World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Research Article)

Check for updates

Research on the measurement and influencing factors of the agglomeration degree of industrial digitalization talents in China

Liu Xiaoyue *

Personnel Division, Central University of Finance and Economics, 100081, China.

World Journal of Advanced Research and Reviews, 2026, 30(01), 1717-1729

Publication history: Received on 10 March 2026; revised on 15 April 2026; accepted on 18 April 2026

Article DOI: https://doi.org/10.30574/wjarr.2026.30.1.1013

Abstract

When the digital economy becomes deeply intertwined with conventional industries, this integration contributes substantially to the overall economy's healthy and rapid expansion. Within this context, the way industrial digitalization talents cluster together emerges as a critical determinant. Against this backdrop, the current study undertakes a systematic assessment of both the size and the concentration patterns of such talents. To this end, we draw upon several analytical tools, including the compilation of input-output tables, the derivation of digital consumption coefficients, and the application of location entropy techniques. Using these methods, we compute agglomeration indices for industrial digitalization talents across 30 Chinese provinces and municipalities over the period 2011–2023. Subsequently, informed by the distinctive features of this talent category, we implement a regression framework to evaluate how economic conditions, industrial structures, cultural settings, and quality-of-life variables collectively shape talent agglomeration. Our empirical findings indicate that, across different provincial-level jurisdictions, industrial digitalization talents clustering continues to be shaped primarily by economic and environmental forces. Nevertheless, as cross-regional integration proceeds, the influence of economic growth on talent agglomeration exhibits a declining trend. These observations suggest the necessity for fresh policy initiatives aimed at fostering a self-reinforcing virtuous cycle linking industrial digitalization and the corresponding talent clustering process.

Keywords: Industrial Digitalization Talents; Talent Agglomeration; Influencing Factors; Agglomeration Degree Measurement

1. Introduction

By placing data at the center of the growth paradigm, the digital economy is reshaping conventional development pathways and is poised to trigger a fresh wave of technological transformation. For China, this phase represents a unique historical opportunity to pursue leapfrog progress and move closer to the goal of national renewal. The State Council released two key documents—the *14th Five-Year Plan for Digital Economy Development* and the *Overall Plan for Building a Digital China*—which weave digital technologies into the "five-sphere integrated" framework that covers economic activity, governance, culture, society, and ecological progress. These policy efforts have fully activated the multiplicative potential of data as a production factor and have paved a digital pathway toward high-quality economic growth.

As the digital economy evolves into the stage of data factorization, algorithms, computing power, and network collaboration have broken through the boundaries of the digital industry and become a general-purpose technology deeply integrated with the real economy. Their spillover effects enable a broader range of traditional industries to achieve optimization and upgrading across the entire production process through digital transformation. Industrial supply chains, logistics, finance, and R&D are being reorganized across larger spatial scales, forming cross-regional

* Corresponding author: Liu Xiaoyue

integrated industrial networks that significantly improve total factor productivity. Compared with digital industrialization, which remains in a period of technological ascent and capital-intensive investment, industrial digitalization is directly embedded in existing assets and constitutes a leading force in China's economic restructuring and regional coordination. From this perspective, industrial digitalization holds greater practical significance for stabilizing employment, growth, and development in the short term. Compared with research on digital industrialization, it also warrants in-depth analysis.

Talent agglomeration is a driver of prosperity, and the same holds true for industrial digitalization. According to economic growth theory, human capital is an important factor influencing economic growth. Data, algorithms, and platforms are merely physical elements; their potential can only be unleashed through activation by "people." The higher the talent density, the more frequent knowledge spillovers become, and the more likely it is to form a regional innovation complex featuring high-frequency industry-university-research-application interactions. The agglomeration of compound digital talents can also generate a virtuous cycle of "talent policy—talent agglomeration—environmental optimization—comprehensive development," serving as a core catalyst for reshaping traditional industries. However, most current research defines digital talents too narrowly, mainly calculating the degree of talent agglomeration within the context of ICT (information and communication technology), and rarely includes industrial digitalization talents in its scope.

