future research could employ more granular digital indicators to better reflect the dynamic nature of digital development. In addition, the analysis of spatial effects in this study focuses primarily on basic spatial interaction patterns. Incorporating advanced approaches such as complex network analysis and multi-scale spatial correlation methods would allow for a deeper examination of cross-regional diffusion mechanisms and enhance the robustness and generalizability of future findings.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

PL: Writing – review & editing. WT: Writing – original draft. YS: Writing – review & editing. LL: Writing – review & editing, Software.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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