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Digital economy and the urban–rural income gap: Impact, mechanisms, and spatial heterogeneity

He Xia[a,1], Haijing Yu[b,1], Senhao Wang[a], Hong Yang[a,*]

[a] College of Economics and Management, Xinjiang Agricultural University, Urumqi, China
[b] Business School, Xiangtan University, Xiangtan, Hunan, China

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ABSTRACT

This study examines how digital economy development in China impacts the urban–rural income gap. We construct a digital economy development index using panel data from 30 provinces and cities in China from 2013 to 2021. By combining a spatially varying coefficient model with a chain–mediated effect model, we quantify the impact of digital economy on the urban–rural income gap and examine its spatial heterogeneity. The results show that the digital economy influences the urban–rural income gap through four different pathways, each of which exhibits significant spatial variation. As these paths offset each other, the digital economy development in Beijing, Inner Mongolia, Shanxi, Henan, Hubei, Jiangxi, Jiangsu, Guangdong, and other provinces has widened the urban–rural income gap, resulting in a digital divide effect. However, in most areas of China's northeast, east coast, and western regions, the digital economy development has narrowed the income gap, resulting in a digital dividend effect. This study investigates the relevant debates among scholars and provides valuable insights and foundations for strategic decision making to reduce the urban–rural income gap in various regions.

Introduction

With changes in major social contradictions, the issue of imbalanced and insufficient development has become the main factor restricting people's growing need for a better life. Among these issues, the urban–rural income gap remains severe (Zhu & Liu, 2022). Although the income gap between urban and rural areas in China narrowed over the past decade, it remains much higher than the international average (Yuan et al., 2020; Sicular et al., 2007). In 2023, the per capita disposable income of urban households in China was 51,800 yuan, whereas the per capita disposable income of rural residents was only 21,700 yuan, much lower than that of urban residents. Narrowing the urban–rural income gap and promoting coordinated development between urban and rural areas as well as developed and underdeveloped areas can promote social stability, reduce social inequality, improve people's living standards, and promote the economic prosperity of the entire country (Wen et al., 2014).

Simultaneously, China's policies to promote digital transformation and digital economy development are continuously deepening. The nation's digital economy development has had a strong influence on a global scale (Li et al., 2020; Murthy et al., 2021), becoming a new driving force for promoting urban–rural development (Zhao et al., 2023). However, this has established development gaps between urban and rural areas due to technological iterations and differing growth effects, affecting urban and rural residents' income distribution patterns. The digital divide can result in income disparities between regions and groups (Qiu et al., 2021; Yin et al., 2021), and controversy exists concerning the impact of digital technology on rural development (Erdiaw–Kwasie & Alam, 2016), raising the question of whether digital economy development bridges or expands urban–rural income inequality (Peng & Dan, 2023). Therefore, it is essential to investigate whether digital economy development can effectively narrow the urban–rural income gap and its impact path. This study has important practical significance for developing strategically targeted policies to narrow the income gap between urban and rural residents and advance common prosperity.

Currently, research on the impact of digital economy on the urban–rural income gap has been increasing and enriching the literature. Although scholars have reached a consensus on the perspective that digital economy development can raise incomes, differences remain

* Corresponding author at: 311 Nongda East Road, Shayibak District, Urumqi City, Xinjiang Uygur Autonomous Region, China.
E-mail address: xjauyh@xjau.edu.cn (H. Yang).
[1] These authors contributed equally to this work.

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regarding the relationship between digital economy development and the urban−rural income gap, which can be summarized into three categories: the digital economy expands and shrinks urban −rural income; the relationship between the two is nonlinear, exhibiting a U-shaped relationship of first shrinking and then expanding; or the relationship has an inverted U-shaped trend of first increasing and then decreasing (Li & Li, 2022a; Yu, 2022; Fan et al., 2022; Si & Li, 2023). This controversy is attributed to incomplete research on the mechanisms of impact of digital economy development on the urban −rural income gap. A majority of studies have neglected to consider regional heterogeneity (Wang & Xiao, 2021). Furthermore, traditional regression analysis methods generally assume that individuals are independent and identically distributed, when, in reality, digital economy development and urban−rural income gaps have spatial autocorrelation. Currently, research on the impact of digital economy on urban−rural income inequality is limited.

To compensate for this deficiency, the main contributions of this study are as follows. First, in contrast to previous studies, we adopt a new variable coefficient spatial Durbin model (MGWPR−SDM) proposed by Yu et al. (2021), which relaxes the traditional implicit assumptions of independent homogeneous distribution and all regions being equal and can simultaneously consider spatial correlation and heterogeneity to reflect the actual impact of digital economy on the urban−rural income gap more accurately. Second, previous research has largely ignored the relationships between mediating variables and does not consider spatial heterogeneity, which can reduce the credibility of the conclusions obtained by producing biased and inconsistent results. This study broadens the scope of policy recommendations by including these considerations. We embed the MGWPR−SDM into a chain−mediating effect model to examine the impact mechanisms and spatial heterogeneity of digital economy development on the urban−rural income gap, effectively addressing this issue. Third, this study responds to the current academic debates and enriches the research on the impact of digital economy development on the urban−rural income gap, providing a theoretical reference for relevant government departments to develop strategically targeted policies to narrow the urban−rural income gap that consider local conditions. Therefore, this study has academic and practical significance.

The remainder of the paper is structured as follows. The second part presents the theoretical mechanism and research hypotheses based on the review of relevant literature, and the controversies and shortcomings of relevant research viewpoints are summarized. The third part is model construction, which mainly introduces the process of embedding the MGWPR-SDM into the chain−mediated effect model. The fourth part is about variable selection and data description, which introduces the selection of variables and data description. Among them, we calculate the level of digital economy development in various regions by constructing a digital economy development index system. The fifth part is empirical result analysis, which displays spatial heterogeneity results through maps. The last part is the conclusion and policy implications.

Theoretical analysis and research hypotheses

The digital economy is a new form of the economy that emerged with the development and application of digital technology. In 1996, Don Tapscott, the father of the digital economy, first proposed the concept of "digital economy" (Tapscott, 1996). The official interpretation of the digital economy in China can be traced back to 2016 when the G20 Hangzhou Summit passed the G20 Digital Economy Development and Cooperation Initiative, providing a clear definition of the digital economy. The digital economy refers to the use of digital knowledge and information as key production factors, a series of economic activities that use modern information networks as an important carrier, and the effective use of information and communication technology as an important driving force for efficiency improvement. Economic structure optimization has been widely recognized by various sectors of society.

Impact of digital economy on the urban−rural income gap

Currently, no consensus has emerged in the academic community regarding the impact of digital economy development on the urban −rural income gap. As briefly described above, the research conclusions can be roughly divided into three categories.