2. Literature review

At present, in the field of talent scale measurement, the research pedigree is mainly divided into two directions. One is to measure the scale and flow level of scientific and technological talents or other professional talents based on location entropy or the entropy method. For example, by modifying the gravity model based on the entropy method, some studies define and measure the flow level of scientific and technological talents in prefecture-level cities, and verify the siphon phenomenon of scientific and technological talents in large cities [[1]]; others concentrate on integrated regions such as the Beijing-Tianjin-Hebei region and the Yangtze River Delta, measuring the overall talent concentration, talent efficiency, and the contribution rate of talent capital to economic growth [[2]]; In some studies, location entropy is first adopted to gauge the degree of concentration among professional talents. Then, quantile regression is employed to explore how different factors exert their influence. Specifically, this method helps identify both the direction and the magnitude of such effects on professionals belonging to various identity categories [[3]]. Relevant research abroad also includes focusing on the differences in the distribution of high-skilled and low-skilled talents [[4]], using company-level data to determine the impact of talent agglomeration on corporate location [[5]], and so on.

The second line of research measures the contribution of human capital and talents using a production function framework. In this approach, the Cobb-Douglas production function serves as the primary modeling tool. Researchers then estimate how much talent capital contributes to economic growth, drawing on macroeconomic data [[6]]; Or some studies use the SBM model, DEA-Malmquist model, Moran I model, and so on to measure and analyze the efficiency of talent development in various regions [[7]]; Some foreign scholars have employed a variety of econometric models. These include fixed-effects models, threshold effects models, adjustment effects models, and spatial econometric models. They use these tools to measure digital talent agglomeration, as well as to examine its nonlinear relationship with green technology innovation and the associated spatial spillover effects [[8]].

In terms of talent agglomeration research, the academic community has accumulated rich results, which intersect with research on talent scale measurement. It can also be divided into two parts: one focuses on "cause," exploring how location, policy, salary, culture, and other factors drive changes in the spatial pattern of talent agglomeration; the second focuses on "effect," using the agglomeration degree as an independent variable or mediating variable to analyze its interaction effects with economic growth, technological iteration, and industrial upgrading. The empirical data generally support a significant positive correlation.

However, the above-mentioned literature mostly integrates "talents" or "scientific and technological talents" as a homogeneous whole, and there is relatively little literature focusing on digital talents, especially on the segmentation and definition of digital talents. Specialized research on its agglomeration mechanism is still scarce.

In terms of talent agglomeration effects, the existing literature mainly includes three mainstream views:

First, a higher concentration of talent tends to be associated with stronger regional innovation capacity, more effective synergy with industrial clustering, an upgraded industrial mix, and accelerated economic expansion. Moreover, through spatial spillovers of both human resources and other inputs, such agglomeration can generate complementary mechanisms that facilitate cross-regional integration and help close economic gaps between different areas [[9]][[10]].

Second, talent clustering is not without its downsides. Overly dense concentrations may give rise to negative externalities—intense competition and scale diseconomies being prime examples—leading to what can be termed agglomeration diseconomies [[11]]. In parallel, this phenomenon can drain talent from less developed neighboring regions [[12]].

Third, while talent agglomeration generally boosts technical efficiency and technological progress—and thereby lifts total factor productivity—an excessive level of clustering can backfire, generating crowding-induced efficiency losses. Furthermore, the degree to which talent concentration yields positive economic outcomes depends heavily on external conditions and on whether it forms a well-coordinated relationship with other developmental factors [[13]].

Therefore, based on the concept of “location entropy,” combined with the division of different parts of the digital economy by the China Academy of Information and Communications Technology (CAICT), this paper defines and measures the scale of industrial digitalization and the agglomeration degree of industrial digitalization talents, and then analyzes the socio-economic environmental factors that affect talent agglomeration in this field.

Drawing on prior studies, this paper highlights two main breakthroughs. First, we follow CAICT’s definition of industrial digitalization. According to this definition, industrial digitalization refers to the gains in output and efficiency that occur when digital technologies are applied to traditional industries. This process gives rise to various integrated new industries, new business models, and new formats [[14]]. In essence, industrial digitalization results from the ongoing advancement of digital technology. It also serves as a key pathway for promoting high-quality socio-economic growth and cultivating new productive forces. Nevertheless, most existing studies adopt a broad perspective on the digital economy. They seldom devote specific attention to industrial digitalization. (2) In addition, previous research on digital talents is not sufficient. The mainstream direction focuses on the demand analysis and training level of related talents. Some cutting-edge literature only quantitatively analyzes it as an intermediary variable in digital economic development or regional economic growth, and lacks a systematic grasp of the agglomeration patterns of digital talents, especially industrial digitalization talents.

