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Digital Talent Mobility and Economic Growth in Guangdong-Hong Kong-Macao Greater Bay Area: The Spatial Mediation Effect of Industrial Restructuring*

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Abstract: This study examines the impact of digital talent mobility on economic growth in the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) using the spatial Durbin model and spatial mediation model. Based on panel data analysis from 2003 to 2022, our findings show that, first, digital talent flow significantly enhances economic growth and generates positive spatial spillovers through knowledge and technology diffusion. Second, industrial structure upgrading positively mediates this relationship, but its spatial mediation negatively affects surrounding cities by causing talent drain. Lastly, future industrial development potential exhibits only a limited local effect while displaying negative spatial mediation. As a policy conclusion, this study proposes that within the complex institutional context of the GBA, dynamic equilibrium between the radiative effects of core cities and balanced regional development should be achieved through cross-regional industrial coordination and integrated talent governance mechanisms.

Keywords: digital talent mobility, economic growth, industrial restructuring, Guangdong-Hong Kong-Macao Greater Bay Area, spatial mediation model

JEL Codes: C13, J61, O47, R12

1. INTRODUCTION

Against the backdrop of rapid global economic transformation, the digital economy has emerged as a significant driving force for economic growth and social change (Li et al., 2020). The widespread application and rapid development of digital technology have not only changed the operating models of traditional industries but also given rise to numerous emerging industries. It significantly enhances productivity and drives the transformation and upgrading of economic structures (Teece, 2018). At the heart of this transformation lies digital talent, which serves as the fundamental human capital of the digital economy. Characterized by advanced technical expertise, extensive knowledge reserves, and strong innovative

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capacity, digital talent enables enterprises to absorb and apply cutting-edge technologies, optimize production efficiency, and ultimately stimulate sustainable economic growth (Luca and Riccaboni, 2021).

The 2023 China Digital Talent Development Report defines digital talent as individuals who possess digital thinking and fundamental knowledge, business capabilities, and development potential for digitalization. As the most active and dynamic production factor in the digital economy era, the mobility of digital talent has become an important indicator of regional economic vitality (Luca and Riccaboni, 2021). Their movement not only facilitates the diffusion of knowledge and technology but also accelerates innovation and productivity gains, thereby fostering sustained economic growth (Shi et al., 2024). Through these processes, digital talent generates pronounced spillover effects, enabling the benefits of economic development to transcend the cities where talent converges and diffuse across a wider regional network.

Furthermore, the mobility of digital talent promotes the agglomeration of high-productivity industries while facilitating the upgrading of low-productivity sectors, thereby optimizing urban industrial structures and advancing the modernization of the overall economy (Zhang et al., 2023). Hence, industrial restructuring emerges as a critical mediating channel linking digital talent mobility to economic growth. Existing research has shown the mechanism between talent flow and economic growth, such as regional innovation (Liu et al., 2023), housing policy (Yang et al., 2022), and the degree of openness (Xu and Li, 2020). But the systematic analysis of the mechanism of industrial restructuring is insufficient.

In addition, industrial restructuring shapes both the scope and intensity of the spillover effects generated by digital talent mobility. On the one hand, optimizing industrial structure can amplify the positive spillovers by extending industrial chains and fostering regional collaboration, thereby promoting economic development in surrounding areas. On the other hand, an uneven industrial structure may exacerbate regional disparities, triggering the spatial redistribution of resources and talent. When high-productivity industries concentrate in specific cities, they attract disproportionate capital and labor, potentially causing talent drain and diminishing economic vitality in neighboring regions. This dynamic can weaken the positive spillover effects of digital talent mobility on economic growth (Zhao, 2022; Ma et al., 2024a). Hence, investigating the spatial mediating role of industrial restructuring is essential for unpacking the complex pathways through which digital talent flow influences regional economic performance.

The Guangdong-Hong Kong-Macao Greater Bay Area (GBA), being one of China's most dynamic and forward-looking economic regions, provides an ideal context for examining the flow of digital talent and its economic implications. The GBA has unique geographical advantages as well as receives strong policy support from both the central and local governments (Patchell, 2023). This region gathers a greater number of high-level digital talents and technological resources. It has a net inflow of talent and stands out as one of the most appealing centers for digital talent in China, surpassing even Beijing and Wuhan in attractiveness. It positions the GBA at the forefront of China's digital economic development (Wang, 2022). Nevertheless, the flow of talent among cities within the region and the mechanisms by which it impacts economic growth have not been thoroughly examined.

The main contributions of this study are reflected in several aspects. First, in contrast to previous research that primarily focused on the direct impact of talent mobility on economic growth, this paper incorporates the spatial Durbin model and spatial mediation model to systematically uncover the pathways through which digital talent mobility influences regional economic growth. It provides new empirical evidence for understanding the interlinked dynamics of talent, industry, and growth in the context of the digital economy. Second, by taking the GBA as the research object, the study aligns with the region's characteristics of cross-administrative and cross-institutional talent flows and economic linkages, thereby enriching the literature on the digital economy and spatial economics within the GBA. Lastly, by incorporating industrial restructuring into the spatial mediation framework, the study reveals how digital talent mobility affects regional economic growth through industrial restructuring within a "local gain-external dilution" spatial pattern, thereby filling a gap in the existing literature regarding the systematic analysis of industrial structure mechanisms.

The study is structured as follows: Section 2 reviews the literature. The methodology is described in Section 3, including model specifications and data. Section 4 discusses the empirical findings, and Section 5 concludes with the key findings and policy implications.

2. LITERATURE REVIEW

The flow of digital talent can directly promote economic growth. Based on human capital theory, the knowledge, skills, and abilities of workers are important driving forces for economic growth (Becker, 1992). Human capital is acquired through various means such as formal schooling, family education, vocational training, healthcare, labor mobility, and the collection and dissemination of labor employment information, which can enhance individuals' skills, knowledge, health, moral standards, and organizational management levels (Deming, 2022). As high-quality human capital, the mobility of digital talent is an important avenue for the diffusion of knowledge and technology. The flow of digital talent can drive technological innovation in local enterprises and increase productivity, thereby directly promoting economic development (Brown et al., 2021; Huang et al., 2023).

In addition, the flow of digital talent can create substantial spatial spillover effects, whereby the flow of digital talent in one city promotes economic development in adjacent areas through the diffusion of knowledge and transfer of technology (Bu et al., 2024; Colombelli et al., 2024). This spatial spillover effect is particularly important in regional economic integration and coordinated development of city clusters, as it can promote the common prosperity of cities within the region. Therefore, in-depth research on the spatial spillover effects of digital talent mobility is vital for understanding the role of talent in regional economic integration.

Existing research widely acknowledges that industrial optimization and upgrading serve as critical mediating links between talent factors and economic growth. Theoretically, classical endogenous growth models emphasize that the reallocation of production factors and the evolution of industrial structures are the core driving forces of long-term economic expansion (Romer, 1994). In the context of the digital economy, the mobility of digital talent can accelerate the transformation and upgrading of traditional industries as well as the cultivation of emerging sectors through technology diffusion, knowledge spillovers, and the agglomeration of innovation capabilities (Garonna and Sica, 2000). Empirical evidence further indicates that the cross-regional flow of high-skilled talent significantly enhances the technological content and added value of local industries, indirectly fostering economic growth via the optimization of industrial structures (Zheng et al., 2023; Li et al., 2021). In the GBA, as an integrated urban cluster spanning multiple administrative jurisdictions, the concentration of digital talent in core cities not only directly stimulates output growth but also generates an amplification effect by facilitating industrial upgrading, thereby enabling higher levels of local economic expansion (Zhang et al., 2021).

Meanwhile, some studies highlight the dual nature of the spatial effects of industrial restructuring. On the one hand, industrial upgrading in core cities can foster the development of surrounding areas through value chain spillovers and regional coordination (Xia et al., 2024). On the other hand, the concentration of high-end industrial factors and digital talent may generate a "siphoning effect" that weakens the growth potential of peripheral cities (Tao et al., 2025).

This "siphoning" phenomenon finds strong theoretical grounding in classical regional development theories. Myrdal's (1957) (Myint, 1965) theory of cumulative causation argues that growth centers absorb capital and labor from surrounding areas through backwash effects, thereby exacerbating regional disparities. The theory of unbalanced growth (Hirschman, 1958) and growth pole theory (Perroux, 1950) further emphasize that the external economies generated by core industries enhance the competitive advantages of central cities, while potentially imposing negative externalities on peripheral areas. Within the framework of new economic geography, the core-periphery model in Krugman (1991) demonstrates that when economies of scale and factor mobility interact, labor and high-end industries tend to concentrate in high-wage core regions, leading to a "shadow effect" in the periphery. Subsequent extensions of this model show that heterogeneous demand and urban diversity can further intensify this uneven spatial pattern (Fujita and Thisse, 2009). Recent empirical studies on Chinese cities also confirm that core cities, in the process of concentrating high-tech industries and skilled talent, exert significant siphoning and growth-suppressing effects on nearby cities, manifesting in what is often termed the "agglomeration shadow" or "radiation decay" effect (Wang et al., 2022; Li et al., 2023).