(1) Research on the expanding effect of the digital economy on the urban−rural income gap. Furuholt and Kristiansen (2007) emphasized that the digital economy, which is characterized by the internet, big data, artificial intelligence, and other forms, may result in imbalanced development between urban and rural areas, resulting in a digital divide (Lorence et al., 2006), which is unfavorable for low−income rural populations (Gorski & Clark, 2002). Tan et al. (2017) argued that a gap is evident between urban and rural residents in digital economy acceptance and application. Rural residents have limited resources, education, and business environments than urban residents (He & Xu, 2019). Furthermore, rural residents cannot identify and use information effectively or fully enjoy the advantages of internet diffusion (Lv, 2021). In contrast, urban residents are in a position of information advantage and can more conveniently access and use digital information through the internet. Furthermore, urban residents' digital awareness and capabilities are continuously enhanced, which ultimately widens urban−rural wealth disparities, particularly income (Li & Ke, 2021). This viewpoint highlights the possibility that the digital economy may widen the income gap between urban and rural areas, reminding policymakers to pay attention to the potential inequality issues. However, this viewpoint may be too pessimistic and may overlook some of the positive impacts of the digital economy.
(2) Research on the reduction effect of digital economy on the urban −rural income gap. This perspective argues that digital economy development contributes to narrowing the urban−rural income gap. Some scholars have demonstrated that the digital economy can increase farmers' income and narrow the urban−rural income gap (Bhavnani et al., 2008; Aker & Dial, 2011). Acemoglu and Restrepo (2016) proposed that digital technologies such as the internet break down spatiotemporal barriers, providing laborers with more employment choices and enhancing market resource allocation efficiency. Liu et al. (2021) argued that digital economy development has facilitated significant achievements worldwide, improving impoverished population's living conditions. Moreover, the digital economy has been found to directly reduce the urban−rural income gap (Liu, 2021). Digital economy development can leverage inclusiveness and resource sharing through deep integration of production, life, and ecology (Fu, 2020). The digital economy functions as an endogenous driving force that overcomes geographical constraints, eliminates information barriers, expands employment opportunities, and advances growth in underdeveloped regions. It also drives optimized factor allocation, promotes the division of labor and collaboration, improves labor productivity, enhances economies of scale, and facilitates coordinated regional development (Duan et al., 2020; Hu et al., 2017; Song, 2012). This viewpoint emphasizes that the digital economy may provide opportunities for narrowing the urban −rural income gap and a possible way to achieve income balance. It can motivate governments and enterprises to increase their investment in related fields and promote the coordinated development of urban and rural economies. However, this viewpoint may be too idealistic, ignoring the new inequality issues that the

development of the digital economy may bring; it may also overlook the complex and diverse impact of the digital economy on different regions and populations, which may not directly lead to the narrowing of the urban−rural income gap.

(3) Research on the nonlinear effect of the digital economy on the urban−rural income gap. A nonlinear relationship exists between digital economy development and the urban−rural income gap. Ashraf et al.(2021) argued that as information and communications technology (ICT) is promoted and adopted, income inequality decreases over time. Jiang et al. (2022) revealed a U-shaped relationship between the digital economy and the urban−rural income gap, with the gap narrowing in early stages and widening in later stages. Zheng and Li (2022) proposed that the impact of digital economy on the urban−rural income gap can have simultaneous expanding and narrowing effects, and the overall impact depends on the relative magnitude of these effects. Considering that the digital economy and the urban−rural digital divide are in a continuous dynamic development process, their relationship is likely to exhibit time−varying characteristics, exhibiting a complex nonlinear relationship. Wang and Xiao (2021) found that the development of the digital economy has a U-shaped relationship with the urban−rural income gap, initially narrowing and then widening. A similar perspective was presented by Chen and Wu (2021), who proposed that while the initial stages of digital economy development can promote urbanization and narrow the urban−rural income gap, further development and the resulting digital divide negatively impact rural surplus labor migrating to cities for employment, widening the urban−rural income gap. Conversely, Li and Li (2022a), and Cheng and Zhang (2019) opined that the impact of digital economy on the urban−rural income gap shows an overall inverted U-shaped trend, with an initial increase and subsequent decrease. They proposed that in the initial stage of digital economy development, due to the disparity in human capital and the existence of the digital divide between urban and rural areas, rural residents cannot fully utilize digital economy resources to increase their income compared to urban residents, resulting in an expanding urban−rural income gap. However, later on, due to the law of diminishing marginal utility, the marginal impact of urban digital economy development on income will gradually be surpassed by rural "latecomers", leading to a narrowing of the urban−rural income gap. Supporting this view, Li and Li (2022b) argued that the impact of digital economy development on the urban−rural income gap follows an inverted U-shaped pattern, and a threshold effect exists in the relationship between digital economy development and the urban−rural income gap. This view is closer to reality, recognizing that the impact of digital economy on urban and rural incomes is complex and varied, not single−linear, and may show different stages of changing trends. However, grasping the specific pattern of nonlinear relationships accurately is difficult, and more empirical research and data support are required.

The divergent findings of the aforementioned studies can be attributed to three main reasons. First, the impact of digital economy development on the urban−rural income gap exhibits spatial heterogeneity, while existing research models often assume a mean regression, assuming that the impact coefficients are the same for all regions. For example, Wang and Xiao (2021) studied 30 provinces in China from 2013 to 2019 and found that the impact of digital economy development on narrowing the urban−rural income gap was mainly concentrated in the central and western regions, with a slight widening effect in the eastern region and unclear effects in the northeastern region. Second, traditional econometric models assume that research subjects are independently and identically distributed, but the levels of digital economy development and the urban−rural income gap in different regions may exhibit spatial spillover effects, violating this assumption. The development of the digital economy and the urban−rural income gap in each province, city, and autonomous region is not only influenced by local factors but also interacts with the development of the digital economy or the urban−rural income gap in neighboring regions. Several studies have demonstrated spatial autocorrelation (Si & Li, 2023; Wei & Chen, 2020), indicating the need to use spatial econometric models instead of traditional regression models. Third, most studies only consider the direct impact of digital economy development on the urban−rural income gap, with less consideration of its indirect effects; even fewer studies involve the spatial heterogeneity of these indirect effects. If the directions of the direct and indirect effects are opposite, the overall effect after aggregation is uncertain.

In summary, a comprehensive understanding of the impact of digital economy development on the urban−rural income gap requires simultaneous consideration of spatial correlation, spatial heterogeneity, and direct and indirect effects. However, limited studies have taken this approach. Therefore, this study proposes the following hypothesis:

H1. The influence of the digital economy on the income gap between urban and rural areas is spatially heterogeneous, and the influence in different regions has expanding, narrowing, or uncertain relationships.

Impact mechanisms of the digital economy on the urban−rural income gap

Digital economy, human capital, and the urban−rural income gap

Contemporary rapid digital economy development, represented by the mobile internet, and the role of internet and ICT development in correcting resource misallocation, expanding rural residents' access to information channels, and enhancing rural residents' human capital has been confirmed by a growing number of scholars. Knowledge and information are non−competitive, and the establishment and improvement of digital infrastructure exposes the rural population to high−quality online education. The rural labor force can access a wealth of information and knowledge through the internet, which can improve the breadth and depth of the rural knowledge base, enhancing rural residents' human capital (Zhu & Liu, 2022; Mi & Qu, 2022) and improving rural residents' ability to increase incomes, effectively bridging the urban−rural income gap (Li & Li, 2022a; Jin & Deng, 2022; Xu & Feng, 2022). Conversely, some scholars have argued that the increasing coverage and depth of the digital economy generates new employment opportunities that favor knowledge-based talent, placing higher demand on human capital. Non-agricultural employees may encounter structural unemployment risks, further widening the urban−rural income gap (Fan et al., 2022).

Additionally, studies have shown that primary rural human capital is mostly concentrated in western provinces, whereas intermediate rural human capital is mostly concentrated in provinces with relatively developed modern agriculture. Areas with high concentrations of advanced rural human capital have experienced a dynamic shift from the Northeast region to the Yangtze River Delta region (Yao & Deng, 2020). Fan and Cui (2018) showed that human capital has regional heterogeneity in its impact on the urban−rural income gap; an increase in the proportion of high−skilled human capital widens the urban−rural income gap in the eastern and central regions, while effectively narrowing the urban−rural income gap in the western regions.

In summary, although a debate remains, the internet and other digital technologies are important influencing factors in improving human capital, which is a key factor of the urban−rural income gap (Song & Gao, 2022). Rural human capital has a significant moderating role in the impact of digital economy development on the urban–rural income gap (Xu et al., 2023). Furthermore, Li and Zhang (2024) pointed out that the upgrading of human capital structure can narrow the income gap between urban and rural areas. Therefore, ample evidence has suggested that the digital economy affects the urban–rural income gap by influencing human capital development. Considering this mediating effect, we propose the following hypothesis:

H2. Human capital development mediates the impact of digital economy on the urban–rural income gap, affecting the income gap through human capital and exhibiting spatial heterogeneity.

