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Digital infrastructure construction and urban inflow of high-skilled talents: evidence from China

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High-skilled talent plays a crucial role in urban innovation and high-quality development. Attracting high-skilled workers has therefore become an important strategy for cities seeking to enhance their long-term competitiveness. We use the number of 4 G base stations in cities as a proxy for digital infrastructure and construct a dataset on the inflow of high-skilled talent into cities. The study finds that digital infrastructure has a significant positive effect on attracting high-skilled talent into cities, and this conclusion remains robust after a series of robustness tests. The underlying mechanism is that digital infrastructure attracts high-skilled talent through income-driven effect, innovation-driven effect, and improved livability. Heterogeneity analysis reveals that the marginal impact of digital infrastructure on attracting high-skilled talent is greater in cities with a more open business environment, higher levels of technological innovation, higher population density, and lower administrative status. Further analysis reveals that digital infrastructure facilitates both the inflow and outflow of high-skilled talent in developed cities, with a net effect of enhancing urban human capital accumulation. However, these effects have not yet manifested in less developed cities. This study provides important insights into how digital infrastructure can be leveraged to attract high-skilled talent and enhance talent competitiveness in the context of a declining demographic dividend.

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Introduction

High-skilled talent, as a source of technological innovation and economic growth, serves as an essential driver of sustainable economic and social development. It plays a critical role in maintaining a city's competitiveness and capacity for innovation (Lucas, 1988; Romer, 1990). However, with the accelerating aging of the population and declining fertility rates, sustained population contraction and the diminishing demographic dividend have become pressing challenges. At this critical juncture, seizing the opportunity to transition from a "quantity-driven" to a "quality-driven" demographic advantage by continuously attracting talent inflows has emerged as a new competitive frontier among cities (Chi, 2008). Figure. 1a illustrates the 2018 development trend of urban innovation levels and the inflow of high-skilled talent, emphasizing the critical relationship between high-skilled talent inflow and the sustained innovative vitality of cities.

In the era of traditional infrastructure, convenient transportation facilities, comprehensive healthcare systems, and high-quality educational environments played a significant role in attracting talent inflow (Baum-Snow & Pavan, 2012). However, with the advent of the digital economy, the rapid development of digital infrastructure has gained prominence. Compared to traditional infrastructure, digital infrastructure is characterized by pronounced digital externalities and spillover effects, offering significantly enhanced capabilities for transmitting information across time and space (Goldfarb and Tucker, 2019). Moreover, unlike traditional infrastructure, which is characterized by large-scale investments and long payback periods, digital infrastructure offers greater investment flexibility and relatively shorter payback periods. Given this, the construction and improvement of digital infrastructure inevitably have an attractive effect on high-skilled talent. In Fig. 1b, this paper illustrates the relationship between the inflow of high-skilled talent into cities in 2018 and the level of 4 G base station construction. This strong positive correlation suggests that high-skilled talent tends to migrate to cities with well-developed digital infrastructure. However, there is currently no literature providing direct evidence to support this observation. Existing literature predominantly falls into two categories: one investigates how various digital technologies reshape the static structure of labor demand, while the other focuses on their influence on broader patterns of labor mobility. Yet, relatively little attention has been paid to the decision-making mechanisms of high-skilled workers—a pivotal component of human capital—when responding to the expansion of digital infrastructure.

To address the gaps in existing research, this paper conducts an empirical study on the impact of digital infrastructure on the inflow of high-skilled talent. Specifically, we manually collect data on urban 4 G base stations from the OpenCelliD database, which serves as a measure of digital infrastructure. Meanwhile, we utilize extensive data from China Migrants Dynamic Survey to estimate the inflow of high-skilled talent into prefecture-level and above cities across the country. Based on this unique city-level dataset, the study focuses on three key questions: whether the development of digital infrastructure can help cities attract high-skilled talent, through which channels this attraction occurs, and how the impact of digital infrastructure on attracting high-skilled talent varies across cities with different characteristics. Answering these questions contributes to clarifying the decision-making mechanisms behind the location choices of high-skilled talent in the digital era. It also provides valuable insights for governments to formulate policies aimed at attracting high-skilled talent and enhancing urban competitiveness.

The findings suggest that the advancement of urban digital infrastructure serves as a key driver in attracting high-skilled talent, a finding that remains robust across a series of tests. Mechanism analysis reveals that digital infrastructure enhances interregional information flows, mitigates information asymmetry in labor markets, and increases the wage income of high-skilled talent. Simultaneously, the improved entrepreneurial vitality and digital industry expansion restructuring driven by digital infrastructure generate a substantial number of high-end employment opportunities in cities, thereby attracting high-skilled talent. In addition, digital infrastructure accelerates the flow of information and enhances overall urban innovation efficiency, thereby increasing the attractiveness of cities to skilled talent. Furthermore, the distinctive features of digital infrastructure empower cities to advance their intelligent development, leading to enhanced natural comfort and living convenience, which further strengthen their appeal to high-skilled talent. Heterogeneity analysis indicates that digital infrastructure exerts a

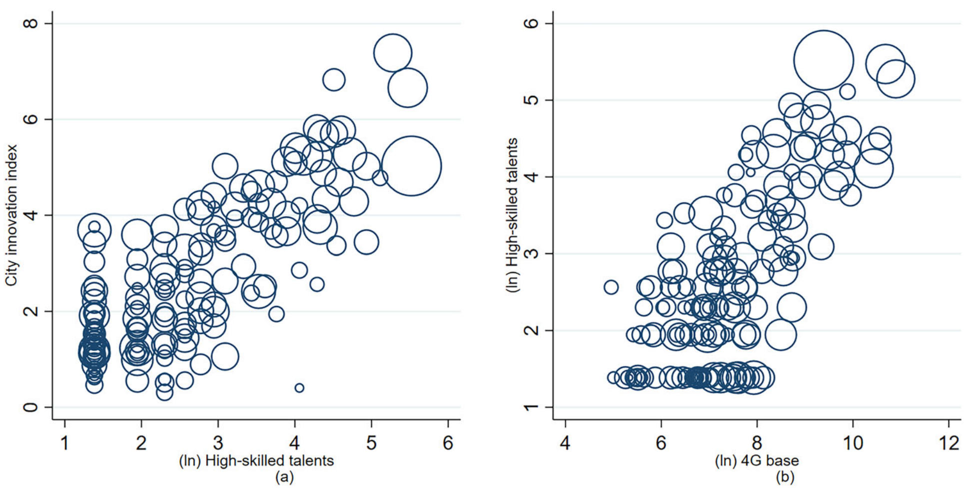

Fig. 1 Digital infrastructure, urban innovation, and high-skilled talent inflow. **a** illustrates the relationship between urban innovation levels and the inflow of high-skilled talent, with circle size representing city population. The levels of city innovation are sourced from the "Urban Innovation Index" published by the Fudan University Research Center for Industrial Development. The inflow of high-skilled talent is calculated based on the CMDS database, with detailed calculation methods provided in Section "The dependent variable". **b** illustrates the relationship between the inflow of high-skilled talent and 4 G base stations, with circle size representing city population.

greater marginal effect on attracting high-skilled talent in cities with open business environments, greater technological innovation, higher population density, and lower administrative ranks. These cities are more capable of leveraging digital infrastructure development to attract high-skilled talent. Finally, since talent inflow reflects a short-term individual migration decision, we conduct an extended analysis to examine the long-term impact of digital infrastructure on urban human capital accumulation. The results show that digital infrastructure promotes both the inflow and outflow of high-skilled talent in developed cities, with a net positive effect on urban human capital accumulation. However, these effects remain largely absent in less developed regions.