In short, this study investigates the mechanisms through which the flow of digital talent in the GBA affects economic growth, exploring its direct impact and spatial spillover effects, as well as the significant mediating role and spatial mediation effect of industrial restructuring in this process. By deeply analyzing the effect of digital talent flow on economic growth, this study provides new perspectives for the development of regional economic theory and offers scientific empirical evidence for the formulation of talent and economic policies in the GBA and other similar regions.

3. METHODOLOGY

3.1. Models

3.1.1. Basic Model

Based on the endogenous growth theory, this study assumes that returns to scale are increasing; that is, $\alpha + \beta > 1$ $(0 < \alpha < 1, 0 < \beta < 1)$, the Cobb-Douglas production function is shown as

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} \tag{1}$$

where Y_{it} represents the city's gross domestic product (GDP). A_{it} is the total factor productivity (TFP). K_{it} is the physical capital. L_{it} is the input of the labor force; this study assumes that it is the population of working age (15-64 years old). i represents the city, and t represents the time.

Total factor productivity (TFP) is regarded as a key indicator that reflects the efficiency of resource allocation, the level of production technology, and the combined impact of institutional and societal factors on productive activities (Lipsey and Carlaw, 2004). From the perspective of new economic geography (Ding and Hu, 2025), this study classifies the pathways to enhancing TFP into three mutually reinforcing mechanisms: advancing the technological frontier, optimizing factor reallocation, and fostering cross-regional knowledge diffusion.

The first pathway centers on technological progress, with artificial intelligence (AI) standing as a prime example. As one of the most transformative and dynamic technologies of the modern era, AI continuously injects vitality into the production frontier. Ding and Hu (2025) employed a two-way fixed effects model and threshold regression. They demonstrate that a one percent increase in AI development can drive a 0.365 percent rise in TFP. It underscores the direct role of AI innovation in propelling productivity through the expansion of the frontier.

The second pathway lies in industrial restructuring, which alters the relative relationships among sectors, guiding capital and labor toward more efficient industries and thus achieving optimal resource allocation. The evidence from Sun et al. (2022) indicates that industrial upgrading significantly boosts TFP, with its core mechanism rooted in improved allocation efficiency.

The third pathway draws on the knowledge innovation-diffusion framework of new economic geography, where economic growth depends on transferring tacit knowledge embedded in the technological frontier to lagging regions through mobile agents, creating a multi-centered network of "local buzz and global pipelines" (Fujita and Krugman, 2004). Digitally skilled talent, equipped with transferable capabilities in coding, algorithms, and data governance, has become the most critical carrier of knowledge in the contemporary economy. Zou et al. (2024) find that the amplifying effect of the digital economy on urban TFP hinges strongly on the net inflow of digital talent. The greater the influx of high-skilled workers, the denser the city's knowledge base, and the stronger the digital economy's potential to enhance TFP.

Hence, the TFP can be shown as

$$A_{it} = e^{\theta_0 + \theta_1 \ln AI_{it} + \theta_2 \ln IR_{it} + \theta_3 \ln flow_{it} + \ln e_{it}} \tag{2}$$

where AI_{it} represents the development of artificial intelligence, IR_{it} denotes the industrial restructuring, $flow_{it}$ measures the mobility of digital talent, and e_{it} is the error term includes the unobserved variables and random factors.

Furthermore, assume the total population of each city is N_{it}, then the model (1) is transformed into

$$\frac{Y_{it}}{N_{it}} = A_{it} \left(\frac{K_{it}}{N_{it}}\right)^{\alpha} \left(\frac{L_{it}}{N_{it}}\right)^{\beta} N_{it}^{\alpha+\beta-1} \tag{3}$$

Suppose that the population of children (0–14 years) is P_{1it}; the aging population (65 years and above) is P_{2it}; and the working-age population (15–64 years) is L_{it}. Then, $N_{it} = P_{1it} + P_{2it} + L_{it}$, and model (3) can be changed into:

$$\begin{aligned} \frac{Y_{it}}{N_{it}} &= A_{it} \left(\frac{K_{it}}{N_{it}}\right)^{\alpha} \left(\frac{L_{it}}{N_{it}}\right)^{\beta} N_{it}^{\alpha+\beta-1} \\ &= A_{it} \left(\frac{K_{it}}{N_{it}}\right)^{\alpha} \left(\frac{1}{(P_{1it}/L_{it}) + (P_{2it}/L_{it}) + 1}\right)^{\beta} N_{it}^{\alpha+\beta-1} \\ &= A_{it} \left(\frac{K_{it}}{N_{it}}\right)^{\alpha} \left(\frac{1}{1 + Depen_{it}}\right)^{\beta} N_{it}^{\alpha+\beta-1} \end{aligned} \tag{4}$$

where $Depen_{it} = (P_{1it}/L_{it}) + (P_{2it}/L_{it})$, representing the dependency ratio. It reflects the current demographic structure in China, characterized by a continuous decline in the number of newborns alongside a steadily rising proportion of the elderly population.

Finally, after taking logarithms from both sides of Equation (4) and combining Equation (2), the following linear model is created for estimation:

$$\begin{gathered} \ln\left(\frac{Y_{it}}{N_{it}}\right) = \ln A_{it} + \alpha \ln\left(\frac{K_{it}}{N_{it}}\right) + \beta \ln\left(\frac{1}{1 + Depen_{it}}\right) + (\alpha + \beta - 1)\ln N_{it} \\ = \theta_0 + \theta_1 \ln AI_{it} + \theta_2 \ln IR_{it} + \theta_3 \ln flow_{it} + \alpha \ln\left(\frac{K_{it}}{N_{it}}\right) - \beta \ln(1 + Depen_{it}) + (\alpha + \\ \beta - 1)\ln N_{it} + \ln e_{it} \end{gathered} \tag{5}$$

Then, the following general model can be derived from model (5):

$$\begin{gathered} \ln y_{it} = \beta_0 + \beta_1 \ln AI_{it} + \beta_2 \ln IR_{it} + \beta_3 \ln k_{it} + \beta_4 \ln flow_{it} + \beta_5 \ln N_{it} \\ + \beta_6 \ln(1 + Depen_{it}) + \mu_i + \pi_t + \varepsilon_{it} \end{gathered} \tag{6}$$

where $y_{it} = \frac{Y_{it}}{N_{it}}$ indicates the per capita GDP in city i in year t. $k_{it} = \frac{K_{it}}{N_{it}}$ is the per capita physical capital input. μ_i is the fixed effect, π_t denotes the time-fixed effect and ε_{it} is the error term.

3.1.2. Spatial Autocorrelation Test and Spatial Weight Matrix

Conducting a spatial autocorrelation test is crucial before spatial regression. This test determines whether the observed value of a variable at one location is influenced by its values at other locations. If a dependency is detected, spatial autocorrelation is present (Cliff and Ord, 1973). Spatial autocorrelation can be determined using various methods, such as Moran's I (Moran, 1950) and Geary's C. This study employs Moran's I to examine the spatial correlation within the data.

Statistical methods for assessing the spatial autocorrelation of geographic data include global and local Moran's I. These measures are used to evaluate global and local autocorrelation in geographical space, respectively.

First, the global Moran's I is shown as follows:

$$I = \frac{N}{W} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{N}(x_i - \overline{x})^2} \tag{7}$$

where w_{ij} are the elements of a matrix of spatial weights, and W is the sum of all w_{ij}, that is $W = \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}$. x is the variable of interest, $\overline{x}$ is the mean of x. N is the number of spatial units indexed by i and j.

Based on the homogeneity assumption, global spatial autocorrelation analysis yields a single statistic that represents the dependence in the whole region. Local Moran's I is used to identify clusters at a local scale. The Local Indicators of Spatial Association (LISA) method employs the calculation of Moran's I as a sum of individual cross-products to evaluate clustering within specific spatial units. LISA achieves this by computing local Moran's I for each spatial unit and then determining the statistical significance for each I_i (Anselin, 1995). For each spatial unit i, the Equations (8)-(10) indicate the Local Moran's I.

$$I_i = \frac{x_i - \overline{x}}{m_2} \sum_{j=1}^{N} w_{ij}(x_j - \overline{x}) \tag{8}$$

$$m_2 = \frac{\sum_{i=1}^{N}(x_j - \overline{x})^2}{N} \tag{9}$$

$$I = \sum_{i=1}^{N} \frac{I_i}{N} \tag{10}$$

where I_i is local Moran's I, I is the global Moran's I. N is the number of spatial units. The value of local Moran's I typically falls within the range of -1 to +1. The results demonstrate that there is positive spatial autocorrelation when I_i is significantly higher than $-1/(N-1)$ and negatively correlated when I_i is significantly lower than $-1/(N-1)$ (Anselin, 1995).