Digital economy, industrial structure, and the urban–rural income gap

From the impact mechanism perspective, the digital economy gives rise to new economic models, production factors, and technological support for industrial upgrades (Jing & Sun, 2019). It reduces information asymmetry and transaction costs (Liu et al., 2023), strengthens industrial links, promotes industrial integration, and establishes a cooperative and mutually beneficial industrial ecosystem (Hui & Yang, 2022). The digital economy can effectively optimize the tertiary industries in the national economy and coordination between industries, significantly promoting industrial structure rationalization (Liu & Chen, 2021), while also exhibiting obvious regional heterogeneity (Gao et al., 2023).

The digital economy development has significantly promoted the upgrading of industrial structure (Liu & Chen, 2021), and exhibits regional heterogeneity, with a more pronounced effect on the upgrading of industrial structure in the central and western regions (Wang, 2023). An optimized industrial structure can narrow the urban–rural income gap by absorbing the rural labor force (Zhou & Wang, 2013). However, some scholars argue conversely, suggesting that because of enormous scientific research and innovation activities in cities, digital technology continues to penetrate secondary and modern service industries, greatly improving their production efficiency. For cities with the main industrial structure of the second and third industries, the urban income level will also increase, which may lead to further expansion of the urban–rural income gap (Yu, 2022). Some scholars also argue that the impact of industrial structure upgrading on the urban–rural income gap exhibits a U-shaped characteristic, but in the eastern region, there is a tendency to widen the urban–rural income gap, while in the western region, it is beneficial to narrow the urban–rural income gap, while in the central region, it is generally located near the transition point (Xu & Liu, 2015).

Previous research has widely recognized that the digital economy can affect the urban–rural income gap by altering the industrial structure; therefore, this study proposes the following hypothesis concerning this mediating effect:

H3. The industrial structure mediates the impact of digital economy on the urban–rural income gap; however, the spatial impact of the digital economy on the income gap is uncertain.

Model construction

The baseline and mediation effect models in this study are based on the Mixed Geographically Weighted Panel Regression model (MGWPR–SDM) proposed by Yu et al. (2021). This model combines the advantages of the semiparametric spatially varying coefficient Geographically Weighted Panel Regression model (MGWPR) and the Spatial Durbin Model (SDM). Whereas, the MGWPR–SDM is a generalized model that can be degenerated into various spatially varying coefficient panel models, such as Spatial Autoregressive (SAR) and Spatial Error models (SEM), to meet different research needs. However, this model is an improvement over traditional regression and spatial econometric models. Classic spatial econometric models, such as the SDM, only consider the spatial correlation of variables and add spatial lag terms of dependent and independent variables as explanatory variables. However, they believe that the coefficients between each region are equal, ignoring spatial heterogeneity. Geographically Weighted Regression (GWR) models focus on spatial heterogeneity and neglect spatial stationarity and correlations. The MGWPR–SDM used in this study combines the advantages of the classical SDM and GWR class models while considering spatial stationarity, spatial correlation, and spatial heterogeneity (Yu & Zhu, 2023).

Spatial weight matrix

The spatial weight matrix is not only the biggest difference between spatial econometric models and traditional mean reversion models but also a key factor in geographically weighted regression and its extension models. In both models, spatial weights are used to represent the interdependence between individuals or regions, which requires a uniform spatial weight setting.

Unlike previous spatial weight settings, this study draws on the concept of gravitational potential to construct an asymmetric spatial weight matrix that incorporates geographical and economic distances. Potential gravitational energy ($F = G\frac{m_i \cdot m_j}{d_{ij}}$) is used to express the mutual gravitational force between two objects, where F is the value of the potential gravitational energy between the two objects, G is a gravitational constant value of $6.67 \times 10 - 11Nm^2/kg^2$, m_i and m_j denote the masses of objects i and j, respectively, and d_{ij} is the distance between the central mass of the two objects. If the numerator is replaced by an economic total of the two regions, it combines economic and geographical distance. Using this approach to construct a spatial weight matrix is more accurate than only using economic or geographical distances. However, the spatial weight matrix is symmetric, and the mutual influence between the two regions is the same, which obviously does not conform to reality. In reality, the impact of regions with large economic output on regions with small economic output is greater than that of regions with small economic output on regions with large economic output. Therefore, we reference Newey and Powell (1987), constructing asymmetric least-squares estimators, rewriting the potential gravitational energy formula, and establishing an asymmetric spatial weight. The specific forms are as follows:

$$w_{ij} = \left|\omega - \mathbb{I}_{(\bar{m_i} > \bar{m_j})}\right| \cdot \frac{m_{it} \cdot m_{jt}}{d_{ij}} \tag{1}$$

where w_{ij} is the influence of spatial unit j on i at time t in the i th row of the spatial weight matrix. To maintain generality, the constant G in the original potential gravitational energy formula is set to 1. $|\omega - \mathbb{I}_{(\bar{m_i} > \bar{m_j})}|$ can be called the asymmetric coefficient, where $\omega = \max(\bar{m_i}, \bar{m_j})/(\bar{m_i} + \bar{m_j})$, and $\bar{m_i}$ and $\bar{m_j}$ respectively represent the means of m_i and m_j over the entire time interval. $\mathbb{I}_{(\bar{m_i} > \bar{m_j})}$ for an indicative function, when the index condition is met, the value of the function is 1, otherwise it is 0.

Verifying the superiority of the asymmetric potential gravitational energy spatial weight proposed in this study requires comparison with traditional spatial weights constructed based on the reciprocal of economic distance $(1/|m_i - m_j|)$ and geographical distance $(1/d_{ij})$. Table 1 estimates the values of the Akaike information criterion (AIC) and Bayesian information criterion (BIC) corresponding to the three weights based on the direct effects model in Eq. (2). The results reveal that the AIC and BIC values of the asymmetric potential gravitational energy spatial weight are the smallest, indicating that they are superior to the traditional spatial weight matrix constructed based on geographic and economic distances.

Table 1
Comparison of fitting effects of three weight matrices.

	W_{grav}	W_{dist}	W_{econ}
AIC	11,712.28	12,624.54	12,292.91
BIC	30,312.52	31,224.78	30,893.15

Notes: W_{grav} represents the asymmetric gravitational potential energy spatial weight matrix proposed in this article, W_{dist} and W_{econ} represent spatial weight matrices constructed based on geographic distance and economic distance, respectively.

Direct effects model

According to the MGWPR−SDM, we construct the following global smooth SDM:

$$Gap_{it} = \alpha_0 + \rho_1 WGap_{it} + \alpha_1 Digi_{it} + \sum_k \alpha_k X_{k,it} + \sum_r \lambda_r C_{r,it} + \sum_q \theta_q WX_{q,it} + u_i + \nu_t + \varepsilon_{it} (\text{K}\geq 2) \quad (2)$$

where Gap_{it} represents the urban−rural income gap, $WGap_{it}$ represents the spatial lag terms of the dependent variable. $Digi_{it}$ represents digital economy development, X_k represents the *k-th* mediating variable, and C_r represents the *r-th* control variable. The corresponding coefficients for mediating and control variables are α_k and λ_r, respectively; WX_q represents the spatial lag terms of the explanatory variables, including core, mediating, and control variables; therefore, $q = k + r + 1$. θ_q represents the coefficient of the spatial lag term of the *q-th* explanatory variable, u_i represents provincial fixed effects, ν_t represents year fixed effects, and ε_{it} represents the randomized perturbation term. All coefficients in the above formula can be fixed or variable and require testing to determine the specific form of the MGWPR−SDM.