The potential marginal contributions of this study can be summarized as follows: First, from a research perspective, while existing literature tends to focus on the factors influencing labor mobility, this study specifically targets the high-skilled talent subgroup. This not only refines the scale of labor mobility research but also offers practical insights for enhancing the targeting of talent attraction policies. Second, in terms of research content, we build on the classical labor location choice framework and develop a more systematic analytical model that incorporates income-driven effect, innovation-driven effect, and livability effect, which together help to capture the mechanisms through which digital infrastructure attracts high-skilled talent and elucidate the structural relationship between the two. Third, we identify the regionally differentiated effects of digital infrastructure on talent mobility by examining multiple dimensions, including business environment, technological innovation, population density, and administrative status. This provides deeper insights into the spatial dynamics of high-skilled talent inflows in the digital era. Finally, we explore the long-term effects of digital infrastructure on urban human capital accumulation, offering valuable implications for the distribution trends of talent in the digital context.

The subsequent sections of this research are organized as follows: section "Literature review and theoretical analysis" conducts a literature review and theoretical analysis, proposing the research hypotheses. Section "Data and empirical specification" presents the data, model, and variable selection. Section "Empirical results" empirically explores the impact of digital infrastructure on attracting high-skilled talent and explores its heterogeneity. Section "Hypothesis testing and further analysis" offers an extended analysis, delving into the mechanisms through which digital infrastructure attracts high-skilled talent and further investigating its long-term effects. The study concludes by summarizing the findings and their implications.

Literature review and theoretical analysis

Literature review. High-skilled talent, as an essential part of human resources, shares the fundamental attributes and behavioral characteristics of individuals, and thus follows the general mobility patterns observed in the labor market. In classical theory, the push-pull theory posits that population migration results from the combined forces of pull factors in the destination area and push factors in the origin area, typically driven by income disparities between regions. Additionally, the level of traditional infrastructure development is also a crucial factor. Numerous studies have explored factors influencing inter-regional labor migration, such as public services, population size, housing prices, employment opportunities, and industrial structure in cities (Baum-Snow & Pavan, 2012; Moretti, 2004; Rabe & Taylor, 2012; Molloy et al., 2011; Holm & Østergaard, 2015). The choice of destination for general labor inflows is primarily influenced by employment opportunities, and they often do not consider the livability of the area (Chiquiar & Hanson, 2005). In contrast, the migration decisions of highly-skilled talent are increasingly linked to the region's comfort level and high wages. Glaeser and Gottlieb (2006) argues that many high-skilled workers move to metropolitan areas like New York due to the irreplaceable high-end consumer venues and the convenience of urban living. Florida (2002) points out that regional inclusiveness plays an important role in attracting high-skilled talent and driving economic development. Qian (2010) concludes that the level of public services and wages in a region are key determinants of high-skilled talent distribution. This suggests that traditional infrastructure indeed plays a crucial role in attracting high-skilled talent.

Digital infrastructure forms the essential cornerstone for the digital economy's development, helping digital technologies penetrate various aspects of social production and daily life more quickly and efficiently. Currently, research on digital infrastructure mainly focuses on examining its impact on the macroeconomy. For example, digital infrastructure development can promote the growth of total factor productivity in the manufacturing sector (Li, Chen, &Miao, 2022), effectively enhance urban economic resilience (Shi, Zheng, &Liu, 2024), and significantly improve urban innovation levels (Luo, Lu, &Wu, 2023). There are also studies that analyze technological innovation at the firm level, such as Tang et al. (2021), who examines the impact of digital infrastructure on green technology innovation.

In studies examining the impact of digital infrastructure on the labor market, most studies primarily focus on analyzing the impact of various digital technologies on labor demand. One group of scholars believes that digital technology has a technology-biased characteristic, where the advancement of digital technologies increases the demand for high-skilled labor while reducing the demand for low-skilled workers (Goldin & Katz, 2008; Acemoglu & Autor, 2011). Another group of scholars holds the view that digital technology has a "polarizing" effect on labor demand, meaning that the development of digital technologies also increases the demand for low-skilled workers (Autor et al., 2006; Dustmann, Ludsteck, & Schönberg, 2009; Michaels, Natraj, & Van Reenen, 2014). Mazzolari and Ragusa (2013) explains this phenomenon from the perspective of consumption spillover, suggesting that the service consumption of high-skilled workers causes income to spill over from the high-skilled labor market to the low-skilled labor market, thereby driving the demand for low-skilled workers. Iranzo and Peri (2009) explains this from the perspective of production complementarities, arguing that in industries that employ many high-skilled workers, the complementary nature of production leads companies to increase their demand for low-skilled labor, thereby promoting employment for low-skilled workers.

In summary, while the literature on the impact of digital technologies on the static demand for labor is relatively abundant, empirical evidence on how digital infrastructure influences the mobility of high-skilled talent remains scarce. Given that high-skilled talent embodies significant human capital, which is crucial for stimulating urban innovation and promoting high-quality urban development, this paper narrows the focus of labor mobility research to this specific group. This is particularly relevant in the context of diminishing demographic dividends, as it helps enhance the targeting of urban talent attraction policies. Specifically, we examine how digital infrastructure influences the flow of high-skilled talent, aiming to clarify the decision-making mechanisms behind their location choices in the digital era. Digital infrastructure not only provides traditional positive externalities but also offers convenience and timeliness, making its development undeniably impactful on high-skilled talent mobility. It attracts high-skilled talent by boosting a city's economic strength and appeal, while also improving urban livability, further encouraging talent inflow.

Theoretical analysis. This paper attempts to analyze the theoretical mechanisms through which digital infrastructure attracts high-skilled talent from three aspects: income-driven effect, innovation-driven effect, and livability effect.

First, digital infrastructure attracts high-skilled talent through income-driven effect. On the one hand, it contributes directly to income improvement. Specifically, digital infrastructure facilitates the rapid flow of information and the proliferation of online learning platforms, enabling high-skilled workers to access information and resources more easily, thereby enhancing their work efficiency and bargaining power in the labor market. In addition, by providing transparent channels of information dissemination (Goldfarb & Tucker, 2019), digital infrastructure reduces information asymmetry in labor markets, allowing high-skilled workers to better improve their market competitiveness. In contrast, low-skilled workers, with generally weaker technical and innovative capacities, often lack the digital literacy and skills needed to utilize information (Autor, 2014), limiting the extent to which their efficiency and bargaining power can be enhanced. On the other hand, digital infrastructure helps create a wide range of high-end job opportunities, expanding career development prospects for high-skilled talent. First, it fosters the emergence and growth of new industries—for instance, by enhancing the regional level of internet development (Li et al., 2023), it stimulates the rise of new internet-based sectors, which generate many digital and technology-intensive jobs. Second, traditional entrepreneurship faces significant geographic and market barriers, resulting in high transaction costs and market entry thresholds that constrain the scale of entrepreneurial activities in cities. Digital infrastructure enables efficient information transmission, helps mitigate information asymmetries, and facilitates the integration of entrepreneurial resources (McCoy et al., 2018). This helps address the spatial mismatch of entrepreneurial opportunities (Nambisan, Wright, &Feldman, 2019), making digital infrastructure an important driver of innovation and entrepreneurship, and thus attracting high-skilled talent. Building on the previous analysis, this paper presents the following research hypothesis:

Hypothesis 1: Digital infrastructure enhances economic incentives for high-skilled talent by increasing their income and generating many high-end job opportunities, thereby attracting their inflow into cities.