Regarding the spatial weight matrix in Equations (7) and (8), Tobler's first law of geography states that everything is related, but near things are more related than distant things (Waldo, 2004). The spatial weight matrix quantifies the degree of connection between entities. This study considers the following spatial weight matrix.

Firstly, the geographic contiguity weight matrix is a spatial weights matrix that defines relationships between geographic units based on whether they share a common border or boundary, which is shown as

$$W_1 = \begin{cases} 1, \text{if city } i \text{ and city } j \text{ share a boundary} \\ 0, \text{if city } i \text{ and city } j \text{ not share a boundary} \end{cases} \tag{11}$$

This paper then quantifies the position of the spatial unit. The geographical distance weight matrix W_2 is as follows:

$$W_2 = \begin{cases} \frac{1}{d_{ij}}, & i \neq j \\ 0, & i = j \end{cases} \tag{12}$$

where d_{ij} is the spatial distance calculated based on the longitude and latitude between cities.

The economic distance weight matrix W_3 is shown in Equations (13) and (14):

$$W_3 = \begin{cases} \frac{1}{|\overline{Y}_i - \overline{Y}_j|}, & i \neq j \\ 0, & i = j \end{cases} \tag{13}$$

$$\overline{Y}_i = \frac{1}{T} \sum_t Y_{it} \tag{14}$$

where Y_{it} represents the real GDP per capita of the city i in year t, and the $\overline{Y}_i$ represents the average real GDP per capita of the city i for all years.

3.1.3. Spatial Durbin Model

Spatial regression models come in various forms, including the Spatial Autoregressive (SAR) model, the Spatial Error Model (SEM), and the Spatial Durbin Model (SDM). The SDM incorporates spatial effects on both the dependent and independent variables (LeSage and Pace, 2009). Therefore, to measure the spatial dependence among cities in the GBA, this study integrates a spatial weight matrix into the model (6) to develop an SDM. The generalized spatial model is as follows:

$$\begin{aligned} \ln y_{it} =& \rho W \ln y_{it} + \beta_0 + \beta_1 \ln AI_{it} + \beta_2 \ln IR_{it} + \beta_3 \ln k_{it} + \beta_4 \ln flow_{it} + \beta_5 \ln N_{it} \\ &+ \beta_6 \ln (1 + Depen_{it}) + \tau_1 W \ln AI_{it} + \tau_2 W \ln IR_{it} + \tau_3 W \ln k_{it} \\ &+ \tau_4 W \ln flow_{it} + \tau_5 W \ln N_{it} + \tau_6 W \ln (1 + Depen_{it}) + \mu_i + \pi_t \\ &+ \varepsilon_{it} \end{aligned} \tag{15}$$

where ρ and $\tau_i (i = 1 - 6)$ are spatial autoregressive parameters that measure the degree of spatial correlation in the dependent variable and explanatory variable, respectively. W is a spatial weight matrix, which means the spatial dependence between two cities changes over time. μ_i is the fixed effect, π_t denotes the time-fixed effect and ε_{it} is the error term.

3.1.4. Spatial Mediation Model

In the spatial econometric model, the spatial mediation effect refers to the process by which one variable transmits its influence to the dependent variable through another mediating variable, considering spatial dependence and interaction. Specifically, it examines how the flow of digital talent in one city affects the economic growth of neighboring cities by influencing the mediating variable.

A generalized spatial mediation effect model is developed (Baron and Kenny, 1986). The stepwise regression method is utilized to design the mediating effect model, encompassing Equations (15), (16), and (17).

$$\begin{aligned}\ln y_{it} =& \rho' W \ln y_{it} + \beta_0' + \beta_1' \ln AI_{it} + \beta_3' \ln k_{it} + \beta_4' \ln flow_{it} + \beta_5' \ln N_{it} \\ &+ \beta_6' \ln(1 + Depen_{it}) + \tau_1' W \ln AI_{it} + \tau_3' W \ln k_{it} + \tau_4' W \ln flow_{it} \\ &+ \tau_5' W \ln N_{it} + \tau_6' W \ln(1 + Depen_{it}) + \mu_i' + \pi_t' + \varepsilon_{it}'\end{aligned} \tag{16}$$

$$\begin{aligned}\ln IR_{it} =& \rho'' W \ln IR_{it} + \beta_0'' + \beta_1'' \ln AI_{it} + \beta_3'' \ln k_{it} + \beta_4'' \ln flow_{it} + \beta_5'' \ln N_{it} \\ &+ \beta_6'' \ln(1 + Depen_{it}) + \tau_1'' W \ln AI_{it} + \tau_3'' W \ln k_{it} + \tau_4'' W \ln flow_{it} \\ &+ \tau_5'' W \ln N_{it} + \tau_6'' W \ln(1 + Depen_{it}) + \mu_i'' + \pi_t'' + \varepsilon_{it}''\end{aligned} \tag{17}$$

After spatial effects decomposition, we can calculate the mediation effect and the spatial mediation effect. Firstly, in Equation (16), assume a_1, a_2, a_3 are the direct, indirect, and total effect of $flow_{it}$ on y_{it}. Secondly, in Equation (17), assume b_1, b_2, b_3 are the direct, indirect, and total effect of digital talent flow on the industrial restructuring (IR_{it}). Thirdly, in Equation (15), assume c_1, c_2, c_3 are the direct, indirect, and total effect of IR_{it} on y_{it} after controlling $flow_{it}$, and d_1, d_2, d_3 are the direct, indirect, and total effect of $flow_{it}$ on y_{it} after controlling IR_{it}.

Hence, the product $b_1 \times c_1$ is the mediation effect. The mediation effect is classified as complete or partial based on the direct effect magnitude (d_1). Complete mediation means that the direct effect of $flow_{it}$ on y_{it} is $0 (d_1 = 0)$, but the mediation effect affecting y_{it} through IR_{it} exists ($b_1 \times c_1 \neq 0$). Partial mediation is a situation where both direct effects and mediation effects exist ($d_1 \neq 0, b_1 \times c_1 \neq 0$). Besides, the spatial mediation effect is equal to $b_1 \times c_2$. And complete spatial mediation exists when $d_1 = 0$ but $b_1 \times c_2 \neq 0$. Partial spatial mediation exists when $d_1 \neq 0$ and $b_1 \times c_2 \neq 0$.

We estimate the model parameters using the spatial maximum likelihood (ML) method, assuming that digital talent mobility is exogenous in the economic growth Equation. However, this exogeneity assumption may not hold. On the one hand, more prosperous cities tend to attract greater inflows of digital talent, suggesting a potential reverse causality between digital talent mobility and economic performance. On the other hand, the SDM model inherently includes a spatially lagged dependent variable. It is naturally correlated with the error term and thus constitutes another source of endogeneity. If these sources of endogeneity are not properly addressed, conventional ML estimators may become biased and inconsistent. In response, we adopt the instrumental variables generalized method of moments (IV-GMM) estimation procedure following the Fingleton & Le Gallo (2008) (Fingleton and Gallo, 2008), Piras (2013) (Piras, 2013), and Anselin et al. (2025) (Anselin et al., 2025). It integrates the strengths of spatial two-stage least squares and GMM techniques.

In this study, we consider the most classic option of using lagged values of endogenous variables as instrumental variables. Lagged values are less likely to be influenced by current shocks, ensuring that they are uncorrelated with the error term. Therefore, we adhere to the approach of Rodríguez-Pose and Peralta (2015), treating the lagged value of the potential endogenous variable (lnflow) as an instrumental variable. Recently, Ricordel (2024) (Ricordel, 2024) and Ma et al. (2024) (Ma et al., 2024b) used the lagged values to control for the reverse causality.

3.2. Data and Variables

3.2.1. Data

This study focuses on 11 cities in the GBA: Macao, Hong Kong, Dongguan, Shenzhen, Huizhou, Guangzhou, Jiangmen, Zhongshan, Zhuhai, Foshan, and Zhaoqing. The data spanning from 2003 to 2022 are sourced from the China Statistical Yearbook, China Urban Statistical Yearbook, China Labor Statistical Yearbook, Macao Statistical Yearbook, and Hong Kong Statistical Yearbook.