Mediating effect model

Previous research has demonstrated that human capital exerts a decisive influence on upgrading industrial structure (Romalis, 2004; Hausmann et al., 2007). Chen and Yang (2014) determined that human capital significantly contributes to upgrading China's industrial structure. Additionally, regional differences are evident concerning the impact of human capital heterogeneity on industrial structure upgrading. High skilled human capital significantly promotes the upgrading of industrial structure in the eastern region, while its promotion effect is not significant in the western region (Zhang et al., 2011). To further analyze the impact mechanism of the digital economy on the urban−rural income gap, we reference Yu and Zhu (2023) constructing a chain-mediating effect model.

$$Hc_{it} = \beta_0 + \rho_2 WHc_{it} + \beta_1 Digi_{it} + \sum_r \lambda_r C_{r,it} + \sum_q \theta_q WX_{q,it} + u_i + \nu_t + \varepsilon_{it} \quad (3)$$

$$Stru_{it} = \gamma_0 + \rho_3 WStru_{it} + \gamma_1 Digi_{it} + \gamma_{2i} Hc_{it} + \sum_r \lambda_r C_{r,it} + \sum_q \theta_q WX_{q,it} + u_i + \nu_t + \varepsilon_{it} \quad (4)$$

where Hc_{it} and $Stru_{it}$ represent the mediating variables, Hc_{it} quantifies human capital, and $Stru_{it}$ represents the industrial structure. C is the matrix of control variables, and its corresponding coefficient matrix is λ; WX in Eqs. (3) and (4) denote the matrix of spatially lagged variables for explanatory variables other than the spatially lagged terms of the explanatory variables, and θ represents the corresponding coefficient matrix; u_i represents provincial fixed effects; ν_t represents year fixed effects; and ε_{it} represents the randomized perturbation term.

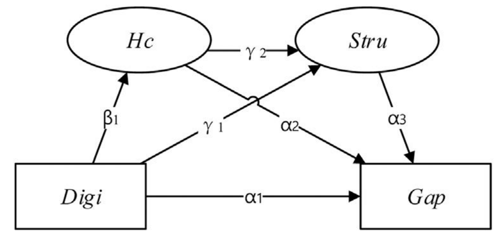

Fig. 1. Diagram of the chain mediating effect model.

Fig. 1 shows that the indirect impact of digital economy development (*Digi*) on the urban−rural income gap (*Gap*) has three paths. (1) *Digi* has an impact on the *Gap* by affecting human capital (*Hc*), with an effect size of $\beta_1{}^*\alpha_2$. (2) *Digi* affects the *Gap* by influencing the industrial structure (*Stru*), with an effect size of $\gamma_1{}^*\alpha_3$. (3) *Digi* has an impact on the *Stru* by influencing *Hc*, which affects the *Gap*, with a magnitude of $\beta_1{}^*\gamma_2{}^*\alpha_3$.

Variable selection and data description

Variable selection

Explained variable

Gap is the explained variable in this study, referencing Wang and Xiao (2021), who adopted the per capita disposable income ratio of urban and rural residents as an alternative indicator of the income gap between urban and rural residents.

Core explanatory variable

Digi is the core explanatory variable. Currently, no common authoritative indicator has been developed for measuring digital economy development. The measurement of the digital economy development index in the existing literature generally includes the "Internet plus" digital economy index designed by the Tencent Research Institute (Jiang & Sun, 2020) and self−constructed indicators. Although the "Internet plus" digital economy indicators cover a relatively comprehensive range, due to the dynamic adjustment of subdivision indicators and weights every year, historical data is incomparable and can only be used as cross−sectional data, which cannot be applied to panel data. Referring to Yu and Zhu (2023), Guo et al. (2020), Pan et al. (2021), and Wang et al. (2023), and considering the data availability, this study constructs a China Provincial digital economy index that includes digital infrastructure, digital industry development, and digital financial services. The model includes 3 primary indicators, 7 secondary indicators, and 53 tertiary indicators, as shown in Table 2. Drawing on Wang et al. (2021), the entropy method is used to determine the weights of the indicators, and a comprehensive score is calculated using the weighting function method to indicate the level of digital economy development.

Mediating variables

(1) *Hc*: We measure per capita education years, referencing Li and Li (2022a). Hu and Lu (2019) suggested that farmers can enhance their learning capabilities through internet information technology, which is beneficial for improving overall *Hc* and increasing rural incomes.
(2) *Stru*: Referencing Wang and Xiao (2021), we use the ratio of the output value of the tertiary industry to that of the secondary industry to measure *Stru*. The service-oriented economic structure driven by information technology is an essential feature of *Stru* upgrading as the growth rate of the tertiary industry is faster than that of the secondary industry, which is a typical fact in the process of China's service-oriented economic transition (Wu, 2005).

Table 2
Indicator System for the Development Level of the Digital Economy.

Primary indicators	Secondary indicators	Tertiary indicator
Digital Infrastructure	Traditional digital infrastructure	Internet broadband access ports
		Length of fiber optic lines
		Number of Internet domain names
		Number of Internet sites
		Number of Internet pages
	New digital infrastructure	Local exchange capacity
		Mobile Internet access traffic
		Number of cell phone base stations
		Ipv4/Ipv6 address number
Digital industry development	digital industrialization	Revenue from telecommunication services
		Mobile Phone Production
		IC production
		Production of microcomputing equipment
		Revenue from software operations
		Revenue from information technology services
		Percentage of Information Technology Employees
	Industrial digitization	express delivery volume
		E−commerce transaction value
		Number of websites per 100 enterprises
		Percentage of enterprises with e−commerce trading activities
Digital financial services	Breadth of coverage	Refer to Guo et al. (2020)
	Depth of application	Refer to Guo et al. (2020)
	Digitization level	Refer to Guo et al. (2020)

As a measure of industrial structure upgrading, the ratio of the output value of the tertiary industry to that of the secondary industry clearly reflects the service−oriented tendencies of the economic structure. If the ratio is upward, the economy is advancing in a service−oriented direction, and the industrial structure is upgraded (Gan et al., 2011). Ji (2023) showed that although the development of an advanced industrial structure will not directly have a significant widening effect on the urban−rural income gap, it will have a certain reverse regulatory effect on the process of digital economy development, affecting the urban−rural income gap.

Control variables

(1) We quantify economic development (*Pgdp*) using the per capita GDP of each region. (2) The study measures urbanization level (*Urban*) as the ratio of the number of permanent urban residents at the end of the year to the total population. (3) We measure the degree of openness to the outside world (*Open*) using the proportion of total imports and exports to GDP. (4) Transportation development (*Traf*) is measured as average road mileage, which is the total road mileage/land area of each province, referencing Wang et al. (2021). (5) The study quantifies agricultural mechanization (*Agri_rate*) as the ratio of the total machinery input in each region to the number of rural residents. (6) We measure fiscal support for agriculture (*Sub_rate*) as the proportion of fiscal expenditure on agriculture, forestry, and water to the total fiscal expenditure at the corresponding level.

Data description and explanation

Table 3 presents the statistical indicators, including minimum value, interquartile, median, mean, interquartile, maximum value, and standard deviation of variables. The minimum value of *Gap* is 1.840 and the maximum value is 3.800, indicating significant differences in *Gap* across China's regions. The minimum value *Digi* is 0.015 and the maximum value is 0.509, which also indicates a digital divide in digital economy development in various regions of China.

Table 3
Descriptive statistics of variables.

	Min	Q1	Median	Mean	Q3	Max	SD
Gap	1.840	2.293	2.485	2.549	2.758	3.800	0.383
Digi	0.015	0.039	0.068	0.098	0.126	0.509	0.087
Hc	7.474	8.824	9.253	9.348	9.618	12.681	0.906
Stru	0.570	0.940	1.150	1.324	1.380	5.300	0.717
Pgdp	2.315	4.185	5.398	6.223	7.213	18.398	2.943
Urban	0.379	0.530	0.593	0.609	0.665	0.896	0.115
Open	0.010	0.090	0.140	0.241	0.308	1.270	0.244
Traf	0.097	0.567	0.946	0.986	1.336	2.237	0.523
Agri_rate	0.330	1.170	1.610	1.806	2.220	6.450	0.961
Sub_rate	0.040	0.093	0.120	0.116	0.140	0.200	0.034

Note: Q1 and Q3 represent the 25th and 75th percentiles, respectively, with SD being the abbreviation for standard deviation.