Second, digital infrastructure attracts high-skilled talent to cities through innovation-driven effect. The improvement of digital infrastructure accelerates the flow of data, connecting businesses to broader information networks. It reduces cross-regional collaboration costs through mechanisms, such as e-commerce and remote collaboration, thereby enhancing the diffusion of new technologies and knowledge (Czernich et al., 2011) and lowering the technological barriers required for R&D activities, creating a favorable environment for innovation. Moreover, high-speed digital infrastructure significantly reduces information transmission time, thus saving transaction costs faced by businesses during the innovation phase (Bertschek, Cerquera & Klein, 2013). As a foundational technology, digital infrastructure also provides more convenient digital platforms for businesses and research institutions, facilitating the establishment of dense networks, such as between firms and universities (Du & Wang, 2024), which supports technology diffusion and knowledge spillovers. This allows for more efficient collaborative R&D and breakthroughs in new technologies. Furthermore, a city's innovation capacity is a key determinant in talent location decisions. On the one hand, regions with dense innovation activities attract high-quality enterprises, offering greater resource availability (Audretsch & Feldman, 2004), thus increasing career match quality for talent. On the other hand, these areas tend to have higher knowledge density and stronger knowledge spillovers, making them more attractive to talent seeking to enhance their skills. Based on the above analysis, this paper proposes the following research hypothesis:

Hypothesis 2: Digital infrastructure enhances urban innovation capacity, thereby attracting high-skilled talent.

Third, the construction of digital infrastructure attracts talent inflows through the livability effect. Rosen-Roback's spatial equilibrium theory posits that urban livability plays a crucial role in the spatial mobility of labor. Compared to low-skilled labor, high-skilled talent has higher demands for quality of life. When making mobility decisions, low-skilled workers prioritize meeting basic survival needs and may tolerate harsher living conditions. In contrast, high-skilled workers, due to their higher human capital, have more employment options and are less influenced by labor market demand (Chen et al., 2022). They seek a life that goes beyond basic survival needs, pursuing a healthy and enjoyable lifestyle. The development of digital infrastructure not only contributes to promoting the green economic transformation of cities and improving the environmental quality of residential areas but also enhances the convenience and comfort of daily life for residents, significantly increasing people's sense of well-being. On one hand, as the foundation for the development of other important digital technologies, digital infrastructure can improve the level of urban intelligence, promote the widespread use of big data analysis and artificial intelligence technologies in regulatory agencies and businesses, thereby improving environmental governance efficiency (Wang et al., 2023). On the other hand, the development of digital infrastructure has facilitated the widespread use of online services, such as e-commerce platforms, online healthcare, and smart transportation. Online shopping, for example, allows people to purchase a variety of goods without leaving their homes. Therefore, digital infrastructure enhances the overall livability of cities and attracting high-skilled talent who are sensitive to environmental quality to migrate into cities. It is important to note that while digital infrastructure improves residential livability, labor mobility in China is not costless. High-skilled workers often face resettlement costs when relocating across cities, including housing expenses, relocation fees, and the disruption of social networks. These practical barriers may partially offset the attractiveness brought by enhanced livability. In making migration decisions, individuals weigh whether their families can maintain a positive income–expenditure balance post-relocation. This study argues that the improvement in urban convenience enabled by digital infrastructure can compensate for these resettlement costs, resulting in a net positive effect on the inflow of high-skilled talent. Based on the above analysis, we propose the following research hypothesis:

Hypothesis 3: Digital infrastructure attracts high-skilled talent to cities by creating a more comfortable living environment through improved urban livability.

Data and empirical specification

Data. This paper constructs a balanced panel dataset for the period 2011–2018 by matching city-level characteristic data with talent inflow data, resulting in a final sample of 269 cities after data cleaning. Our core explanatory variable, the level of digital infrastructure development, is sourced from the OpenCelliD database. The main dependent variable, "number of high-skilled talent inflows to cities," is derived from the China Migrants Dynamic Survey (CMDS) for 2011-2018. The CMDS provides

Table 1 Definition of main variables and descriptive statistics.

Variable	Description	N	Mean	Sd	Min	Max
Migrant	The logarithm of the number of high-skilled talent inflows	2152	1.73	1.30	0.00	5.76
Base	The cumulative number of 4 G base stations in the city (in thousands)	2152	0.84	3.39	0.00	53.81
College students	The logarithm of the number of college students	2152	10.56	1.35	5.44	13.90
Green rate	The green coverage rate of the city (%)	2152	39.67	5.22	14.00	64.78
Average wage	The logarithm of average employee wage (in thousand yuan)	2152	10.56	1.12	1.74	15.02
Population size	The logarithm of the population size measured per million	2152	5.91	0.68	2.97	8.13
Hospital	The logarithm of total number of hospitals and health centers (in hundreds)	2152	5.06	0.76	1.61	8.02
Housing price	The logarithm of the average housing price	2152	8.42	0.43	7.23	10.78
Fiscal spending	The logarithm of local fiscal budget expenditure	2152	14.71	0.76	11.71	18.14
GDP	The logarithm of GDP	2152	7.28	0.91	4.83	10.40

high-quality micro-level data with strong national representation and it has been widely used in existing literature to study intercity population migration and talent mobility in China (Jiao et al., 2023; Gong et al., 2024). Data for control variables are obtained from various years of the China City Statistical Yearbook, the CSMAR database, and the Wind database. Detailed variable definitions and descriptive statistics are presented in Table 1.

Empirical model. We use city-level panel data to examine the impact of digital infrastructure on the inflow of high-skilled talent. The baseline regression employs a two-way fixed effects model. The regression equation is specified as follows:

$$Migrant_{it} = \beta_0 + \beta_1 Base_{it} + \beta_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

In the equation, the subscript i denotes the city and t represents the year. $Migrant_{it}$ represents the number of high-skilled talents inflowing into city i in year t. $Base_{it}$ refers to the cumulative number of 4 G mobile base stations in city i in year t, which is used to represent the level of digital infrastructure development in the city. X represents city-level control variables, all introduced in their lagged form to mitigate potential endogeneity issues. μ_i represents city fixed effects, which control for time-invariant factors at the city level. λ_t denotes year fixed effects, which control for time-varying factors that affect all cities during the sample period. ε_{it} is the random disturbance term. β_1 is the key coefficient of interest in this study, representing the impact of digital infrastructure on the inflow of high-skilled talent. In the empirical estimation, standard errors are clustered at the city level.

Variable selection

The dependent variable. The dependent variable, the inflow of high-skilled talent, represents the number of high-skilled individuals flowing into city i in year t. This variable is constructed using the CMDS data from 2011 to 2018. The construction process is as follows: (1) Using the CMDS database, samples with education levels of "Associate Degree, Bachelor's Degree, or Master's Degree" were selected. (2) According to the "inflow time" variable in the database, the samples obtained in the first step were aggregated at the city level by inflow year and city name. During the accumulation process, we strictly construct annual inflow volumes based on the "inflow time" variable rather than the survey year, thereby fully avoiding the misclassification of historical inflows as current-year inflows. Following CMDS sampling principles, it is assumed that the sample is randomly distributed. The probability of a sample being selected for a city in 2011 is 8 times higher than in 2018, meaning that the data for 2011 are counted 8 times, and subsequent years are counted proportionally. This introduces a sampling bias in the raw count of migrant inflows across years. To correct for this distortion and enhance the comparability of annual migrant inflows, we adjust the raw counts by dividing them by the cumulative number of possible observation years. (3) The processed data from each year were concatenated vertically to form a balanced panel dataset for 2011–2018.

key explanatory variable. Most of existing literature typically selects the "Broadband China" policy impact or indicators, such as per capita internet access, fiber optic cable length, etc., as proxy variables for digital infrastructure. While the former is more broadly applicable, the latter, although directly related to urban digital infrastructure supply, is more susceptible to being influenced by communication demand. In this study, 4 G base station data at the city level is manually collected from the OpenCelliD database and matched to city-level data. Using the number of urban 4 G base stations as an indicator helps to minimize the influence of demand-side factors and constitutes a mainstream, scientifically sound approach to measuring digital infrastructure (Chao & Xue, 2023; Liao & Liu, 2024). In subsequent robustness checks, we replace it with a composite index.