3.2.2. Explained and Explanatory Variables

The dependent variable in this study is per capita GDP (y_{it}) that represents the economic growth. The independent variable is digital talent flow among cities in the GBA. In this study, digital talents are the employees in information transmission, computer services, and the software industry. Traditional gravity models and intervening-opportunities models rely on scenario-specific calibration parameters, which limit their predictive performance in the absence of detailed mobility records. To avoid dependence on pre-estimated elasticity coefficients, this study adopts the radiation model proposed by Simini et al. (2012) (Simini et al., 2012) to measure intercity digital-talent mobility. This model relies solely on the spatial distribution of talent and distance information, enabling the derivation of potential migration flows without external parameters, and has been shown to possess strong predictive power at the intercity scale (Astero et al., 2022).

Let city i have m_{it} digital talents in year t, and city j have n_{jt} digital talents in the same year. Assume r_{ij} denotes the distance between the two cities, and s_{ijt} represents the total number of digital talents within a circle centered at city i with radius r_{ij}, (excluding cities i and j). The flow of digital talents T_{ijt} from city i to city j derived from the radiation model is given by:

$$T_{ijt} = T_{it}\frac{m_{it}n_{jt}}{(m_{it}+s_{ijt})(m_{it}+n_{jt}+s_{ijt})} \tag{18}$$

where $T_{it} = m_{it}\frac{N_{ft}}{N_t}$, N_{ft} is the total number of digital talent mobility in the country, and N_t is the total number of digital talents in the country. Hence, the radiation model can be shown as

$$T_{ijt} = \frac{N_{ft}}{N_t}\frac{m_{it}^2 n_{jt}}{(m_{it}+s_{ijt})(m_{it}+n_{jt}+s_{ijt})} \tag{19}$$

It should be emphasized that this study sets a minimum threshold for talent mobility of 1. Hence, the digital talent mobility of city i in year t is shown as

$$flow_{it} = \sum_{j=1}^{11} T_{ijt} + \sum_{k=1}^{11} T_{kit} \tag{20}$$

3.2.3. Control Variables

Firstly, artificial intelligence, representing technological progress, can be measured by the number of AI patent applications (Nguyen and Vo, 2022). The AI patent data is sourced from the Information for Industry (IFI) Claims patents dataset, accessible through Google Cloud Public Datasets[1]. This global bibliographic database is updated quarterly and includes all worldwide patent documents. To screen patents that meet the requirements, this study follows the data collection method outlined by Nguyen & Vo (2022) (Nguyen and Vo, 2022). Regardless of their forms and applications, the approach entails creating scheme clusters that cover all AI-related patent coverages. To compile the patent data, two important categorization schemes are employed: International Patent Categorization (IPC) and Cooperative Patent Classification (CPC). World Intellectual Property Organization (WIPO) (World Intellectual Property Organization (WIPO), 2019) describes the AI techniques, AI functional applications, and AI application fields that are included in the query applied to the CPC and IPC codes.

Secondly, industrial restructuring includes two aspects: rationalization and upgrading of industrial structure (Goldsmith, 1951). The rationalization of industrial structure can be measured by the Theil index, as can be seen in Equation (21).

$$RL_{it} = \sum_{n=1}^{3} \frac{Y_{int}}{Y_{it}} \ln \left(\frac{\frac{Y_{int}}{Y_{it}}}{\frac{L_{int}}{L_{it}}} \right) \tag{21}$$

where i represents a specific city, n denotes an industry encompassing primary, secondary, and tertiary sectors, and t represents a year. RL_{it} characterizes the level of rationalization of industrial restructuring of cities in GBA during year t. Y_{int} indicates the GDP of industry n of city i in year t, while Y_{it} corresponds to the GDP of all industries of the city i in the same period. L_{int} signifies the number of workers in industry n of the city i during year t, and L_{it} denotes the number of workers in all industries of the city i for the specified year.

When RL_{it} equals zero, it indicates the industrial structure has achieved equilibrium. For non-zero values, the increasing magnitude implies a greater level of industrial structural irrationality.

Industrial structural upgrading involves not only the improvement in quantity but also the enhancement in quality. The quantity of industrial structural upgrading (ISU_quan) can be measured using the industrial structure hierarchy coefficient (Goldsmith, 1951) as follows:

$$ISU_{quan_{it}} = \sum_{n=1}^{3} \frac{Y_{int}}{Y_{it}} \times m, \ m = 1, 2, 3 \tag{22}$$

[1]Refer to https://cloud.google.com/bigquery/public-data?hl=zh-cn, accessed on 1 Jan 2025

For the quality of industrial structural upgrading (ISU_qual), higher labor productivity industries are only a sign of a higher degree of industrial structural upgrading when they account for a sizable portion of the total industrial structure (Goldsmith, 1951). The ISU_qual is shown in Equation (23).

$$ISU_{qual_{it}} = \sum_{n=1}^{3} \left(\frac{Y_{int}}{Y_{it}} \times \frac{Y_{int}}{L_{int}} \right) \tag{23}$$

where $\frac{Y_{int}}{L_{int}}$ represents the labor productivity. The proportional relationships $\frac{Y_{int}}{Y_{it}}$ is dimensionless, while the labor productivity $\frac{Y_{int}}{L_{int}}$ has dimensions. Therefore, this study employs the min-max standardization method to eliminate dimensions for each city separately.

In addition, to capture the aspects of industrial quality upgrading in the digital economy era, this study employs the stock of AI enterprises at the city level as a measure of future industrial development potential (IDP). The data are sourced from the China National Intellectual Property Office (CNIPO) and the China Stock Market & Accounting Research (CSMAR) database. It first identifies the enterprises in each city that applied for AI-related patents each year using CNIPO records, then obtains the survival duration of these enterprises from CSMAR, and subsequently calculates the annual stock of AI enterprises.

Thirdly, per capita physical capital input (k_{it}) can be measured as capital stock divided by the total population. Perpetual inventory is used to compute capital stock (Goldsmith, 1951), which can be formed as follows:

$$K_{it} = \frac{I_{it}}{P_{it}} + (1 - \delta_{it})K_{i,t-1} \tag{24}$$

where K_{it} is the capital stock at the end of year t in city i, $K_{i,t-1}$ is the capital stock at the end of year $t-1$ in the city i. I_{it} is the nominal investment amount in the year t in the city i. This study uses total fixed asset investment to measure I_{it}. P_{it} represents the price index of fixed assets investment and δ_{it} is the constant depreciation rate.

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistics

Table 1 indicates the results of descriptive statistics. It shows that the average logarithmic value of per capita GDP is approximately 11.38, ranging from 9.38 to 13.26, highlighting significant disparities in regional economic development. The average log value for digital talent mobility is around 7.706, with a standard deviation of 1.204 and a range from 0 to 12.390, indicating substantial variability in talent movement across different regions. Additionally, the data for industrial structure rationalization and upgrading also show considerable dispersion, suggesting uneven progress and effectiveness in industrial transformation across regions. These findings corroborate the presence of imbalances in the economy, talent, and industry within the GBA, thereby justifying further in-depth analysis and validation using spatial econometric models.

Table 1: Descriptive Statistics

Variable	Define	Mean	Std Dev	Minimum	Maximum
lngdp	Per capita GDP	11.381	0.803	9.385	13.264
lnflow	Digital talent flow	7.706	1.204	0	12.390
lnAI	Artificial intelligence	4.768	2.094	-4.605	10.394
lnRL	Rationalization level of industrial restructuring	-2.529	1.249	-7.032	-0.081
lnISU_quan	The quantity of industrial structure upgrading	0.911	0.089	0.736	1.101
lnISU qual	The quality of industrial structure upgrading	-1.330	1.778	-13.816	0.006
lnIDP	Future industrial development potential	6.111	2.420	0	11.293
lnk	Per capita physical capital input	17.999	1.142	15.651	20.044
lnN	Total population	14.849	0.786	13.019	16.152
ln(1+Depen)	Dependency ratio	0.251	0.077	0.109	0.434

4.2. Spatial Autocorrelation Test

4.2.1. Global Moran's I

This study selects the spatial weight matrices W_1, W_2, and W_3 to calculate the global Moran's I for the spatial autocorrelation of lngdp and lnflow, as presented in Table 2.

Table 2 indicates that when using the geographical contiguity matrix, the spatial autocorrelation coefficient of lngdp is mostly statistically insignificant. Replacing the spatial weights with an inverse-distance matrix raises the autocorrelation to a significant level, though the magnitude remains relatively low. When the economic distance matrix W_3 is introduced, the Moran's I for lngdp increases substantially. It suggests that regional economic agglomeration is driven more by economic linkages than by mere geographical proximity. In contrast, lnflow exhibits consistently strong and significant positive spatial autocorrelation under all three weight matrices, with its Moran's I rising from the moderate levels of W_1 and W_2 to the higher levels of W_3, and overall values significantly exceeding those of lngdp. It highlights the more robust and resilient spatial clustering of digital talent mobility.