Data related to e−commerce have only been available since 2013 and do not include data from Hong Kong, Macao, Taiwan, and Xizang. Therefore, this study uses panel data from 30 provinces in China from 2013 to 2021 for empirical analysis. The data are sourced from the "China Population and Employment Statistical Yearbook" from 2014 to 2022, the official website of the National Bureau of Statistics, and the "Peking University Digital Inclusive Finance Index Report" published by the Peking University Digital Finance Research Center.

Empirical results analysis

Model selection

We first determine whether a spatial econometric model is required. Moran's Index (Moran's I) is an important indicator for measuring spatial correlation, and uses the Moran's I statistic to test whether sample individuals are spatially independent of one another. The Moran's I test results in Table 4 that when *Gap, Hc*, and *Stru* are used as explanatory variables, the p-values corresponding to the Moran's I statistic are all 0.000, which significantly rejects the null hypothesis that the variables do not have spatial correlation at the 5 % level. All three variables have significant spatial autocorrelation; therefore, a spatial lag term should be added to the model as an explanatory variable, employing a spatial econometric model.

Table 4
Morans'I test results.

	Gap	Hc	Stru
2013	0.100 (0.000)	0.063 (0.000)	0.009 (0.000)
2014	0.084 (0.000)	0.056 (0.000)	0.007 (0.000)
2015	0.087 (0.000)	0.052 (0.000)	0.008 (0.000)
2016	0.087 (0.000)	0.052 (0.000)	0.015 (0.000)
2017	0.086 (0.000)	0.041 (0.000)	0.016 (0.000)
2018	0.085 (0.000)	0.041 (0.000)	0.020 (0.000)
2019	0.084 (0.000)	0.044 (0.000)	0.007 (0.000)
2020	0.086 (0.000)	0.049 (0.000)	0.007 (0.000)
2021	0.087 (0.000)	0.049 (0.000)	0.011 (0.000)

The p−values corresponding to Morans'I statistic are in parentheses.

Table 5
LR test results.

	Model (1)	Model (2)	Model (3)
SDM or SAR	27.57 (0.002)	75.76 (0.000)	24.29 (0.004)
SDM or SEM	31.32 (0.000)	61.07 (0.000)	30.65 (0.000)

Second, spatial econometric models have various forms such as the spatial autoregression (SAR), the spatial error model (SEM), and the SDM. Model selection requires appropriate testing. This study uses the likelihood ratio approach to test whether the SDM degenerates into SAR or SEM, and Table 5 summarizes the results. The p-values corresponding to the chi-square statistics of Models (1)– (3) are all less than 5 %, indicating that all three models reject the original assumption that SAR and SEM models are true; therefore, the SDM with bidirectional fixed effects should be chosen.

Variable selection: spatial varying or fixed coefficient variable

As some variable coefficients may occur in Models (1)– (3), it is necessary to identify the coefficients that change with spatial variation through testing. Regarding the variable selection problem in the mixed geographic weighted regression model, Mei et al. (2016) proposed applying a bootstrap method for variable coefficient selection, which is more robust than the F-test proposed by Brunsdon et al. (1999). Table 6 presents the test results obtained using this method.

Combining the results of variable selection in Table 6 and compared with the model in Equation (11) from Yu et al. (2021) reveals that Models (1) and (2) have some explanatory variables with insignificant bootstrap tests, and the corresponding p-values are more significant than 0.05, indicating that they are fixed coefficients and the other explanatory variables are variable coefficients. This confirms suitability for employing the MGWPR−SDM because the spatial lag term WY of the explanatory variables in Model (1) is a variable coefficient, and suitable for applying the MGWPR−SDM (1, kc, kv), while the spatial lag term WY of the explanatory variables in Model (2) is a fixed coefficient, which is suitable for applying the MGWPR−SDM (0, kc, kv). Similarly, the p-values corresponding to the explanatory variables in Model (3) are less than 0.05, indicating that all the explanatory variables, including WY, are variable coefficients; therefore, the MGWPR−SDM (0, 0, kv) is applicable.

Table 6
Bootstrap test results (P−value).

Variables	Model (1)	Model (2)	Model (3)
Intercept	0.051	0	0.001
WY	0.008	0.088	0
Digi	0.002	0.001	0
Hc	0.033	–	0
Stru	0.24	–	–
Pgdp	0.194	0.004	0
Urban	0.062	0	0.002
Open	0.008	0	0
Traf	0.032	0	0
Agri_rate	0.027	0	0
Sub_rate	0.051	0.002	0.011
w_Digi	0	0	0
w_Hc	0.025	–	0.004
w_Stru	0.002	–	–
w_Pgdp	0.148	0.007	0
w_Urban	0.109	0	0
w_Open	0	0	0
w_Traf	0.01	0	0
w_Agri_rate	0.025	0.004	0
w_Sub_rate	0.033	0	0

WY is the spatial lag term of the explained variables of each model, the variable starting with "w_" represents the spatial lag term of the variable, and "-" represents the missing value. Same as the following tables.

Varying coefficient regression results

As this study focuses on the core explanatory variable *Digi* and the mediating variables of *Hc* and *Stru*, we do not interpret the remaining control variables. Table 7 reveals that only *Stru* in Model (1) has a fixed coefficient that is statistically significantly positive at the 1 % level, suggesting that upgrading the *Stru* will widen the *Gap*, and its impact varies less across regions. The *Stru* of neighboring regions (*w_Stru*) in Model (1) and the core explanatory variable *Digi*, the mediating variable *Hc*, and *Stru* in the other two models are variable coefficients (Table 7).

Varying coefficient regression results

Table 8 presents the mediation results for Model (1), revealing that the coefficients of *Digi* are both positive and negative, with a maximum value of 0.094 and a minimum value of −0.145, indicating that digital economy development widens the *Gap* in some regions, while the opposite is true for other regions. Similarly, the coefficients of *Hc* are both positive and negative, suggesting that the enhancement of human capital in some regions reduces the *Gap*, while the opposite is true for other regions.

Table 9 presents the results of mediation Model (2), revealing that the coefficients of *Digi* are both positive and negative, with a maximum value of 1.698 and a minimum value of −1.196, indicating that digital economy development in some regions enhances human capital, while the opposite is true for other regions. Furthermore, digital economy development in the neighboring regions (*w_Digi*) also exhibits both a positive and negative impact on the region's human capital, revealing that some neighboring regions can promote human capital improvement, whereas others have the opposite effect.

Table 7
Fixed coefficient results.

Variables	Model (1)	Model (2)
WY	†	−0.769*** (0.003)
Digi	†	†
Hc	†	–
Stru	0.164*** (0.000))	–
Pgdp	−0.01 (0.310)	†
Urban	−3.231*** (0.000)	†
Open	†	†
Traf	†	†
Agri_rate	†	†
Sub_rate	0.043 (0.938)	†
w_Digi	†	†
w_Hc	†	–
w_Stru	†	–
w_Pgdp	−0.105 (0.123)	†
w_Urban	−2.697 (0.335)	†
w_Open	†	†
w_Traf	†	†
w_Agri_rate	†	†
w_Sub_rate	†	†
R^2	0.304	0.038

"†" indicates varying coefficient variables. "–" represents the missing value. *, **, and *** indicate statistically significance at the 0.1, 0.05, and 0.01 levels, respectively, with standard deviations in parentheses.

Table 8
Varying coefficient results of model (1).