Control variables. To minimize the potential impact of omitted variable bias, we draw on existing literature and incorporate a series of city-level characteristic variables to control for factors influencing talent inflows: (1) Urban living facilities: These are proxied by the urban green coverage rate, the number of hospitals and health centers, and the average housing price. (2) Economic fundamentals: This includes local fiscal expenditures, city GDP, and the number of university students. (3) Average employee wages: This directly reflects wage levels in the labor market and is an important factor affecting talent inflows. (4) Population size: Controlling for population size is important because an expanding population not only exerts a positive impact on workers through "knowledge spillovers," but also increases the likelihood of employment (Johnson, 2000). The inclusion of city fixed effects accounts for unobservable city-specific factors, which may contribute to variation in talent inflows. To address potential bidirectional causality, we use lagged independent variables, meaning that both digital infrastructure and city-level control variables are treated with a one-period lag.

Empirical results

Baseline results. Table 2 presents the baseline regression results regarding the impact of digital infrastructure on the inflow of high-skilled talent. Columns (1) and (2) do not include any fixed effects; columns (3) and (4) incorporate year fixed effects; and columns (5) and (6) include both year and city fixed effects, along with control variables, to account for unobserved factors, such as environmental, historical, and cultural differences that may contribute to inter-city variations in talent inflow. After controlling for all variables, including year and city fixed effects, the estimated coefficient continues to be significantly positive at the

Table 2 Baseline results.

	(1)	(2)	(3)	(4)	(5)	(6)
Base	0.023***	0.006	0.029***	0.020***	0.023***	0.018***
	(0.005)	(0.004)	(0.007)	(0.007)	(0.007)	(0.006)
College students		0.261***		0.230***		0.046
		(0.062)		(0.058)		(0.064)
Green rate		0.000		0.001		0.003
		(0.005)		(0.005)		(0.005)
Average wage		0.002		-0.007		-0.012
		(0.017)		(0.018)		(0.019)
Population size		-0.217*		-0.276**		0.891**
		(0.115)		(0.112)		(0.354)
Hospital		0.299***		0.053		0.020
		(0.054)		(0.049)		(0.049)
Housing price		0.298**		0.357***		0.049
		(0.121)		(0.124)		(0.145)
Fiscal spending		-0.122		0.376***		0.145
		(0.078)		(0.117)		(0.101)
GDP		0.536***		0.416***		0.315
		(0.130)		(0.125)		(0.195)
Year fixed-effects	N	N	Y	Y	Y	Y
City fixed-effects	N	N	N	N	Y	Y
Observation	2152	2152	2152	2152	2152	2152
R^2	0.010	0.064	0.123	0.123	0.124	0.143

Note: Robust standard errors clustered at city level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This format is consistent across the following tables.

1% level, suggesting that urban digital infrastructure fosters the inflow of high-skilled talent. The coefficient of 0.018 suggests that for every additional 4 G base station per thousand people corresponds to an average 1.8% increase in the inflow of high-skilled talent.

Endogeneity issue. Although the city-level data has been lagged by one period in the previous analysis to mitigate some of the bidirectional causality, on the one hand, the inflow of high-skilled talent may contribute to the availability of more digital talent in the city, which can positively impact the development of local digital infrastructure. On the other hand, the factors influencing the inflow of high-skilled talent are numerous, not all of them could be included as control variables in the model. Therefore, the issue of omitted variables cannot be ignored. To address the potential reverse causality and omitted variable concerns, we will employ instrumental variable methods to alleviate the endogeneity issue. A valid instrumental variable needs to satisfy both the relevance and exogeneity constraints. Following the approach of Chen et al. (2022), we construct a panel data instrument variable by multiplying the number of post offices in each region in 1984 by the national internet user penetration rate from the preceding year. On the one hand, the development of the Internet in China originated from the diffusion of fixed-line telephones, and the historical distribution of post offices significantly shaped the spatial layout of fixed-line infrastructure, thereby influencing regional Internet accessibility. This supports the relevance of the instrumental variable. On the other hand, the historical number of post offices is unlikely to directly affect contemporary talent inflows, satisfying the exogeneity requirement. To account for fixed effects in the panel model, the historical number of post offices is interacted with the national Internet user penetration rate in the previous year, rather than being used directly. The model is estimated using the standard two-stage least squares (2SLS) process:

$$Base_{it} = \alpha_0 + \alpha_1 IV_{it} + \alpha_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

Table 3 IV estimation results.

	Migrant		
	(1) First-stage estimation	(2) Second-stage estimation	(3) Reduced form
Base		0.042^{***}	
		(0.011)	
IV			0.005^{***}
			(0.002)
Control variables	Y	Y	Y
Year fixed-effects	Y	Y	Y
City fixed-effects	Y	Y	Y
Observation	2008	2008	2008
R^2	0.370	0.132	0.150
First-stage result			
iv	0.121^{***}		
	(0.017)		
Underidentification test		41.841	
(p-value)		(0.000)	
KP-F test		48.371	

Note: Column (3) presents the reduced-form results, in which the instrumental variable Z directly replaces the endogenous explanatory variable in the baseline regression. The 2SLS coefficient equals the reduced-form coefficient divided by the first-stage coefficient. This provides an intuitive approach to assessing the validity of the chosen instrument and the overall effectiveness of the instrumental variable estimation.

$$Migrant_{it} = \beta_0 + \beta_1 \widehat{Base}_{it} + \beta_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

In Eq. (2), IV_{it} represents the number of post offices in each region in 1984 multiplied by the previous year's national internet user penetration rate, which serves as the instrument for digital infrastructure. In Eq. (3), $\widehat{Base}_{it}$ is the predicted value of digital infrastructure.

In column (1) of Table 3, the results show that the coefficient of instrumental variable is positively correlated with digital

Table 4 Robustness checks.

	Migrant								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Base	0.249***	0.003*	0.050***		0.041***	0.001***	0.033**	0.131***	0.006**
	(0.084)	(0.002)	(0.012)		(0.008)	(0.000)	(0.016)	(0.043)	(0.003)
treat×year				0.150**					
				(0.061)					
Control variables	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed-effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
City fixed-effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observation	2152	2152	1880	2152	2152	2152	2152	2152	2152
R^2	0.139		0.121	0.141	0.150	0.146	0.138	0.145	0.232
Log-likelihood		-4100.5816							
Wald chi2(16)		531.75							

Note: Column (1) uses city-level data derived from disaggregated provincial digital infrastructure. Column (2) reports estimates using the panel negative binomial model. Column (3) excludes cities with high administrative status. Column (4) applies a quasi-natural experiment to address endogeneity. Column (5) uses winsorized data. Column (6) replaces the dependent variable with the proportion of high-skilled talent inflow. Column (7) uses the logarithmic value of 4 G base stations. Column (8) employs the number of 4 G base stations per capita. Column (9) redefines high-skilled labor as individuals with a bachelor's degree or higher. The provincial-level digital infrastructure index is constructed using principal component analysis, based on six representative indicators that reflect the capacity of communication networks and the level of information infrastructure: (1) capacity of long-distance automatic switches, (2) capacity of local telephone exchanges (in ten thousand lines), (3) capacity of mobile telephone switches (in ten thousand users), (4) length of long-distance optical cable lines (in kilometers), (5) length of optical cable lines (in kilometers), and (6) number of mobile base stations (in ten thousand units). Winsorization is employed as a robustness check to enhance the credibility of the empirical results.

infrastructure at the 1% level. This indicates that historically, cities with more post offices tend to have higher levels of digital infrastructure, which is consistent with theoretical expectations. Additionally, the F-statistic is 48.37, which is greater than the threshold value of 10, rejecting the hypothesis of weak instruments and confirming that the choice of the instrument is valid. Both the two-stage and reduced-form regression coefficients are significantly positive at the 1% level, implying that urban digital infrastructure development significantly promotes the inflow of high-skilled talent. From the second-stage regression results, after using the instrumental variable, the coefficient for digital infrastructure is significantly positive at the 1% level, at 0.042. This suggests that for every additional 4 G base station per thousand people, the number of high-skilled talent flowing into the city increases by 4.2% on average. The absolute value of the second-stage coefficient is significantly higher than that in the baseline regression, indicating the potential issues of reverse causality and omitted variables in model (1).