Hence, Table 2 confirms that both talent flows and economic output share spatial dependence. This study will adopt the W_2 and W_3 to capture these dependencies.

4.2.2. Local Moran's I

The cross-sectional data on per capita GDP and digital talent flow are selected for the years 2003, 2008, 2013, 2018, and 2022. Local Moran scatter plots are created and organized into Table 3 and Table 4 for W_2, and Table 5 and Table 6 for W_3. The cities are categorized into four quadrants as follows. Under the different spatial weight matrices, the results exhibit

Table 2: Global Moran's I for lngdp and lnflow

	W_1		W_2		W_3	
year	lngdp	lnflow	lngdp	lnflow	lngdp	lnflow
2003	0.105	0.396**	0.009*	0.071**	0.247**	0.178*
2004	0.076	0.401**	0.016*	0.074**	0.255**	0.179*
2005	0.069	0.426**	0.043**	0.080**	0.196**	0.178*
2006	0.072	0.417**	0.035**	0.078**	0.211**	0.193**
2007	0.057	0.406**	0.035**	0.076**	0.220**	0.183*
2008	0.029	0.399**	0.040**	0.073**	0.231**	0.193**
2009	0.052	0.411**	0.045**	0.077**	0.189**	0.195**
2010	-0.008	0.407**	0.048**	0.073**	0.248**	0.193**
2011	0.069	0.399**	0.053**	0.075**	0.181**	0.195**
2012	0.000	0.401**	0.047**	0.077**	0.243**	0.195**
2013	0.075	0.417**	0.046**	0.081**	0.171**	0.196**
2014	0.100	0.423**	0.034**	0.083**	0.199**	0.193**
2015	0.092	0.420**	0.031**	0.084**	0.195**	0.190**
2016	0.108	0.423**	0.042**	0.082**	0.169**	0.189**
2017	0.130	0.414**	0.020*	0.081**	0.199**	0.201**
2018	0.133	0.416**	0.018*	0.080**	0.195**	0.201**
2019	0.161	0.414**	0.020*	0.080**	0.168*	0.203**
2020	0.163	0.408**	0.023*	0.080**	0.148*	0.209**
2021	0.157	0.397**	0.020*	0.075**	0.175*	0.204**
2022	0.158	0.116	0.020*	0.010**	0.145*	0.344**

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

similar trends.

Table 3 and Table 5 reveal marked spatial polarization in city-level economic growth within the GBA. Hong Kong, Macao, Shenzhen, Guangzhou, and Zhuhai cluster in the high-high (H-H) quadrant, displaying high growth and positive spillovers to adjacent areas. By contrast, Zhaoqing, Jiangmen, Huizhou, and Dongguan occupy the low-low (L-L) quadrant, where low growth fails to stimulate their neighbors. Foshan gravitates toward the high-growth core, whereas Zhongshan aligns with lower-growth surroundings, so the overall diffusion pattern radiates from the Pearl River Delta's central cities to its periphery.

Table 4 and Table 6 indicate a similar, though even stronger, spatial clustering of digital-talent flows. Macao, Shenzhen, and Hong Kong sit in the H-H quadrant, acting as hubs that elevate inflows in nearby cities. Guangzhou and Foshan fall into the L-H quadrant, local inflows are modest, and benefits from talent-rich neighbors are limited. Zhuhai records high inflows but transmits little impetus outward, while Zhongshan, Zhaoqing, Jiangmen, Dongguan, and Huizhou remain in the L-L quadrant with mutually weak flows. Consequently, talent spillovers originate mainly from Hong Kong, Macao, and Shenzhen and attenuate as they spread outward.

Table 3: Spatial Clustering of lngdp in Cities in the GBA for W_2

lngdp	H-H	L-H	L-L	H-L
2003	Hong Kong, Macao, Guangzhou, Shenzhen, Zhuhai, Dongguan	Zhongshan, Foshan	Zhaoqing, Jiangmen, Huizhou	
2008	Hong Kong, Macao, Guangzhou, Shenzhen, Foshan, Zhuhai	Zhongshan, Dongguan	Zhaoqing, Jiangmen, Huizhou	
2013	Hong Kong, Macao, Guangzhou, Shenzhen, Zhuhai	Zhongshan, Foshan, Dongguan	Zhaoqing, Jiangmen, Huizhou	
2018	Hong Kong, Macao, Guangzhou, Shenzhen, Zhuhai	Zhongshan, Foshan, Dongguan	Zhaoqing, Jiangmen, Huizhou	
2022	Hong Kong, Macao, Guangzhou, Shenzhen, Zhuhai	Zhongshan, Foshan, Dongguan	Zhaoqing, Jiangmen, Huizhou	

Table 4: Spatial Clustering of lnflow in Cities in the GBA for W_2

lnflow	H-H	L-H	L-L	H-L
2003	Hong Kong, Macao, Shenzhen, Zhuhai	Dongguan, Foshan, Guangzhou	Zhaoqing, Jiangmen, Huizhou, Zhongshan	
2008	Hong Kong, Macao, Shenzhen, Zhuhai	Dongguan, Foshan, Guangzhou, Zhongshan	Zhaoqing, Jiangmen, Huizhou	
2013	Hong Kong, Macao, Shenzhen, Zhuhai	Dongguan, Foshan, Guangzhou	Zhaoqing, Jiangmen, Huizhou, Zhongshan	
2018	Hong Kong, Macao, Shenzhen, Zhuhai	Dongguan, Foshan, Guangzhou	Zhaoqing, Jiangmen, Huizhou, Zhongshan	
2022	Hong Kong, Macao, Shenzhen, Zhuhai, Dongguan	Foshan, Guangzhou	Zhaoqing, Jiangmen, Huizhou, Zhongshan	

Table 5: Spatial Clustering of lngdp in Cities in the GBA for W_3

lngdp	H-H	L-H	L-L	H-L
2003	Hong Kong, Macao, Guangzhou, Shenzhen, Zhuhai, Dongguan		Foshan, Zhongshan, Zhaoqing, Jiangmen, Huizhou	
2008	Hong Kong, Macao, Guangzhou, Shenzhen, Foshan, Zhuhai		Zhaoqing, Jiangmen, Huizhou, Dongguan, Zhongshan	
2013	Hong Kong, Macao, Guangzhou, Shenzhen, Zhuhai	Foshan, Zhongshan	Zhaoqing, Jiangmen, Huizhou, Dongguan	
2018	Hong Kong, Macao, Guangzhou, Shenzhen, Zhuhai	Foshan	Zhaoqing, Jiangmen, Huizhou, Dongguan, Zhongshan	
2022	Hong Kong, Macao, Guangzhou, Shenzhen, Foshan, Zhuhai		Zhaoqing, Jiangmen, Huizhou, Dongguan, Zhongshan	

4.3. The Results of the Spatial Durbin Model

Table 7 and Table 8 present the SDM regression results for W_2 and W_3, with four industrial structure variables included in the model separately. They also compare the results of the ML method and IV-GMM estimate, and the overidentification test (Hansen) is listed. Hansen test of overidentification for all models in Table 7 and Table 8 do not support rejecting the H_0 correct specification. Hence, using IV-GMM estimation is appropriate.

In all models, the coefficients estimated using IV-GMM are generally smaller than those obtained using ML estimation. It indicates that after controlling for endogeneity, the IV-GMM method provides more robust parameter estimates and more accurately reflects the dynamic relationship between digital talent mobility and economic growth.

When using the IV-GMM method, regardless of whether W_2 or W_3 is used, the spatial autocorrelation coefficients (W*lngdp) in all models are significantly positive, suggesting that economic growth exhibits a positive spatial agglomeration effect, with high-growth regions positively influencing the economic growth of neighboring areas. Additionally, digital talent mobility has a significant positive effect on economic growth. Regarding industrial restructuring, only industrial upgrading (lnISU_quan) and future industrial development (lnIDP) have a significant impact on economic growth. Therefore, the subsequent analysis

Table 6: Spatial Clustering of lnflow in Cities in the GBA for W_3

lnflow	H-H	L-H	L-L	H-L
2003	Hong Kong, Macao, Shenzhen, Zhuhai	Guangzhou, Foshan	Zhongshan, Zhaoqing, Jiangmen, Huizhou, Dongguan	
2008	Hong Kong, Macao, Shenzhen	Zhongshan, Dongguan, Guangzhou, Foshan	Zhaoqing, Jiangmen, Huizhou	Zhuhai
2013	Hong Kong, Macao, Shenzhen	Guangzhou, Foshan, Zhongshan	Zhaoqing, Jiangmen, Huizhou, Dongguan	Zhuhai
2018	Hong Kong, Macao, Shenzhen	Guangzhou, Foshan	Zhaoqing, Jiangmen, Huizhou, Dongguan, Zhongshan	Zhuhai
2022	Hong Kong, Macao, Shenzhen, Zhuhai	Guangzhou, Foshan	Zhaoqing, Jiangmen, Huizhou	Dongguan, Zhongshan

will focus on these two variables as potential mediating factors.