3. Measurement of the Agglomeration Degree of Provincial-Level Industrial Digitalization Talents in China

In this section, we introduce the input-output table compilation method. Using this method, we first select the digital core industries. Our selection follows the “Statistical Classification of the Digital Economy and Its Core Industries” issued by the National Bureau of Statistics. We then match these digital core industries with the corresponding product sectors in the input-output table. Next, we compute the direct consumption coefficient. This coefficient captures how much traditional industries consume products from the digital core industries. We multiply this coefficient by the value added of traditional industries. The result is the scale of digital added value for China’s provincial industries. Finally, we use this digital added value to calculate both the scale and the agglomeration degree of industrial digitalization talents.

3.1. Compiling Input-Output Tables for Years with Missing Data

This paper draws mainly on two existing studies. One is by Li Baoyu and Zhang Jing (2012) [[15]]. The other is by Zhang Hongxia, Xia Ming, Su Rujie, and their colleagues (2021) [[16]]. Following their approaches, we apply the RAS method to compile input-output tables for provinces and cities in years where data are missing. The RAS method is also called the double proportional matrix balancing technique. It is used to estimate the direct consumption coefficients within an input-output table. This estimation relies on two underlying principles: the substitution effect and the manufacturing effect. By making proportional adjustments to both rows and columns in a uniform way, the method updates an existing input-output table. This updating allows the table to reflect the economic conditions of each target period. The basic calculation steps are outlined below:

The procedure begins by setting, for a given target year t, three quantities: $U^t = Z^t 1, V^t = 1Z^t$, and X^t. In these expressions, Z^t denotes the matrix of intermediate transactions, X^t is the vector of total outputs for year t, the symbol “1” represents a column vector of ones, and U^t (respectively V^t) gives the row sums (respectively column sums) of the intermediate matrix for that year. A key maintained assumption is that the direct-coefficient matrix of year t does not differ from that of the base year—formally, $A(0) = A(t)$—with $A(0)$ being the base-year matrix.

The next step involves a row-wise adjustment. We compute an initial intermediate use matrix as $Z^0 = A(0)X^t$, and its row sums are given by $u^0 = Z^t 1$. The row adjustment coefficient is then defined as $r(1) = U^t/u^0$. Consequently, the direct consumption coefficient matrix after this first adjustment becomes:

$$A^1 = \hat{r}(1)A(0) \qquad (1)$$

This is followed by a column-wise adjustment. Using $Z^1 = A^1X^t$ we obtain the intermediate use matrix after the first adjustment; its column sums are $v^0 = 1Z^0$. Let $s(1) = V^t/v^0$ denote the column adjustment coefficient. The direct consumption coefficient matrix after the second adjustment is therefore:

$$A^2 = A^1\hat{s}(1) = \hat{r}(1)A(0)\hat{s}(1) \qquad (2)$$

Taking A^2 (the matrix resulting from the second adjustment) as the new starting point, we iterate the entire procedure. The iteration continues until both discrepancies $|U^t - u^n|$ and $|V^t - v^n|$ fall below 0.001. The successive updates follow the pattern:

$$A^3 = \hat{r}(2)A^2$$

$$A^4 = A^3\hat{s}(2)$$

$$= \hat{r}(2)\hat{r}(1)A(0)\hat{s}(1)\hat{s}(2) \qquad (3)$$

$$A^{2n} = A^{2n-1}\hat{s}(n)$$

$$= [\hat{r}(n) \ldots \hat{r}(1)]A(0)[\hat{s}(1) \ldots \hat{s}(n)]$$

Applying the above iterative procedure, the paper next harmonizes the statistical coverage with the National Economic Industry Classification. This harmonization is performed on the basis of the 42-sector input-output tables that were published for various provinces and municipalities in benchmark years such as 2007 and 2012. Subsequently, we separately compile the final use matrix, the value-added matrix, and the intermediate flow matrix. The outcome is a complete set of input-output tables for each province and municipality in China, covering the period from 2011 to 2023.