Robustness checks. First, we construct a composite index for digital infrastructure using principal component analysis (PCA) based on available provincial-level data. Additionally, following the approach of Bartik (Bartik, 1991), we calculate the proportion of each city's cumulative 4 G base stations relative to the total in the province. This proportion is then used as an exogenous weight to decompose the provincial-level digital infrastructure composite index down to the city level:

$$infras_{it} = weight_{it} * infras\_index_{it}$$

In this context, the weight represents the proportion of each city's cumulative 4 G base stations relative to the total in the province. Due to data availability, the proportions for the years 2010–2012 are replaced with the value for 2013. The variable *infras_index* refers to the composite index for digital infrastructure at the provincial level, calculated using PCA. Table 4, Column (1) reports a coefficient of 0.249, which is significantly positive at the 1% level, consistent with the baseline results. This helps mitigate concerns about potential measurement errors in the explanatory variable interfering with the regression results.

Second, given that the dependent variable is a count variable, we consider an alternative specification of the baseline regression model by employing a count data model to further assess the robustness of our results. Poisson regression assumes that the variance and mean are approximately equal, while negative binomial regression is appropriate when the variance exceeds the mean, indicating overdispersion. After verifying the data, we observe that the variance is larger than the mean, suggesting the presence of overdispersion. Consequently, we adopt a negative binomial regression model. The model is specified as follows:

$$P(Y_{it} = y_{it}|Base_{it}, X_{it}) = \frac{e^{-\lambda_{it}}\lambda_{it}^{y_{it}}}{y_{it}!} \tag{4}$$

In Eq. (4), y_{it} represents the number of high-skilled talents flowing into city i in year t, $Base_{it}$ represents the level of digital infrastructure in city i in year t, X_{it} denotes other characteristic variables of city i in year t, and λ_{it} is the Poisson arrival rate, defined as $\lambda_{it} = \beta_0 + \beta_1 base_{it} + \beta_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$. Column (2) presents the results from the panel negative binomial model. The log-likelihood value of -4100.5816 indicates a good fit. The coefficient remains positively significant, aligning with theoretical expectations. This suggests that after changing the model, the baseline findings remain robust.

Next, cities with high administrative status hold significant positions in national politics, economy, science, culture, and transportation. Their economic development level, technological advancement, and preferential policies often surpass those of other prefecture-level cities. Therefore, we excluded samples of municipalities, provincial capitals, and sub-provincial cities and conducted a new regression analysis. The results, shown in Column (3) of Table 4, indicate that the coefficient of digital infrastructure remains positively significant at the 1% level. This suggests that our findings remain robust.

Next, we draw on the approach to addressing endogeneity issues proposed by Fuchs-Schundeln and Hassan (2016). We use the "Broadband China" pilot policy, which was implemented starting in 2014, as an exogenous shock policy, and apply the "difference-in-differences" (DID) technique to provide additional support for the regression results. The cities designated as "Broadband China" demonstration cities are at the forefront of broadband development nationwide. This exogenous event provides an excellent experimental setting for using the DID method to analyze the impact of digital infrastructure on talent

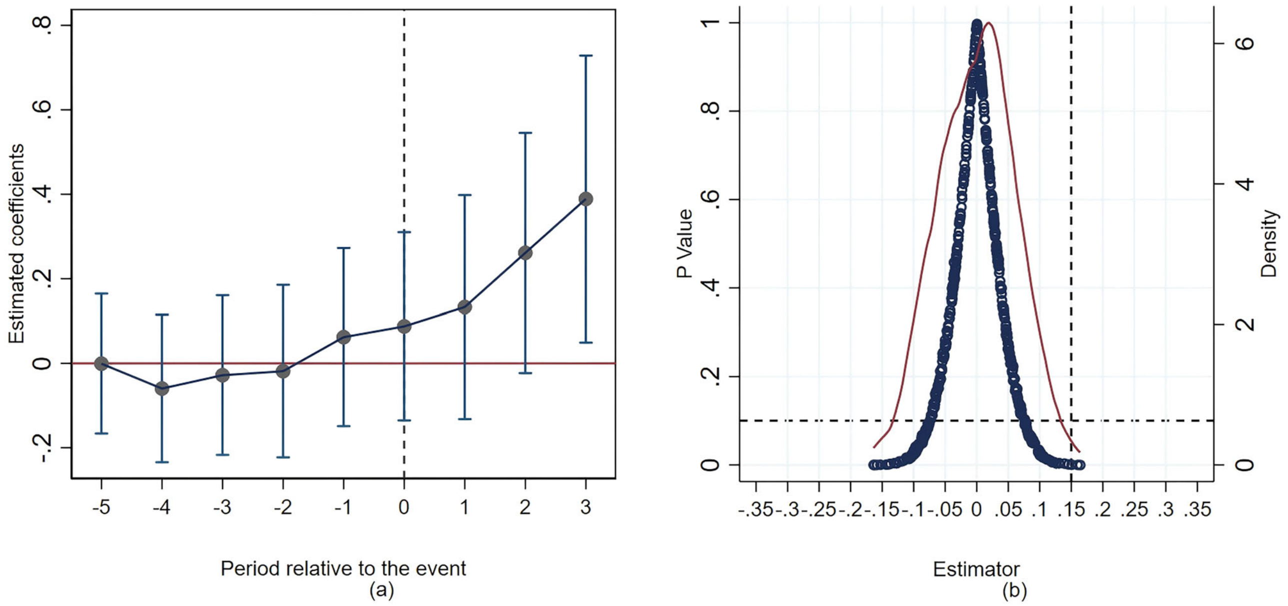

Fig. 2 Parallel trend and placebo tests. a presents the parallel trend test. **b** reports the results of the placebo test.

inflows. The model is specified as follows:

$$Migrant_{it} = \gamma_0 + \gamma_1 treat_{it} \times year_{it} + \gamma_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

In this context, $Migrant_{it}$ denotes the dependent variable, representing the inflow of high-skilled talent; treat is a grouping dummy variable assigned a value of 1 for "Broadband China" pilot cities and 0 otherwise; year serves as a policy time dummy variable, set to 0 before a city's approval and 1 afterward. The interaction term captures the "Broadband China" pilot policy, used here as a proxy variable for digital infrastructure, with the estimated coefficient γ_1 reflecting the policy's effect. X_{it} represents a set of control variables, μ_i indicates city fixed effects, λ_t represents year fixed effects, and ε_{it} is the stochastic error term. The parallel trend test, shown in Fig. 2a, reveals a significant difference in talent inflow between the treatment and control groups before and after the implementation of the "Broadband China" policy. This indicates that the policy did not impact the inflow of high-skilled talent in the same year it was implemented, but rather showed a positive effect two years later, suggesting a certain lag in its impact. Additionally, we conduct a placebo test using a random assignment of the treatment group. The kernel density distribution of the estimated coefficients and the p-values are shown in Fig. 2b. The results indicate that the kernel density distribution of the estimated coefficients generated during the random treatment process is centered around zero, with most random samples yielding p-values greater than 0.100, confirming the robustness of the estimated effect. As shown in Column (4) of Table 4, the results from the progressive DID regression reveal a significantly positive coefficient for the "Broadband China" policy at the 5% level, suggesting its effectiveness in attracting high-skilled talent. This confirms the robustness of the baseline results.