We further decompose these spatial effects and explore their specific mechanisms, as can be seen in Table 9. It examines the impact of lnISU_quan and lnIDP under the spatial weight matrices W_2 and W_3. Using the IV-GMM estimate, digital talent mobility exhibits a significant positive effect in all models. It not only has a direct positive impact on local economic growth but also exerts a positive effect on the economic growth of neighboring cities through spatial spillover effects. Both industrial restructuring variables show a suppression of economic growth in surrounding areas through spatial spillover effects. Under W_2, the negative spatial spillover from industrial upgrading is significantly larger than its positive direct effect on economic growth, resulting in its negative total effect.

4.4. The Results of the Spatial Mediation Effect Model

This study employs the IV-GMM method to estimate the spatial mediation model. Table 10 and Table 11 present the results using lnISU_quan and lnIDP as mediating variables, with W_2 and W_3 serving as the spatial weight matrix, respectively. The results show that regardless of whether W_2 or W_3 is used, lnflow is significant across all models, and both lnISU_quan and lnIDP are significant. The lnISU_quan and lnIDP serve as significant mediating variables.

Table 12 presents the decomposition results of the spatial mediation model, from which both the mediation effect and the spatial mediation effect can be calculated. For the model using W_2 as the spatial weight matrix, the direct effect of lnISU_quan on economic growth, after adjusting for digital talent flow, is 2.299 and significant at the 1% level. The direct effect of digital talent flow on economic growth, when controlled for the mediating variable, is 0.282 and significant. In model (2), the direct effect of digital talent flow on economic growth is 0.503, which is significant at the 5% level. Model (3) shows that the influence of digital

Table 7: The Results of the Spatial Durbin Model for W_2

	ML				IV-GMM			
	Model(1)	Model(2)	Model(3)	Model(4)	Model(1)	Model(2)	Model(3)	Model(4)
Variables	lngdp	lngdp	lngdp	lngdp	lngdp	lngdp	lngdp	lngdp
lnflow	0.385***	0.262***	0.412***	0.353***	0.211***	0.111***	0.224***	0.141*
	(0.025)	(0.033)	(0.032)	(0.029)	(0.039)	(0.030)	(0.038)	(0.045)
lnRL	-0.074*				-0.021			
	(0.019)				(0.028)			
lnISU_quan		1.846***				2.681***		
		(0.530)				(0.416)		
lnISU_qual			0.026**				0.002	
			(0.011)				(0.018)	
lnIDP				0.078***				0.060*
				(0.017)				(0.031)
lnAI	0.020	-0.013	-0.002	0.017	0.011	-0.033**	0.011	0.014
	(0.019)	(0.017)	(0.020)	(0.019)	(0.024)	(0.013)	(0.027)	(0.024)
lnk	0.195***	0.352***	0.227***	0.495***	0.132	0.186***	0.141	0.372*
	(0.059)	(0.053)	(0.056)	(0.068)	(0.086)	(0.054)	(0.089)	(0.085)
lnN	-0.366***	-0.444***	-0.350***	-0.650***	-0.161	-0.266***	-0.171*	-0.488**
	(0.063)	(0.055)	(0.058)	(0.088)	(0.100)	(0.061)	(0.102)	(0.110)
ln(1+Depen)	0.158	0.915***	-0.133	2.030***	0.845**	1.077***	0.776**	1.523*
	(0.408)	(0.342)	(0.349)	(0.333)	(0.427)	(0.266)	(0.389)	(0.416)
W*lngdp	0.385**	0.602***	0.858***	0.253**	0.158	0.390***	0.189*	0.193***
	(0.191)	(0.192)	(0.179)	(0.096)	(0.110)	(0.078)	(0.106)	(0.100)
W*lnflow	0.349***	0.320***	0.351***	0.289**	0.321***	0.338***	0.282***	0.225***
	(0.096)	(0.096)	(0.087)	(0.075)	(0.098)	(0.0941)	(0.100)	(0.095)
W*lnRL	0.030				0.104*			
	(0.094)				(0.054)			
W*lnISU_quan		-6.911***				-3.778***		
		(2.251)				(1.425)		
W*lnISU_qual			0.095				0.073	
			(0.071)				(0.089)	
W*lnIDP				-0.166***				-0.125**
				(0.030)				(0.042)
W*lnAI	0.049	0.155	-0.190	0.017	0.030	0.083***	0.024	0.012
	(0.120)	(0.101)	(0.126)	(0.051)	(0.046)	(0.030)	(0.047)	(0.063)
W*lnk	-0.664**	-0.058	-0.223	0.455***	0.081	-0.0006	0.073	0.345**
	(0.314)	(0.264)	(0.287)	(0.158)	(0.123)	(0.082)	(0.128)	(0.185)
W*lnN	0.253	0.156	-0.033	-0.471**	-0.073	0.109	-0.093	-0.350*
	(0.353)	(0.125)	(0.327)	(0.184)	(0.178)	(0.126)	(0.183)	(0.225)
W* ln(1+Depen)	-0.793*	0.932***	0.581	-1.254	-0.569	-0.913*	0.033	-0.930
	(0.266)	(0.223)	(0.209)	(0.779)	(0.809)	(0.484)	(0.819)	(0.930)
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	220	220	220	220	220	220	220	220
Number of City	11	11	11	11	11	11	11	11
Hansen					56.340	51.263	54.630	52.675

Note: Robust standard errors in parentheses; ***, **, * indicate significance at 1%, 5% and 10%, respectively.

talent flow on lnISU_quan is 0.072 and significant. Consequently, the partial mediation effect of lnISU_quan on the impact of digital talent flow on economic growth is calculated as $0.072 \times 2.299 = 0.166$. Similarly, for the model using W_3 as the spatial weight matrix, lnISU_quan continues to exhibit a partial mediation effect, where the product of the indirect path coefficients satisfies $0.050 \times 4.101 = 0.205$.

Table 8: The Results of the Spatial Durbin Model for W_3

	ML				IV-GMM			
Variables	Model(1) lngdp	Model(2) lngdp	Model(3) lngdp	Model(4) lngdp	Model(1) lngdp	Model(2) lngdp	Model(3) lngdp	Model(4) lngdp
lnflow	0.272***	0.112***	0.264***	0.272***	0.161**	0.513**	0.253*	0.377*
	(0.034)	(0.024)	(0.030)	(0.035)	(0.057)	(0.027)	(0.061)	(0.071)
lnRL	-0.039				-0.069			
	(0.024)				(0.083)			
lnISU_quan		4.860***				2.446**		
		(0.289)				(0.111)		
lnISU_qual			0.023				0.154	
			(0.018)				(0.134)	
lnIDP				0.024				0.101*
				(0.026)				(0.016)
lnAI	0.029	0.003	0.056**	0.041*	0.167	0.186	0.238	-0.179
	(0.020)	(0.014)	(0.022)	(0.022)	(0.248)	(0.241)	(0.273)	(0.195)
lnk	0.276***	0.210***	0.234***	0.365***	1.077**	1.202	1.046*	0.872
	(0.072)	(0.053)	(0.079)	(0.074)	(0.065)	(0.762)	(0.525)	(0.494)
lnN	0.298***	-0.414***	-0.319***	-0.444**	-1.697	-2.041*	-1.699	-1.338**
	(0.078)	(0.054)	(0.084)	(0.087)	(1.173)	(0.724)	(0.945)	(0.554)
ln(1+Depen)	-2.247**	0.888***	1.776***	1.242***	0.425**	0.592**	0.171**	-0.704***
	(0.390)	(0.229)	(0.352)	(0.366)	(0.471)	(0.125)	(0.180)	(0.182)
W*lngdp	0.432***	0.434***	0.479***	0.391***	0.020***	0.501**	0.390***	0.388**
	(0.110)	(0.101)	(0.111)	(0.112)	(0.127)	(0.175)	(0.189)	(0.115)
W*lnflow	0.320*	0.582***	0.492**	0.384**	0.232**	0.412**	0.323**	0.601*
	(0.185)	(0.139)	(0.204)	(0.192)	(0.132)	(0.132)	(0.229)	(0.091)
W*lnRL	0.277***				-0.232			
	(0.058)				(0.304)			
W*lnISU_quan		-1.815				-5.451*		
		(1.232)				(6.423)		
W*lnISU_qual			0.095				0.154	
			(0.071)				(0.134)	
W*lnIDP				-0.339***				-0.038*
				(0.062)				(0.022)
W*lnAI	-0.016	-0.112	0.098**	-0.040	0.217	0.212	0.360	-0.179
	(0.043)	(0.028)	(0.045)	(0.041)	(0.400)	(0.366)	(0.505)	(0.195)
W*lnk	1.515***	0.894***	1.389***	0.956***	-1.347	-1.314	-1.009	-0.792
	(0.252)	(0.176)	(0.258)	(0.254)	(0.822)	(0.928)	(0.700)	(0.622)
W*lnN	1.470***	1.116***	1.504***	-0.731**	2.140**	2.272**	1.736*	1.208*
	(0.210)	(0.148)	(0.221)	(0.245)	(0.223)	(0.352)	(0.801)	(0.224)
W* ln(1+Depen)	4.730	6.361***	9.479***	2.854	0.209	-1.647	0.9024	4.884
	(3.070)	(1.947)	(2.999)	(2.897)	(5.079)	(5.973)	(4.974)	(9.274)
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	220	220	220	220	220	220	220	220
Number of City	11	11	11	11	11	11	11	11
Hansen test					55.176	49.610	50.601	53.620