Variables	Min	1st Qu	Median	3rd Qu	Max
WY	−0.794	−0.020	0.245	0.511	1.683
Digi	−0.145	−0.078	−0.020	0.014	0.094
Hc	−0.938	−0.115	−0.011	0.107	0.477
Open	−0.244	0.087	0.153	0.193	0.310
Traf	−0.073	−0.046	−0.012	−0.003	0.081
Agri_rate	−2.493	0.465	1.013	2.632	6.261
w_Digi	−0.034	0.294	0.450	0.637	1.011
w_Hc	−0.569	−0.345	−0.157	0.009	0.433
w_Stru	−2.729	−0.597	−0.401	0.066	0.913
w_Open	0.551	0.809	0.971	1.111	1.778
w_Traf	−0.509	−0.151	−0.053	0.053	0.365
w_Agri_rate	−9.667	−4.872	−2.228	−0.391	7.486
w_Sub_rate	−0.747	0.215	0.456	0.751	1.251
R^2	0.009	0.083	0.104	0.118	0.148

Table 10 presents the mediation results for Model (3), revealing that the coefficients of *Digi* are both positive and negative, with a maximum value of 0.130 and a minimum value of −0.303. This indicates that digital economy development in some regions can promote the *Stru* integration and upgrading and the opposite occurs in other regions. Furthermore, the impact of the digital economy development in neighboring regions (*w_Digi*) on *Stru* is positive and negative. *Digi* in neighboring regions (*w_Digi*) has positive and negative effects on the local *Stru*; that is, some neighboring regions promote local *Stru* upgrading, whereas others have the opposite effect. The coefficient of *Hc* is both positive and negative, with a maximum value of 0.058 and a minimum value of −0.055, indicating that enhancing human capital in some regions promotes *Stru* integration and upgrading, while the opposite is true in other regions. The influence of *Hc* in neighboring regions (*w_Hc*) on *Stru* upgrading is also both positive and negative; that is, some neighboring regions promote *Stru* upgrading, while others do not.

Mediating effect analysis

To clearly illustrate the spatial heterogeneity of the mechanism of impact of *Digi* on *Gap*, this study presents each mediating effect in the form of maps. The left sides of Figs. 2–4 present the effect values and the right sides show the p-values corresponding to the Sobel (1982) test.

Fig. 2 reveals significant spatial heterogeneity in *Digi*'s effect on *Gap* through Pathway 1. The coefficients of Jilin, Inner Mongolia, Shanxi, Hubei, Guangdong, and other regions are positive at a 10 % significance level, indicating that *Digi* widens the *Gap* by enhancing *Hc*. The coefficients of Fujian, Chongqing, and other regions are negative, indicating that *Digi* can effectively narrow the *Gap* by enhancing *Hc*. Most regions in central China are positive, and northwestern regions and Heilongjiang and Liaoning are negative, but none of them are significant.

Table 9
Varying coefficient results of model (2).

Variables	Min	1st Qu	Median	3rd Qu	Max
Digi	−1.196	−0.564	−0.171	0.074	1.698
Pgdp	−0.055	−0.035	−0.013	0.003	0.055
Urban	−4.244	−2.189	−1.551	−0.730	3.913
Open	−1.032	−0.669	−0.331	−0.179	0.355
Traf	−0.342	−0.040	0.117	0.331	0.620
Agri_rate	−0.078	−0.020	0.018	0.041	0.127
Sub_rate	−3.055	−0.217	0.887	1.521	4.514
w_Digi	−3.141	0.177	2.901	6.091	14.593
w_Pgdp	−0.612	−0.221	−0.154	−0.061	0.068
w_Urban	−1.531	12.794	15.895	18.866	22.850
w_Open	−6.435	−4.545	−3.697	−2.831	1.283
w_Traf	−1.581	−0.681	−0.325	0.205	1.365
w_Agri_rate	−1.290	−0.726	−0.369	−0.200	0.183
w_Sub_rate	−32.820	−8.570	−3.944	1.607	13.224
R^2	0.070	0.108	0.138	0.154	0.199

Table 10
Varying coefficient results of mediation model (3).

Variables	Min	1st Qu	Median	3rd Qu	Max
WY	−2.967	−0.999	−0.363	0.081	0.836
Digi	−0.303	−0.107	−0.076	−0.019	0.130
Hc	−0.055	−0.030	−0.018	0.002	0.058
Pgdp	−10.649	−8.801	−6.507	−5.673	−3.638
Urban	−0.652	−0.074	0.130	0.382	0.639
Open	0.091	0.290	0.405	0.546	0.779
Traf	−0.170	−0.034	0.019	0.085	0.161
Agri_rate	0.896	1.879	3.138	3.830	4.315
Sub_rate	−12.055	−1.031	0.523	4.030	9.046
w_Digi	−0.467	0.551	0.947	1.204	2.245
w_Hc	−0.301	−0.226	−0.098	−0.041	0.277
w_Pgdp	−14.957	−6.947	−3.365	−1.772	5.487
w_Urban	−1.732	−0.160	1.288	1.986	3.958
w_Open	−1.099	0.279	0.619	1.087	1.868
w_Traf	−1.120	−0.673	−0.450	−0.270	0.199
w_Agri_rate	−10.407	3.848	7.774	14.595	22.178
w_Sub_rate	−2.848	−1.517	−1.047	−0.699	0.151
R^2	0.206	0.289	0.318	0.332	0.365

Fig. 3 reveals that Pathway 2 also exhibits significant spatial heterogeneity. The coefficients in most regions of east, central–west, and northeast China are negative at a 10 % significance level, with Jiangxi and Hubei having the largest effects. This indicates that *Digi* has narrowed the *Gap* in these regions by upgrading the industrial structure. In contrast, Beijing, Shanxi, Ningxia, Inner Mongolia, and other regions exhibit positive coefficients, indicating that *Digi* has widened the *Gap* in these areas by upgrading the industrial structure.

Fig. 4 illustrates the magnitude and significance of the chain-mediated effects, indicating that *Digi* influences the *Gap* by altering *Hc*, which subsequently affects *Stru*. The coefficients in regions such as Jilin, Tianjin, Hubei, and Guangxi are positive at the 10 % significance level, whereas regions such as Shanxi, Inner Mongolia, Henan, and Fujian exhibit negative coefficients. The coefficients in other regions have both positive and negative values, but are not statistically significant.

Direct and total effects analyses

In addition to examining the indirect effects mediating variables such as *Hc* and *Stru* on the *Gap* through, *Digi* also directly impacts the *Gap*. Fig. 5 presents the direct effects and their significance, revealing that the *Digi* in Jiangxi, Chongqing, and Shaanxi has significantly widened the urban–rural income gap. In contrast, the *Digi* in Jilin, Shandong, Zhejiang, Yunnan, Hebei, Sichuan, Guizhou, Liaoning, Hainan, and Xinjiang significantly narrowed the *Gap. Digi* had no significant impact on the *Gap* in other areas.

The analysis above reveals that the three indirect pathways through which *Digi* affects the *Gap* exhibit significant spatial heterogeneity, with both positive and negative effects. These effects tend to offset each other, making it necessary to investigate the weight of the three mediating effects to examine overall indirect impact.

Fig. 6 presents the weights of the indirect and total effects. The left graph in Fig. 6 shows that the total mediating effect of *Digi* on the *Gap* is negative in most regions. Only 12 provinces and cities exhibit a positive total mediating effect, and Jilin Province in the northeast had the largest effect, followed by Beijing, Inner Mongolia, and Shanxi in north China; Henan, Hubei, and Jiangxi in the central region; and Shandong, Jiangsu, Guangdong, and Hainan in the east coast area, with relatively smaller effects. The graph on the right of Fig. 6 presents the spatial distribution of the total effects after combining