Last, winsorization is commonly used to test whether results are sensitive to extreme values (Almeida et al., 2004; Wang et al., 2023; Shao et al., 2024). Accordingly, we winsorize the 4 G base station count and high-skilled talent inflow at the 1% and 99% quantiles, and re-estimate the regression. The results show that the coefficient remains significantly positive at the 1% level, confirming the robustness of the findings.

Additional robustness checks. To distinguish whether the main results reflect a rising proportion of high-skilled labor or merely an absolute increase driven by overall population growth, we replace the dependent variable with the share of high-skilled talent inflows. Column (6) of Table 4 shows that the coefficient of digital infrastructure remains significantly positive, suggesting that it selectively attracts high-skilled workers rather than simply driving population agglomeration. To further rule out concerns regarding functional form specification, we replace the core explanatory variable with the logarithm of the number of 4 G base stations. The result remains robust. Additionally, to control for the impact of city size, we employ the number of 4 G base stations per capita as an alternative measure. The estimated coefficient is consistent with the baseline results. Finally, we conduct a robustness check using an alternative definition of high-skilled labor by excluding individuals with associate degrees from the original sample and re-estimating the regression. As shown in Column (9) of Table 4, the coefficient for digital infrastructure remains significantly positive, confirming the robustness of our findings.

Heterogeneous effects. In this section, we conduct heterogeneity analyses to gain further insights into the specific impact of digital infrastructure on attracting high-skilled talent. First, the business environment is a key determinant of institutional efficiency, market openness, and entrepreneurial vitality at the city level. A favorable business environment reduces institutional transaction costs for firms, thereby fostering entrepreneurial activity and supporting the development of digital industries. This, in turn, helps to fully realize the income and employment effects of digital infrastructure. Therefore, the role of digital infrastructure in promoting high-skilled talent inflow may be more significant in cities with better business environments. Using the China City Commercial Credit Environment Index (CEI), we group the sample based on the median of the CEI to further examine the impact of digital infrastructure on talent inflow. The results in columns (1) and (2) of Table 5 show that, in the low business environment group, the coefficient for digital infrastructure is insignificant, while in the high business environment group, the coefficient is positively significant at the 5% level. This indicates that in cities with a better business environment, the positive effect of digital infrastructure on talent inflow is stronger, confirming the heterogeneity in the impact of digital infrastructure on talent inflow across business environments.

Table 5 Heterogeneity analysis based on business environment, technological innovation, and population density.

	Migrant					
	(1)	(2)	(3)	(4)	(5)	(6)
	Business environment		Technological innovation		Population density	
	High CEI	Low CEI	High-Innov	Low-Innov	High-dens	Low-dens
Base	0.013**	0.000	0.012**	0.069	0.014**	0.057
	(0.006)	(0.064)	(0.005)	(0.084)	(0.006)	(0.052)
Control variables	Y	Y	Y	Y	Y	Y
Year fixed-effects	Y	Y	Y	Y	Y	Y
City fixed-effects	Y	Y	Y	Y	Y	Y
Observation	1076	1076	1080	1072	1080	1072
R^2	0.252	0.115	0.238	0.119	0.186	0.136

Note: The CEI Index (see http://www.chinacei.org/) is a comprehensive evaluation metric for the business environment of Chinese cities, developed by the Chinese Academy of Management Sciences. This index objectively measures the strengths and weaknesses of the urban business environment.

Table 6 Heterogeneity analysis based on administrative status.

	Migrant		
	(1)	(2)	(3)
	High-status	Low-status	Interaction term
Base	-0.001	0.050***	0.040***
	(0.004)	(0.012)	(0.012)
Interaction term			-0.025*
			(0.013)
Control variables	Y	Y	Y
Year fixed-effects	Y	Y	Y
City fixed-effects	Y	Y	Y
Observation	272	1880	2152
R^2	0.706	0.121	0.146

Next, the level of technological innovation reflects a city's capacity for knowledge production and technological breakthroughs. In cities rich in innovation resources, digital infrastructure facilitates faster information flow and significantly enhances the efficiency of collaborative innovation among institutions, thereby improving overall innovation performance. This implies that in cities with higher levels of technological innovation, digital infrastructure can more effectively activate innovation-driven effect, thus increasing their attractiveness to high-skilled talent. We categorize cities into high-tech and low-tech groups based on their average scientific expenditure, allowing for a segmented analysis. The subsample regression results indicate that in high-tech cities, the effect of digital infrastructure on high-skilled talent inflow is positively significant at the 5% level. In contrast, in cities with lower levels of technological innovation, the coefficient remains positive but statistically insignificant. This suggests that in cities with stronger innovation capacity, digital infrastructure can more effectively activate innovation-driven mechanism, thereby enhancing their ability to attract talent.

Next, densely populated cities are more prone to agglomeration effects and knowledge spillovers, which enhance the capacity of digital infrastructure to facilitate rapid information flow, overcome innovation and entrepreneurial barriers, and improve overall innovation efficiency. Consequently, the attraction of high-skilled talent by digital infrastructure is likely to be more pronounced in cities with higher population density. We use population density as a grouping variable and divide the sample into low and high population density groups for heterogeneity analysis. The regression results show that in the high population density group, the coefficient for digital infrastructure is significantly positive at the 5% level, whereas in the low population density group, it is not significant. This indicates that, in cities with higher population density, the effect of digital infrastructure on high-skilled talent inflow is stronger.

Finally, cities with higher administrative status benefit from more favorable policy support and are typically more developed, leading to more advanced digital infrastructure where talent can generally access high-quality digital services. Additionally, these cities can leverage their inherent administrative advantages—such as policy guidance and tax incentives—to directly attract talent, thus reducing the relative impact of digital infrastructure on talent attraction. In contrast, in lower-administrative-status cities, digital infrastructure development lags significantly behind that of high-status cities, making digital infrastructure a more influential factor in attracting high-skilled talent. We categorize the sample into low and high administrative status groups for a segmented regression analysis, with results shown in columns (1) and (2) of Table 6. The regression results indicate that, in low-administrative-status cities, the impact of digital infrastructure on talent attraction is more direct and significant, whereas in high-administrative-status cities, the coefficient is not significant. This suggests that high-status cities rely more on their administrative advantages to attract talent directly. Given the substantial sample size difference between groups, we further introduce an interaction term between a dummy variable for administrative status (coded as 1 for high administrative status and 0 otherwise) and digital infrastructure to provide additional validation. Column (3) shows that the interaction term coefficient is significantly negative at the 10% level, supporting the conclusions drawn from the segmented regression.

Hypothesis testing and further analysis

Hypothesis testing. In this section, we undertake a detailed analysis of the mechanisms by which digital infrastructure attracts high-skilled talent to urban areas, empirically testing the three potential channels outlined in section "Theoretical analysis".

Income-driven effect. Based on the theoretical analysis above, digital infrastructure enhances economic incentives for high-skilled talent by increasing their income and generating a significant number of high-end job opportunities, thus attracting high-skilled talent. This section further tests this channel. Regarding income, the net income variable is constructed using

Table 7 Mechanism: Income-driven effect.