3.2. Measurement of the Economic Scale of Industrial Digitalization

We begin by constructing a complete sequence of input-output tables. Our study then draws on the methodological approach documented by Zhao Yuhan, Yang Feiyang, Song Xuguang (2024), and their co-authors [[17]]. The first step is identification. We refer to China's National Economic Industry Classification and the sectoral breakdown of the input-output table. Based on these, we pick out the product categories that correspond to the core sectors of the digital economy. The matching sectors are as follows: electrical machinery and equipment (code 19); communication equipment, computers, and other electronic devices (code 20); instruments and meters (code 21); information transmission, software, and information technology services (code 32); and scientific research and technical services (code 36). From the input-output table, we directly extract the value added contributed by these five sectors. Taken together, this value added represents the total value added of the digital industry.

Next, we compute the consumption coefficient that reflects how much traditional industries rely on products from the digital sectors. Using this coefficient, we then derive the digital value added of traditional industries—that is, the value created when traditional sectors employ digital industry products as intermediate inputs. The detailed calculation procedure is presented below.

(1) Calculate the digital consumption coefficient of traditional industries:

$$Digital\ Consumption\ Coefficient = 1 - \frac{Intermediate\ Inputs\ from\ Traditional\ Industries\ to\ Digital\ Industries}{Total\ Inputs\ of\ Traditional\ Product\ Sectors} \qquad (4)$$

(2) Calculate the value-added of industrial digitalization:

$$Value - added\ Rate\ of\ Industrial\ Digitalization = 1 - \frac{Inputs\ from\ Traditional\ Industries\ to\ Digital\ Industries}{Total\ Output\ of\ the\ Digitalized\ Segment\ of\ Traditional\ Industries} \qquad (5)$$

In this step, we apply the BEA calculation method. We make a key assumption. The share of intermediate inputs from the traditional product sector in the digital part's total output equals the share of intermediate inputs from non-digital industries in that same part's total output. This implies a simple equivalence. The value-added rate of the industry's digital portion is the same as the value-added rate of the industry as a whole:

$$Value - Added\ Rate\ of\ Industrial\ Digitalization\ = Value - Added\ Rate\ of\ the\ Industry \quad (5)$$

（3）Calculate the Value-added of Industrial Digitalization:

$$Value - added\ of\ Industrial\ Digitalization\ = Digital\ Consumption\ Coefficient\ \times Total\ Output\ of\ Traditional\ Industries\ \times\ Value\ldots - Added\ Rate\ of\ the\ Industry \quad (6)$$

The above steps allow us to measure the scale of industrial digitalization. This measurement covers 30 provinces and cities in China (excluding Tibet, Hong Kong, Macao, and Taiwan) over the period from 2011 to 2023. We then use this result to calculate both the size and the agglomeration degree of industrial digitalization talents.

3.3. Calculation of the Agglomeration Degree of Industrial Digitalization Talents

Next, we follow the method outlined in the White Paper on China's Digital Economy Development and Employment (2019), published by the China Academy of Information and Communications Technology (CAICT). This method allows us to derive the scale of industrial digital employees. Specifically, we compare the scale of the industrial digital economy with the average labor productivity of the whole industry. After obtaining this employee scale, we then apply location entropy calculations. Through this step, we finally obtain the agglomeration degree of industrial digitalization talents. This covers 30 provinces and cities in China from 2011 to 2023. The relevant formulas are as follows:

$$Average\ Labor\ Productivity\ of\ the\ Regional\ Entire\ Industry = \frac{Regional\ Gross\ Domestic\ Product\ (GDP)}{Year-end\ Number\ of\ Regional\ Employed\ Persons} \quad (7)$$

$$Scale\ of\ Industrial\ Digitalization\ Practitioners\ = \frac{Scale\ of\ the\ Industrial\ Digitalization\ Economy}{Average\ Labor\ Productivity\ of\ the\ Entire\ Industry} \quad (8)$$