Note: Robust standard errors in parentheses; ***, **, * indicate significance at 1%, 5% and 10%, respectively.

In addition, for the model using W_2 as the spatial weight matrix, the spillover effect of the mediating variable lnISU_quan on economic growth, after accounting for digital talent flow, is -5.365 and significant at the 10% level. The indirect effect of digital talent flow on economic growth, controlling for the mediating variable, is significant and equal to 0.236. In model (2), the total spillover effect of digital talent flow on economic growth is 0.814, significant

Table 9: The Results of Spatial Effect Decomposition of SDM

			ML			IV-GMM		
		Effect	Direct	Indirect	Total	Direct	Indirect	Total
W_2	Model(2)	lnflow	0.048***	0.461***	0.509***	0.282***	0.236*	0.518**
		lnISU_quan	5.288***	-3.092***	2.196*	2.299***	-5.365*	-3.066
	Model(4)	lnflow	0.249***	0.219	0.468***	0.390***	0.187**	0.577***
		lnIDP	0.058**	-0.281***	-0.222***	0.105	-0.095*	0.010
W_3	Model(2)	lnflow	0.366**	0.214***	0.580***	0.035**	0.327**	0.362**
		lnISU_quan	4.278***	-3.044***	1.244***	4.101***	-2.276**	1.825**
	Model(4)	lnflow	0.390***	0.817***	1.207**	0.210***	0.202*	0.412***
		lnIDP	0.094***	-0.316***	-0.223***	0.085	-0.080*	0.005

Note: Robust standard errors in parentheses; ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Table 10: The Results of the Spatial Mediation Effect Model for W_2 Using IV-GMM

Variable	(1) lngdp	(2) lngdp	(3) lnISU_quan	(4) lngdp	(5) lngdp	(6) lnIDP
lnflow	0.111***	0.410***	0.061***	0.141*	0.410***	1.083***
	(0.030)	(0.022)	(0.003)	(0.045)	(0.022)	(0.086)
lnISU_quan	2.681***					
	(0.416)					
lnIDP				0.060*		
				(0.031)		
W*lnflow	0.338***	0.325***	0.066***	0.225**	0.325***	0.280**
	(0.094)	(0.063)	(0.010)	(0.095)	(0.063)	(0.058)
W*lnISU_quan	-3.778***					
	(1.425)					
W* lnIDP				-0.125**		
				(0.042)		
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	220	220	220	220	220	220
Number of City	11	11	11	11	11	11

Note: Robust standard errors in parentheses; ***, **, * indicate significance at 1%, 5% and 10%, respectively.

at the 5% level. In model (3), the spillover effect of digital talent flow on lnISU_quan is 0.102. Consequently, the partial spatial mediation effect of lnISU_quan on the impact of digital talent flow on economic growth is calculated as $0.072 \times (-5.365) = -0.386$. Similarly, for the model using W_3 as the spatial weight matrix, lnISU_quan continues to exhibit a partial spatial mediation effect, where the product of the indirect path coefficients satisfies $0.050 \times (-2.276) = -0.114$.

For the lnIDP, it does not exhibit a significant direct mediation effect. However, it shows a significant partial spatial mediation effect. As can be seen in Table 12, for the model using

Table 11: The results of the spatial mediation effect model for W_3 using IV-GMM

Variable	(1) lngdp	(2) lngdp	(3) lnISU_quan	(4) lngdp	(5) lngdp	(6) lnIDP
lnflow	0.513**	0.592**	0.022***	0.377*	0.592**	0.283**
	(0.027)	(0.089)	(0.004)	(0.071)	(0.089)	(0.082)
lnISU_quan	2.446**					
	(0.111)					
lnIDP				0.101*		
				(0.016)		
W*lnflow	0.412**	0.300***	0.037*	0.601*	0.300***	0.142*
	(0.132)	(0.037)	(0.018)	(0.091)	(0.037)	(0.052)
W*lnISU_quan	-5.451*					
	(0.423)					
W* lnIDP				-0.038*		
				(0.022)		
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	220	220	220	220	220	220
Number of City	11	11	11	11	11	11

Note: Robust standard errors in parentheses; ***, **, * indicate significance at 1%, 5% and 10%, respectively.

W_2 as the spatial weight matrix, the partial spatial mediation effect of lnIDP is equal to $1.068 \times (-0.316) = -0.337$. For the model using W_3 as the spatial weight matrix, the partial spatial mediation effect of lnIDP is equal to $0.557 \times (-0.080) = -0.045$.

In summary, digital talent mobility influences economic growth through both direct effects and a dual pathway mediated by industrial restructuring. On the one hand, digital talent mobility accelerates local industrial upgrading, thereby amplifying local growth. But the same upgrading imposes a negative spatial mediation effect on neighboring areas. It suggests that core cities, while attracting high-end factors and leaping ahead industrially, may drain the growth potential of adjacent cities. By contrast, the future industry development (lnIDP) shows no significant local mediation effect, but its negative spatial mediation implies that pioneer cities in emerging-industry deployment crowd out nearby regions and, in the short term, fail to foster regional synergy. Overall, digital talent mobility within the GBA produces a spatial pattern of "local gain and external dilution."

It should be noted that, under W_2, the negative spatial spillover from industrial upgrading is significantly larger than its positive direct effect on economic growth, making its negative spatial mediation in the talent-growth nexus exceed the positive direct mediation. While under economic distance weights W_3, the total effect of lnISU_quan is positive. It likely reflects fiercer competition among geographically proximate cities during upgrading: core cities rapidly absorb high-end factors and market share from nearby areas, generating a stronger "siphoning" effect. In contrast, the economic-distance matrix emphasizes functional

Table 12: The Results of Spatial Effect Decomposition of the Spatial Mediation Effect Model

				IV-GMM		
	Mediating variable	Effect		Direct	Indirect	Total
W_2	lnISU_quan	lnflow	Model (1)	0.282***	0.236*	0.518**
			Model (2)	0.503**	0.814**	1.317***
			Model (3)	0.072***	0.102***	0.174***
		lnISU_quan	Model (1)	2.299***	-5.365*	-3.066
	lnIDP	lnflow	Model (4)	0.390***	0.187**	0.577***
			Model (5)	0.503**	0.814**	1.317***
			Model (6)	1.068***	0.749*	1.817***
		lnIDP	Model (4)	0.094	-0.316***	-0.223
W_3	lnISU_quan	lnflow	Model (1)	0.035**	0.327**	0.362**
			Model (2)	0.227***	0.207*	0.434***
			Model (3)	0.050***	0.025*	0.075***
		lnISU_quan	Model (1)	4.101***	-2.276**	1.825**
	lnIDP	lnflow	Model (4)	0.210***	0.202*	0.412***
			Model (5)	0.227***	0.207*	0.434***
			Model (6)	0.557***	0.590***	1.147***
		lnIDP	Model (4)	0.085	-0.080*	0.005

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

linkages and intercity specialization, enabling economically close cities yet geographically farther apart to share value-chain gains and thus temper negative externalities. Similarly, the total effect of lnIDP is either negative or insignificant, indicating the impact of future industrial development on spatial spillovers is relatively limited.