Panel A: Promoting effect

	Income level		High-end job creation		
	(1) Full sample	(2) Including interaction term	(3) Entrepreneurial activity	(4) Output of the information services industry	(5) New enterprises in the information services sector
Base	0.003*** (0.000)	0.001*** (0.000)	3.727** (1.600)	0.016*** (0.006)	0.187*** (0.053)
Base×edu		0.005*** (0.000)			
Control variables	Y	Y	Y	Y	Y
Year fixed-effects	Y	Y	Y	Y	Y
City fixed-effects	Y	Y	Y	Y	Y
Observation	762809	762809	2152	2152	2152
R^2	0.034	0.038	0.441	0.070	0.536

Panel B: Income amplifying effect

	Panel quantile regression				
	(4) QR10	(5) QR30	(6) QR50	(7) QR70	(8) QR90
Base	1.425 (1.059)	1.423 (1.020)	1.400** (0.576)	1.366*** (0.491)	1.364*** (0.526)
Control variables	Y	Y	Y	Y	Y
Year fixed-effects	Y	Y	Y	Y	Y
City fixed-effects	Y	Y	Y	Y	Y
Observation	3042	3042	3042	3042	3042

Note: Columns (1) and (2) use net income as the dependent variable, which is calculated by deducting housing rent expenditure from individual income.

data from the CMDS database, with an interaction term between digital infrastructure and individuals' education levels. Additionally, panel data is constructed using tracking data from the 2012, 2014, and 2016 waves of the China Labor-force Dynamics Survey (CLDS). We use a panel quantile regression model to analyze how the impact of digital infrastructure on income varies across different quantiles, providing insights into its income-amplifying effect for high-skilled talent. The panel quantile regression model is specified as follows:

$$Q_\tau(Income_{ict}) = \delta_0 + \delta_{1\tau}Base_{ct} + \delta_{2\tau}X_{ct} + \mu_c + \lambda_t + \varepsilon_{ict} \quad (6)$$

Here, $Income_{ict}$ represents the income level of individual I in city c during year t, with other variables defined as in Eq. (1). $\delta_{1\tau}$ denotes the quantile regression coefficient of digital infrastructure on individual income at quantile τ, and $\delta_{2\tau}$ represents the corresponding coefficient for control variables. The selected quantiles τ are 10%, 30%, 50%, 70%, and 90%.

Regarding job creation, we analyze two aspects: the entrepreneurial environment and the development of digital industries. As urban entrepreneurial activity increases, more innovative enterprises emerge, which require high-skilled talent with specialized knowledge, skills, and experience to meet demands in technology, management, and marketing. Additionally, the growth of the information services sector signifies an increased demand for talent. For example, the development of information services has led to significant job growth in industries, such as telecommunications equipment manufacturing, computer software and hardware, and office automation. These digital industries typically require large numbers of high-skilled workers in areas, such as technological research and development, project management, and market analysis.

Table 7 present the corresponding regression results. In Column (1) of Panel A, the coefficient for digital infrastructure and the interaction term in Column (2) are both significantly positive at the 1% confidence level, indicating that the development of digital infrastructure effectively increases the income of high-skilled talent. Columns (3) to (5) show that the coefficients for the effects of digital infrastructure on urban entrepreneurial environment and digital industry development are significantly positive at least at the 5% level, suggesting that digital infrastructure indeed attracts high-skilled talent by creating more high-end job opportunities. Panel B further displays the panel quantile regression results, where the effect of digital infrastructure on income is not significant at lower quantiles but is significantly positive at the 1% level at higher quantiles, indicating that the impact of digital infrastructure on income is stronger for higher-income individuals. In conclusion, Hypothesis 1 is validated.

Innovation-driven effect. Based on the previous theoretical analysis, the innovation-driven effect refers to the ability of digital infrastructure to indirectly attract high-skilled talent by enhancing urban innovation capacity. This study verifies the channels through which digital infrastructure attracts high-skilled talent under the innovation effect by examining three aspects: government scientific expenditure, the number of invention patent applications, and urban innovation efficiency. Government scientific expenditure measures the local government's resource allocation willingness for innovation investment, representing the level of urban innovation input; the number of invention patent applications reflects the vitality of knowledge creation, used to gauge the activity level of innovation output; urban innovation efficiency is derived from the Urban Innovation Index published by the Fudan University Industrial Development Research Center, representing the efficiency of cities in utilizing technological resources. The results in Table 8 show that digital infrastructure

Table 8 Mechanism: innovation-driven effect.

	Government scientific expenditure	Patent applications	Urban innovation efficiency
	(1)	(2)	(3)
Base	0.024**	0.932***	11.181***
	(0.010)	(0.068)	(2.309)
Control variables	Y	Y	Y
Year fixed-effects	Y	Y	Y
City fixed-effects	Y	Y	Y
Observation	2152	2152	2152
R^2	0.275	0.691	0.714

Note: The levels of city innovation are sourced from the "Urban Innovation Index" published by the Fudan University Research Center for Industrial Development.

Table 9 Mechanism: livability effect.

	Natural comfort	Life convenience			Subjective well-being	Include costs
	PM2.5	Payment_level	Investment_level	Digitization_level	Life satisfaction	Household surplus
	(1)	(2)	(3)	(4)	(5)	(6)
Base	−0.135**	0.918***	0.745***	0.851***	0.006**	0.245***
	(0.063)	(0.254)	(0.088)	(0.172)	(0.003)	(0.048)
Control variables	Y	Y	Y	Y	Y	Y
Year fixed-effects	Y	Y	Y	Y	Y	Y
City fixed-effects	Y	Y	Y	Y	Y	Y
Observation	2152	2152	1345	2152	34120	123673
R^2	0.663	0.978	0.981	0.945		0.065
Pseudo R2					0.1060	
Wald Test					2275.03	
ll					−23264.67	

Note: Since life satisfaction is a discrete variable, a fixed-effects ordered Logit model was employed. Household surplus accounting for resettlement costs is calculated as household income minus expenditure for high-skilled individuals in the CMDS dataset.

has a significantly positive impact on urban innovation input, output, and efficiency at least at the 5% level, indicating that the development of urban digital infrastructure can, to some extent, promote urban R&D investment and innovation levels, thereby enhancing the attraction of high-skilled talent.

livability effect. As previously discussed, digital infrastructure enhances urban intelligence, thereby improving environmental governance efficiency and the quality of the natural environment. At the same time, it significantly increases the convenience and comfort of daily life, which in turn enhances residents' overall well-being.

Firstly, we use air quality as an indirect measure of urban natural environment quality, specifically employing annual PM2.5 concentration data for Chinese cities. Column (1) in Table 9 demonstrates that the coefficient for digital infrastructure on urban PM2.5 concentration is significantly negative at the 5% level, indicating that the development of digital infrastructure reduces air pollution and improves urban natural environment comfort, thereby partially confirming Hypothesis 3. For validating the impact on residents' daily life convenience, we use the payment index, investment index, and digitalization index from the Peking University Digital Financial Inclusion Index of China as proxies for life convenience. Columns (2)-(4) of Table 9 show significantly positive coefficients at the 1% level, suggesting that digital infrastructure significantly improves residents' life convenience. Moreover, residents' subjective well-being is an important indicator of urban livability. The China Family Panel Studies (CFPS) provides data on life satisfaction (on a scale of 0-5, with higher values indicating greater satisfaction). Using CFPS data from 2011-2018, we selected high-skilled talent samples and matched them with corresponding city variables to construct a panel dataset for regression. Column (5) provides a positive coefficient for digital infrastructure on high-skilled talent life satisfaction at the 10% level, indicating that digital infrastructure effectively enhances high-skilled talent life satisfaction. Finally, considering that the resettlement costs faced by migrants may weaken the livability effect brought by digital infrastructure, we further construct "total household income minus total expenditure" as an indirect proxy for resettlement costs. Column (6) shows that digital infrastructure significantly increases household surplus at the 1% level, indicating that even after accounting for resettlement costs, the talent attraction effect resulting from improved livability remains robust. Thus, Hypothesis 3 is fully validated.