Once the number of practitioners engaged in industrial digitalization has been estimated, we turn to location entropy as a tool for quantifying the concentration level of industrial digitalization talents. Location entropy, a standard concept within regional economics, is defined as the ratio of two shares: the numerator is the share of a given industry in a region's total output value, and the denominator is that same industry's share in the nation's overall output value. This metric is commonly employed to identify whether an industry functions as a specialized sector at the regional level. As a rule of thumb, a higher location entropy value reflects a stronger regional specialization in that industry. A value exceeding 1 indicates that the industry's local concentration surpasses the national benchmark, implying greater competitive strength. A value equal to 1 suggests parity with the national average, whereas a value below 1 signals a more dispersed distribution and weaker competitiveness relative to the national level.

Drawing on this logic, we operationalize the agglomeration degree of industrial digitalization talents by comparing regional and national employment patterns. Specifically, we take the ratio of (i) the share of industrial digital practitioners in a region's total workforce to (ii) the share of such practitioners in the national total workforce. This yields the following formula:

$$Agglomeration\ Degree\ of\ Industrial\ Digitalization\ Talents = \frac{Scale\ of\ Regional\ Industrial\ Digitalization\ Practitioners\ /\ Total\ Employed\ Persons\ in\ the\ Region}{National\ Scale\ of\ Industrial\ Digitalization\ Practitioners\ /\ National\ Total\ Employed\ Persons} \quad (9)$$

Table 1 presents the resulting agglomeration degree of industrial digitalization talents across 30 provincial-level jurisdictions in China (data for Tibet, Hong Kong, Macao, and Taiwan are not included) over the period 2011–2023, based on the step-by-step calculations described above:

Table 1 Industrial Digitalization Talent Agglomeration by Region (30 Provinces, Excluding Tibet, Hong Kong, Macao, Taiwan), 2011–2023

Region	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Beijing	2.44	2.44	2.42	2.42	2.19	2.37	2.69	2.34	2.35	2.34	2.31	2.39	2.37
Tianjin	1.91	1.90	1.90	1.98	2.02	2.06	1.60	2.14	2.19	2.22	2.24	2.27	2.29
Hebei	0.76	0.78	0.82	0.82	0.76	0.88	0.74	0.93	0.93	0.91	0.92	0.92	0.92
Shanxi	0.52	0.54	0.58	0.60	0.75	0.73	0.71	0.66	0.66	0.64	0.56	0.52	0.55