4.5. Robustness Test

Considering the border controls and lockdowns that severely disrupted labor mobility, industrial evolution, and economic growth during COVID-19, we truncate the sample at 2018 and re-estimate the baseline spatial Durbin model and the spatial mediation model with the W_2 and W_3 weight matrices using IV-GMM. Table 13 reports the estimates, and Table 14 decomposes the effects. The signs and significance of all key variables remain unchanged relative to the full sample. The directions of the direct, indirect, and total effects are likewise stable. Specifically, digital talent mobility still exerts a significant positive direct effect and spillover effect, lnISU_quan continues to display a positive local mediation effect coupled with a negative spatial mediation effect, and lnIDP retains its negative spatial mediation role. Notably, the absolute magnitudes of the effects grow overall.

Once the 2019-2022 pandemic shock is excluded, the positive link between digital talent mobility and economic growth, together with the gain-and-siphon dual effect of industrial restructuring, becomes even stronger. It implies that mobility restrictions during the pandemic compressed talent agglomeration and industrial upgrading effects, introducing a downward bias in the full-sample estimates. In other words, under normal mobility conditions, the

Table 13: The Results of the First Robustness Test (2003-2018)

	Variable	(1) lngdp	(2) lngdp	(3) lnISU_quan	(4) lngdp	(5) lngdp	(6) lnIDP
W_2	lnflow	0.854**	0.153**	0.027***	0.287**	0.153**	0.543**
		(0.079)	(0.050)	(0.003)	(0.064)	(0.050)	(0.096)
	lnISU_quan	8.909*					
		(0.500)					
	lnIDP				0.124*		
					(0.051)		
W_3	lnflow	0.262***	0.410***	0.078***	0.353***	0.410***	1.164***
		(0.033)	(0.022)	(0.003)	(0.029)	(0.022)	(0.086)
	lnISU_quan	1.846***					
		(0.530)					
	lnIDP				0.078***		
					(0.017)		

Note: Robust standard errors in parentheses; ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Table 14: The Results of Spatial Effect Decomposition (2003-2018)

	Mediating variable	Effect		IV-GMM Direct	Indirect	Total
W_2	lnISU_quan	lnflow	Model (1)	0.658**	0.535**	1.193***
			Model (2)	0.183**	0.284**	0.467***
			Model (3)	0.038***	0.018*	0.056**
		lnISU_quan	Model (1)	6.432***	-2.703**	3.729**
	lnIDP	lnflow	Model (4)	0.246***	0.229**	0.475***
			Model (5)	0.183**	0.284**	0.467***
			Model (6)	0.672***	0.718***	1.390***
		lnIDP	Model (4)	0.105	-0.095*	0.010
W_3	lnISU_quan	lnflow	Model (1)	0.356**	0.498***	0.854***
			Model (2)	0.627***	0.593***	1.220***
			Model (3)	0.059***	0.037**	0.096***
		lnISU_quan	Model (1)	4.562***	-2.412***	2.150**
	lnIDP	lnflow	Model (4)	0.342***	0.314**	0.656***
			Model (5)	0.627***	0.593***	1.220***
			Model (6)	1.175***	0.915***	2.090***
		lnIDP	Model (4)	0.097	-0.082*	0.179

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

growth-enhancing power of digital talent is more pronounced, and the competitive crowding of high-end industries into core cities is more acute. These findings confirm the robustness of the baseline conclusions.

To further verify the robustness of the main findings, this study re-estimates the models by replacing the dependent variable with the GDP growth rate of each city. It captures

Table 15: The Results of the First Robustness Test (GDP_growth)

	Variable	(1) GDP_growth	(2) GDP_growth	(3) lnISU_quan	(4) GDP_growth	(5) GDP_growth	(6) lnIDP
W_2	lnflow	0.103**	0.300**	0.061***	0.117**	0.300**	1.083***
		(0.021)	(0.012)	(0.003)	(0.016)	(0.012)	(0.086)
	lnISU_quan	1.314***					
		(0.327)					
	lnIDP				0.148**		
					(0.096)		
W_3	lnflow	0.495**	0.166***	0.022***	0.334***	0.166***	0.283**
		(0.016)	(0.013)	(0.004)	(0.016)	(0.013)	(0.082)
	lnISU_quan	1.698***					
		(0.191)					
	lnIDP				0.029***		
					(0.012)		

Note: Robust standard errors in parentheses; ***, **, * indicate significance at 1%, 5% and 10%, respectively.

dynamic economic performance and allows us to test whether the effect of digital talent mobility and industrial restructuring remains consistent when focusing on economic growth trajectories rather than income levels. The regression results are presented in Table 15, and the decomposition results are shown in Table 16. It demonstrates that the signs and statistical significance of key variables are consistent with those in the baseline model. Digital talent flow continues to exert a significant positive effect on local economic growth, while the spatial spillover effects of industrial restructuring persist in both direction and magnitude. These findings confirm that the conclusions are not sensitive to the specific measurement of economic performance and remain robust across different outcome indicators.

5. CONCLUSION AND POLICY IMPLICATIONS

Drawing on 2003-2022 panel data for cities in the GBA, this study employs an IV-GMM spatial Durbin model and spatial mediation model with economic distance and time-varying economic distance matrices. The findings reveal that digital talent mobility propels local growth and, through positive spillovers, reinforces neighboring cities. Industrial upgrading amplifies this local boost but generates a negative spatial mediation effect through a "siphoning" mechanism. In contrast, although future industrial deployment does not markedly raise local output, it suppresses growth in neighboring cities, producing a dual pattern of "local gain and external dilution." When the pandemic shock is excluded, all effect coefficients become larger, confirming the robustness of the findings and underscoring that under normal mobility conditions, digital talent exerts an even stronger impetus on regional economic growth.

Despite the robust findings and multiple robustness checks, this study has certain limitations. The analysis is conducted at the city level, which may obscure intra-city heterogeneity, especially in large metropolitan areas such as Shenzhen and Guangzhou, where digital talent and industrial structures are highly segmented. Besides, due to data availability, we are unable to incorporate firm-level or individual-level information. Future research could

Table 16: The Results of Spatial Effect Decomposition (GDP Growth)

				IV-GMM		
	Mediating variable	Effect		Direct	Indirect	Total
W_2	lnISU_quan	lnflow	Model (1)	0.112**	0.502**	0.614***
			Model (2)	0.272*	0.212**	0.484***
			Model (3)	0.072***	0.102*	0.174**
		lnISU_quan	Model (1)	1.231***	-2.468**	-1.237**
	lnIDP	lnflow	Model (4)	0.181***	0.380**	0.561***
			Model (5)	0.272*	0.212**	0.484***
			Model (6)	1.068***	0.749*	1.817***
		lnIDP	Model (4)	0.079	-0.049**	0.030
W_3	lnISU_quan	lnflow	Model (1)	0.384**	0.155***	0.539***
			Model (2)	0.349***	0.149***	0.498***
			Model (3)	0.050***	0.025*	0.075***
		lnISU_quan	Model (1)	3.641***	-2.574***	1.067**
	lnIDP	lnflow	Model (4)	0.242***	0.176**	0.418***
			Model (5)	0.349***	0.149***	0.498***
			Model (6)	0.557***	0.590***	1.147***
		lnIDP	Model (4)	-0.004	-0.087*	-0.091

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

extend this work by leveraging micro-level data, which would allow for a more granular understanding of how talent mobility interacts with industrial dynamics and productivity at the enterprise or neighborhood scale.

In short, the spatial dynamics among talent flows, industrial restructuring, and economic expansion highlight the coexistence of both diffusion and crowding-out effects from core cities. Therefore, when formulating policies for digital talent and industrial development, governments should exercise greater caution in designing regional coordination mechanisms, particularly in balancing the growth gap between core and peripheral cities.

Firstly, within the unique institutional context of the GBA, the “One Country, Two Systems” arrangement and the reality of fragmented regional governance make cross-city policy collaboration and industrial coordination a gradual rather than immediate process. To fully unlock the potential of talent mobility and its impact on economic growth, regional authorities and relevant departments must actively explore more flexible and effective institutional coordination mechanisms under the “One Country, Two Systems” framework. For example, governments can establish cross-jurisdictional industrial cooperation platforms, create unified talent evaluation systems, and implement mutual recognition of qualifications to gradually reduce the transaction costs arising from institutional discrepancies, thereby mitigating the spatial polarization of talent and industries.

Secondly, since industrial restructuring generates both local growth effects and potential “siphoning” effects across space, future policies should adopt a more refined approach to balancing industrial positioning and layout among different cities. On one hand, policy design should respect the existing industrial base and functional role of each municipality, preventing the blind replication of upgrading trajectories seen in core cities. On the other hand, peripheral cities should be encouraged to actively integrate the spillover benefits of innovation and value-chain segments from core cities. Through differentiated industrial policies, it is possible to effectively reduce spatial competition and the crowding-out effects of talent and industrial resources.

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