Long-term effects of digital infrastructure: urban human capital accumulation and talent retention. The previous sections have validated the channels through which digital infrastructure attracts high-skilled talent. In this part, we empirically examine whether digital infrastructure can promote long-term human capital accumulation in cities. Using CMDS data from 2011 to 2018, we select high-skilled individuals, aggregating the data at the city level by year. Unlike the baseline regression, which aggregates data based on the questionnaire's "inflow time", here the data is aggregated using the year the questionnaire was issued. After aggregation at the city level, the data is divided by the corresponding year's urban resident population, which serves as a proxy for the city's human capital accumulation, denoted as HC.

Table 10 Effects of digital infrastructure on high-skilled human capital and retention.

Panel A:The impact of digital infrastructure on urban human capital accumulation

	(1)	(2)	(3)	(4)
	All	**FTC**	**STC**	**LTC**
Base	0.047***	0.074***	0.009	−0.003
	(0.017)	(0.021)	(0.021)	(0.031)
Control variables	Y	Y	Y	Y
Year fixed-effects	Y	Y	Y	Y
City fixed-effects	Y	Y	Y	Y
Observation	2152	152	240	1760
R^2	0.187	0.344	0.467	0.150

Panel B: The impact of digital infrastructure on the retention intention of high-skilled talents.

	(5)	(6)	(7)	(8)
Base	-0.013***	-0.014***	-0.028**	0.034
	(0.001)	(0.002)	(0.011)	(0.026)
Control variables	Y	Y	Y	Y
Year fixed-effects	Y	Y	Y	Y
City fixed-effects	Y	Y	Y	Y
Observation	125721	58353	32770	34,598
LR	13509.18	6733.25	3817.82	3106.21
Log likelihood	−77556.828	−35423.822	−19995.055	−21991.619
Pseudo R^2	0.0801	0.0868	0.0871	0.0660

Note: We measure retention intention using survey data from 2014 to 2018, based on the question: "Are you willing to reside locally for more than five years?" A binary variable is defined, taking the value of 1 if the respondent answers affirmatively, and 0 otherwise. A logit regression model is then employed for estimation. The city tier system used in this paper originates from the annual "China City Business Attractiveness Ranking" published by the New First-tier City Research Institute of Yicai Media Group. It evaluates 337 prefecture-level and above cities based on five primary dimensions.

Panel A in Table 10 reports the effects of digital infrastructure on urban human capital accumulation. Column (1) shows that the coefficient is significantly positive at the 1% level, indicating that digital infrastructure facilitates human capital accumulation in cities. Further breakdown by city category shows the results for first-tier and new first-tier cities (FTC), second-tier cities (STC), and third, fourth, and fifth-tier cities (LTC) in columns (2), (3), and (4), respectively. It can be observed that in FTC, the positive effect of digital infrastructure on human capital accumulation is stronger; in STC, there is no significant effect, but the coefficient remains positive; and in LTC, although still not significant, the coefficient has turned negative. This may be due to the insufficient infrastructure and underdeveloped levels in less developed regions, where relying solely on digital infrastructure development is not sufficient to accelerate human capital accumulation. The above analysis examines how digital infrastructure can enhance urban human capital by attracting talent. However, some individuals may choose to leave the city after relocation. To further investigate the long-term effects of digital infrastructure, we examine the retention intention of high-skilled talent after their arrival in the city.

Panel B displays the regression results. Column (5) presents a significantly negative relationship between digital infrastructure and high-skilled talent retention intention at the 1% level, implying that digital infrastructure diminishes the intention to stay. When the cities are further categorized, Column (6) shows a coefficient is significantly negative at the 1% level, suggesting that in FTC, digital infrastructure still suppresses the retention intention of high-skilled talent. This could be attributed to the swift expansion of digital infrastructure in major cities, which allows high-skilled talent more flexibility in choosing cities based on their needs and quality of life, rather than being confined to a single city. Consequently, they may be less likely to stay long-term in one city. The results show that in LTC digital infrastructure has no significant impact on talent retention intention. This may be attributed to the relatively underdeveloped entrepreneurial environment and industrial base in these areas, which limits the functional effectiveness of digital infrastructure. As a result, it does not substantially enhance job opportunities, wage increases, or living comfort, and thus fails to influence talent's intention to stay.

The preceding analysis indicates that digital infrastructure has facilitated the inflow and outflow of high-skilled talent in developed cities, contributing positively to the accumulation of human capital. However, its long-term effects in underdeveloped regions differ significantly. In these areas, digital infrastructure does not directly influence high-skilled talent's intention to stay in these regions, as it has not fully leveraged its inherent advantages. Furthermore, digital infrastructure has no significant impact on the overall human capital accumulation in these cities. This suggests that while digital infrastructure yields positive long-term effects in large cities, its impact on enhancing long-term retention intentions is limited due to factors, such as heavy workloads and psychological stress.

Conclusion

In the context of a diminishing demographic dividend, talent has become the primary resource. With the development of digital technologies, leveraging digital infrastructure to attract high-skilled talent is significant. We innovatively construct a high-skilled talent inflow indicator for cities at and above the prefecture level using the 2011–2018 China Migrants Dynamic Survey. This indicator is matched with the number of 4 G base stations in each city, alongside other city-specific characteristics, to create a panel dataset for 269 cities. We employ a two-way fixed-effects model to empirically examine the role of digital infrastructure in attracting high-skilled talent to cities. First, the results show that digital infrastructure has a significant positive effect on attracting high-skilled talent. This result holds after addressing endogeneity issue and conducting a series of additional robustness checks. Second, the mechanism analysis identifies three main channels through which digital infrastructure attracts high-skilled talent: income-driven effect, innovation-driven effect, and livability effect. Third, the heterogeneity analysis indicates that the effect of digital infrastructure on high-skilled talent inflow is stronger in regions with more open business environments, higher levels of technological innovation, and higher population densities. Moreover, cities with lower administrative status show more pronounced effects in attracting talent through digital infrastructure. Finally, the study further reveals that digital infrastructure promotes the inflow and outflow of high-skilled talent in developed cities, resulting in a net positive effect on human capital accumulation, while such effects have not yet emerged in underdeveloped cities.

The research provides key policy implications for Chinese cities seeking to enhance their human capital and attract high-skilled talent by advancing digital infrastructure: First, sustained investment in urban digital infrastructure—particularly in sectors related to the digital economy—should be strengthened. Enhancing such investments can facilitate collaborative innovation and technological breakthroughs among various actors, thereby contributing to the accumulation of urban innovation capacity. Second, region-specific policies should be formulated to support the digital development of economically disadvantaged areas and promote a more balanced spatial distribution of digital infrastructure. Efforts should be directed toward improving infrastructure in low-population-density cities, while simultaneously enhancing local technological innovation capacity and fostering a favorable business environment to amplify the attractiveness of digital infrastructure to high-skilled talent. Third, while developing digital infrastructure, it is equally important to advance the construction of traditional infrastructure. In the absence of adequate traditional facilities, reliance on digital infrastructure alone may not be sufficient to effectively attract talent inflows.

Data availability

The datasets supporting the findings of this study are available as supplementary materials.

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Author contributions
Siyu Meng developed the research idea, designed the overall study, and wrote the main manuscript text. Xuan Zou contributed to data collection, software development, and supervision. Chun Liu prepared figures and provided materials and tools for the research. All authors reviewed the manuscript.

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The authors declare no competing interests.

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