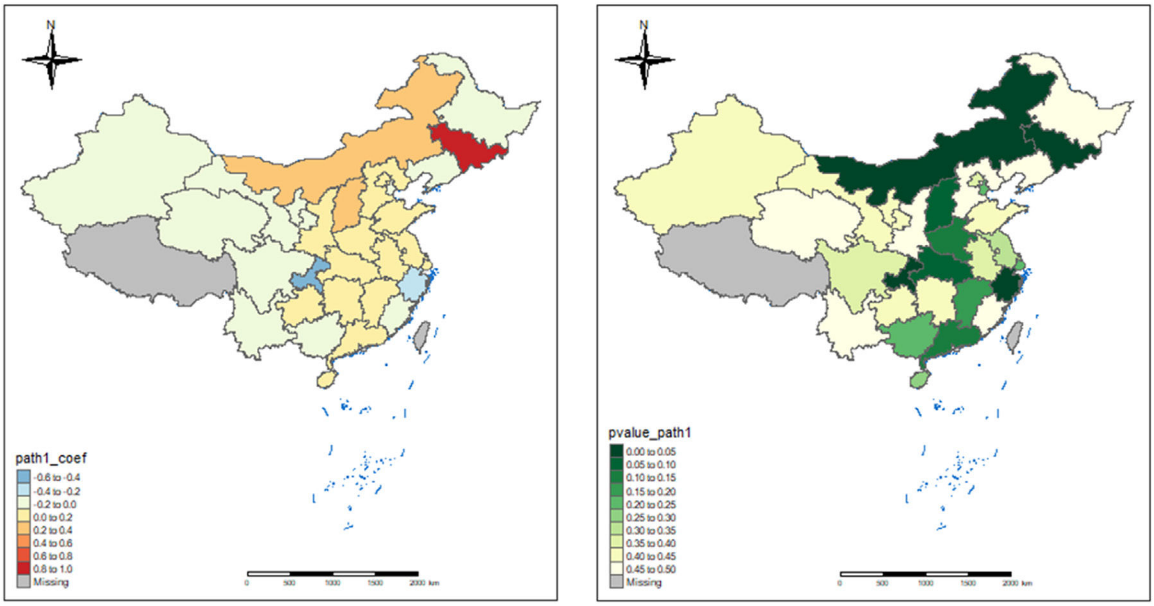

Fig. 2. Mediating effect and statistical significance of path 1.

the total and direct mediating effects. Notably, the impact of *Digi* on the *Gap* varies across regions, with some regions exhibiting a reduction in the income gap, while others show an expansion. Additionally, the spatial distribution of the total effects closely resembles the total mediating effects on the left graph, indicating that the total mediating effects are significantly larger than the direct effects.

Conclusions and policy implications

Conclusions

This study constructs a digital economy development index to measure the *Digi* of 30 provinces and cities in China from 2013 to 2021. Embedding the MGWPR−SDM into a chain−mediated effect model and considering spatial autocorrelation and spatial heterogeneity, we analyze the mechanism of *Digi*'s impact on the *Gap* and its spatial heterogeneity. The results demonstrate that *Digi* can affect the *Gap* through one direct path and three indirect paths, all of which exhibit obvious spatial heterogeneity. The effects of each path cancel each other out, resulting in the same spatial heterogeneity for *Digi*'s total effect on the *Gap*. For example, *Digi* in areas such as Jilin, Inner Mongolia, and Shanxi widened the *Gap*, while *Digi* in areas such as Chongqing and Zhejiang narrowed the *Gap*.

Regarding the mechanism of *Digi*'s impact on the *Gap, Digi* widens the *Gap* in most regions by upgrading human capital, with the largest effect in Jilin Province in Northeast China, followed by Inner Mongolia and Shanxi in North China, and a relatively small effect in most provinces in Central and East China (Fig. 2). Furthermore, *Digi* narrows the *Gap* in the vast majority of regions by promoting the upgrading of industrial structure. Among them, Hubei and Jiangxi provinces in the central region had the largest effect, followed by central, southern, northeastern, and northwestern China; only Beijing, Inner Mongolia,

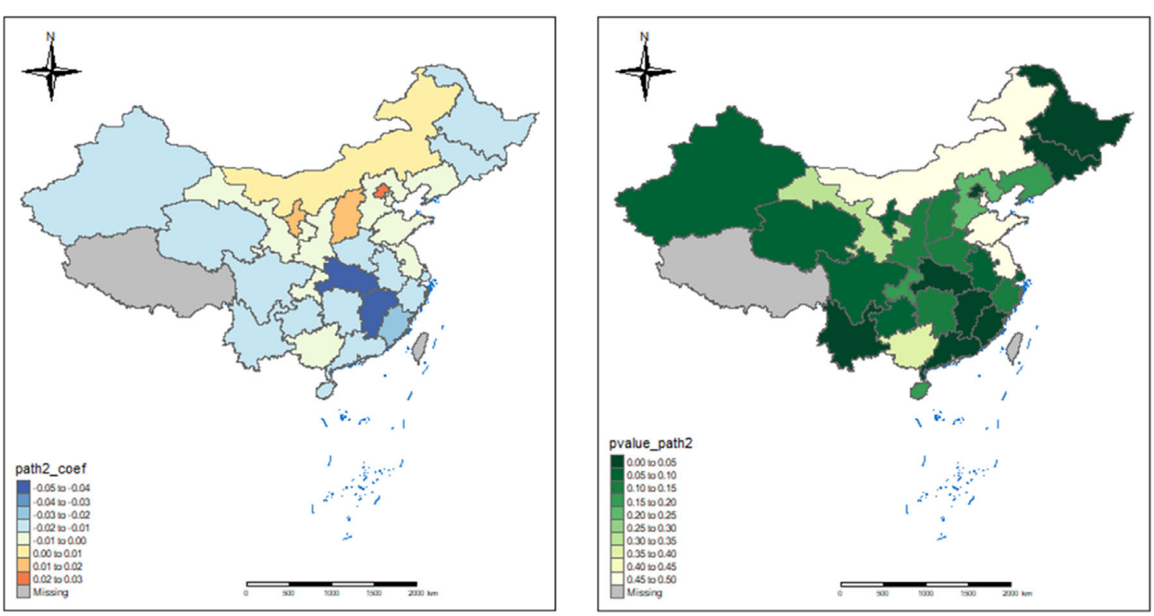

Fig. 3. Mediating effect and statistical significance of path 2.

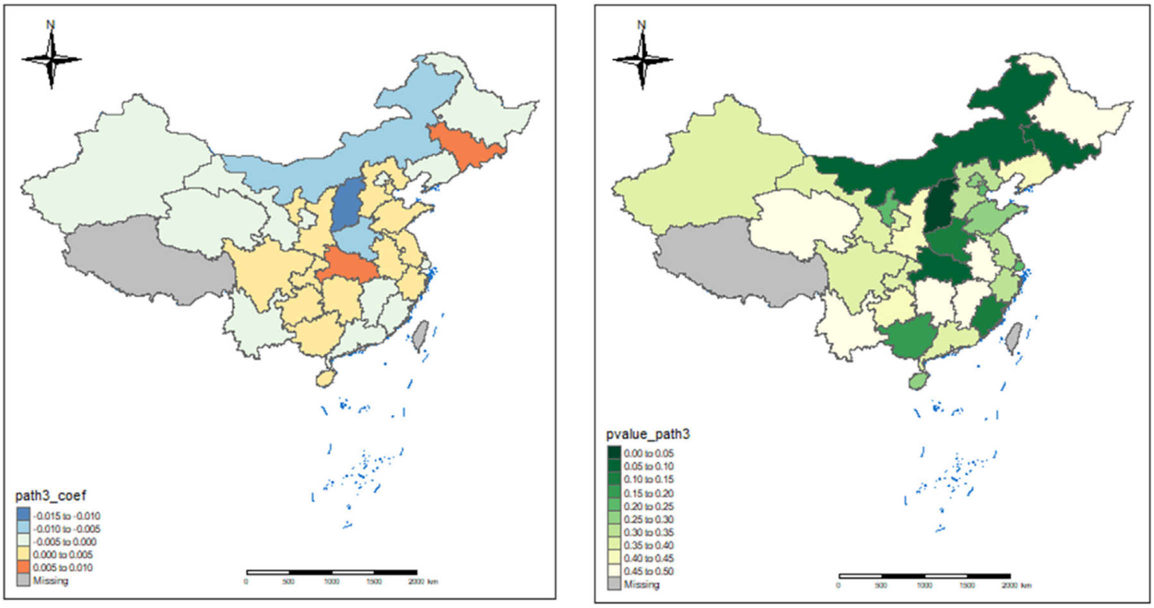

Fig. 4. Chain mediating effect and statistical significance of path 3.

and Shanxi in northern China and Ningxia in northwestern China had a positive path 2 effect (Fig. 3). *Digi* affects the *Gap* by upgrading human capital and thus promoting industrial structure upgrading (i.e., the chain mediation effect) in the eastern region of Tianjin, Hebei, Shandong, Jiangsu, Zhejiang, Anhui, and Hunan in the central region, Ningxia, and Shaanxi in the western region, and most of the southwestern region is positive, indicating that *Digi* widens the *Gap* through Path 3, while other regions narrow the *Gap* through Path 3 (Fig. 4). Additionally, *Digi*'s direct impact reduces the *Gap* in most regions (Fig. 5). Combining the above four paths shows that there is also significant spatial heterogeneity in the total impact of *Digi* on the *Gap*. *Digi* in Beijing, Inner Mongolia, Shanxi, Henan, Hubei, Jiangxi, Jiangsu, Guangdong, and other provinces has widened the *Gap*, resulting in a digital divide effect. However, in most areas of the Northeast, eastern coastal regions, and western regions, *Digi* has narrowed the *Gap*, resulting in a digital dividend effect (Fig. 6).

Policy implications

Based on these findings, this study presents the following policy implications. First, interregional cooperation and coordination must be strengthened. Due to the spatial autocorrelation of the *Gap*, local governments should collaborate to address the associated externalities rather than developing policies independently. This means that local governments should collaborate with neighboring regions and other local governments to jointly develop policies that can coordinate income disparities between different areas. Second, some regions—especially Fujian and Chongqing—should increase efforts to enhance *Hc*. It is possible to consider integrating digital education resources, remote vocational training, digital talent matching platforms, data−driven talent cultivation, and digital innovation and entrepreneurship support to fully leverage digital economy dividends, effectively improve rural labor's *Hc*, promote rural economic

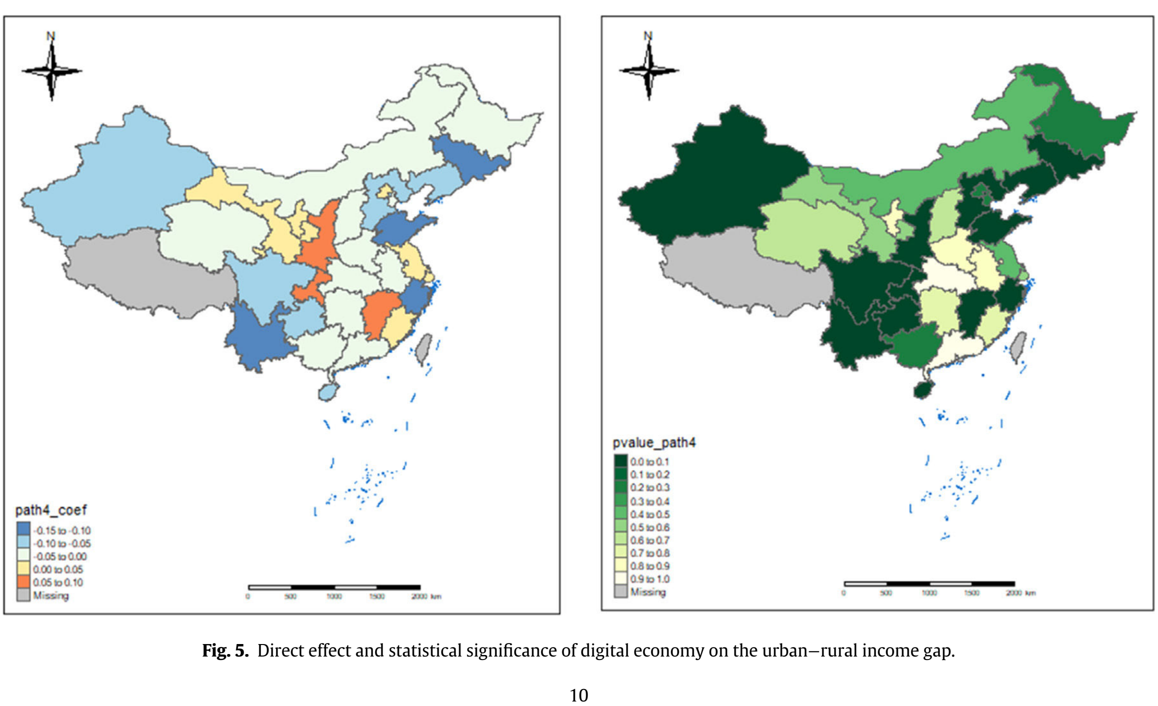

Fig. 5. Direct effect and statistical significance of digital economy on the urban−rural income gap.

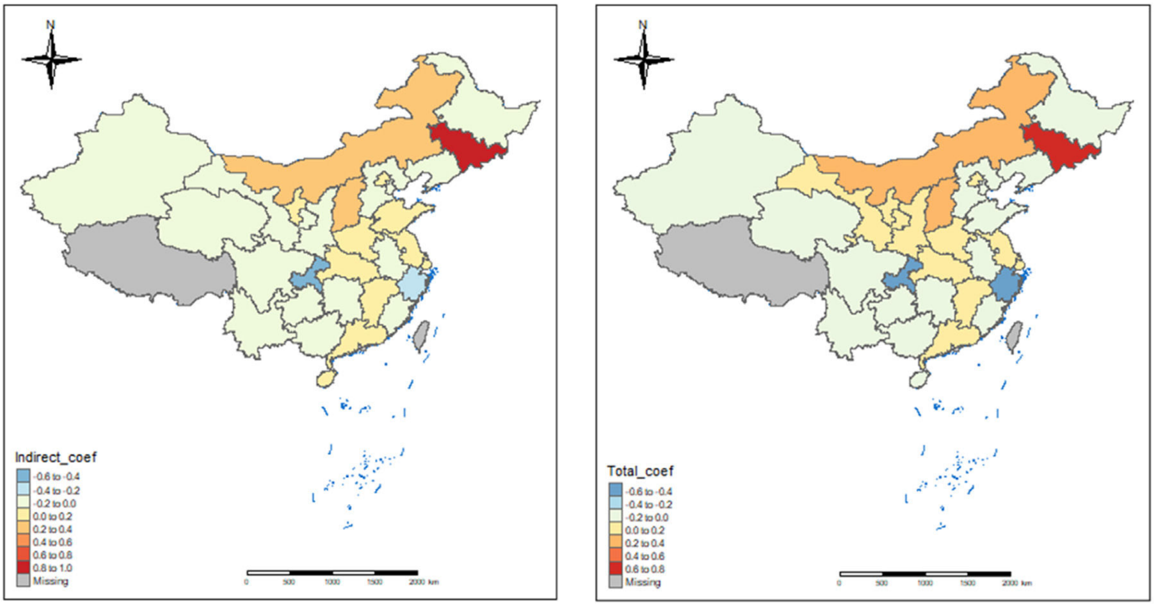

Fig. 6. Total indirect effect and total effect of the digital economy on the urban−rural income gap.

development, and narrow the *Gap*. We also focus on the integrating and upgrading *Stru*. Hubei and Jiangxi provinces in the central region and local governments in central, southern, northeastern, and northwestern regions can promote *Stru* upgrading and transformation by advancing digital agricultural technology, digital industry upgrading, and digital service industry development. This will improve rural employment opportunities and incomes, promote sustainable development of the regional economy, achieve integrated development of urban and rural economies, and balance the growth of society by narrowing the *Gap*. Additionally, policies should be strategically tailored to local conditions. Each region should develop corresponding policies based on its socioeconomic conditions and natural resource endowments, reasonably develop the digital economy, and narrow the *Gap* in a context−specific manner. Regional disparities must be considered, and policies must be targeted and feasible to achieve the optimal results.

CRediT authorship contribution statement

He Xia: Writing – original draft, Funding acquisition, Conceptualization. **Haijing Yu:** Software, Methodology, Formal analysis. **Senhao Wang:** Resources, Data curation. **Hong Yang:** Writing – review & editing, Supervision.

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