Inner Mongolia	0.66	0.66	0.66	0.63	0.62	0.69	0.50	0.71	0.71	0.72	0.66	0.63	0.62
Liaoning	1.14	1.15	1.18	1.23	0.93	1.39	0.69	1.46	1.48	1.49	1.53	1.52	1.53
Jilin	0.70	0.69	0.70	0.73	0.70	0.80	0.58	0.89	0.92	0.89	0.93	1.00	0.99
Heilong jiang	0.61	0.61	0.62	0.68	0.71	0.77	0.50	0.87	0.88	0.89	0.92	0.90	0.94
Shanghai	1.51	1.57	1.59	1.69	1.51	1.55	1.62	1.55	1.58	1.56	1.57	1.59	1.59
Jiangsu	1.83	1.84	1.83	1.88	1.74	1.77	1.65	1.77	1.80	1.75	1.72	1.73	1.73
Zhejiang	1.08	1.11	1.13	1.08	1.15	1.12	1.30	1.10	1.10	1.07	1.06	1.04	1.04
Anhui	0.99	0.97	0.95	1.00	0.94	0.94	1.09	0.88	0.87	0.85	0.86	0.85	0.85
Fujian	1.00	0.98	0.97	0.92	0.81	0.92	0.86	0.85	0.84	0.82	0.82	0.81	0.81
Jiangxi	0.81	0.81	0.80	0.78	0.88	0.78	1.03	0.76	0.75	0.73	0.71	0.71	0.72
Shandong	0.86	0.87	0.87	0.83	0.94	0.88	0.64	0.94	0.95	0.93	0.92	0.91	0.91
Henan	0.72	0.73	0.73	0.74	0.77	0.72	0.83	0.71	0.70	0.71	0.74	0.77	0.80
Hubei	0.97	0.95	0.93	0.91	1.02	0.89	0.86	0.85	0.84	0.90	0.87	0.87	0.86
Hunan	0.94	0.92	0.92	0.87	0.89	0.88	0.89	0.90	0.88	0.85	0.88	0.88	0.88
Guang dong	1.62	1.67	1.67	1.78	1.71	1.60	1.93	1.59	1.58	1.55	1.56	1.57	1.57
Guangxi	0.69	0.70	0.70	0.67	0.77	0.68	0.65	0.67	0.67	0.65	0.64	0.64	0.65
Hainan	0.61	0.60	0.59	0.59	0.48	0.56	0.53	0.57	0.56	0.54	0.52	0.52	0.49
Chong qing	1.18	1.14	1.12	0.98	1.08	1.02	1.02	1.03	1.01	0.96	0.97	0.99	0.98
Sichuan	1.05	1.02	1.01	0.97	1.11	1.02	1.03	0.95	0.94	0.91	0.92	0.92	0.91
Guizhou	0.57	0.52	0.49	0.44	0.46	0.41	0.50	0.38	0.38	0.36	0.37	0.38	0.38
Yunnan	0.58	0.55	0.52	0.50	0.46	0.51	0.61	0.49	0.47	0.45	0.46	0.46	0.45
Shaanxi	0.75	0.72	0.70	0.73	0.77	0.74	1.02	0.71	0.71	0.71	0.69	0.66	0.67
Gansu	0.76	0.75	0.74	0.75	0.60	0.81	0.55	0.83	0.83	0.82	0.81	0.77	0.76
Qinghai	0.70	0.70	0.69	0.76	0.67	0.65	0.71	0.65	0.65	0.64	0.65	0.63	0.63
Ningxia	0.67	0.67	0.68	0.65	0.66	0.71	0.56	0.68	0.68	0.65	0.64	0.60	0.60
Xinjiang	0.48	0.47	0.46	0.47	0.59	0.50	0.36	0.45	0.46	0.46	0.44	0.41	0.41

To make the analysis easier, we rank the average agglomeration values. Table 2 presents this ranking for industrial digitalization talents across 30 provinces and cities in China from 2011 to 2023:

Table 2 Average agglomeration degree of industrial digitalization talents: ranking of 30 Chinese provinces, municipalities, and autonomous regions

Ranking	Region	Average Agglomeration Degree	Ranking	Region	Average Agglomeration Degree	Ranking	Region	Average Agglomeration Degree
1	Beijing	2.39	11	Hubei	0.90	21	Shaanxi	0.74
2	Tianjin	2.06	12	Hunan	0.89	22	Guangxi	0.68
3	Jiangsu	1.77	13	Shan dong	0.88	23	Qinghai	0.67
4	Guang dong	1.65	14	Fujian	0.88	24	Inner Mongolia	0.65
5	Shang hai	1.57	15	Hebei	0.85	25	Ningxia	0.65
6	Liao ning	1.29	16	Jilin	0.81	26	Shanxi	0.62
7	Zhe jiang	1.11	17	Jiangxi	0.79	27	Hainan	0.55
8	Chong qing	1.04	18	Heilongjiang	0.76	28	Yunnan	0.50
9	Sichuan	0.98	19	Gansu	0.75	29	Xinjiang	0.46
10	Anhui	0.92	20	Henan	0.74	30	Guizhou	0.43

Looking at the calculation outcomes and the ranking in the table above, we see an uneven pattern. The agglomeration of industrial digitalization talents across China is not balanced. Eight provinces and cities have an agglomeration degree above 1. These are Beijing, Tianjin, Jiangsu, Guangdong, Shanghai, Liaoning, Zhejiang, and Chongqing. Among them, Beijing and Tianjin stand out. Their industrial digital human capital is clearly more competitive.

Hebei's agglomeration degree is below the national average. Still, it ranks in the middle. So the Beijing-Tianjin-Hebei region is the most concentrated area for industrial digitalization talents. Next come the Yangtze River Delta region, with Jiangsu, Zhejiang, and Shanghai as its core, and the Pearl River Delta region, with Guangdong as its core. The Chengdu-Chongqing urban agglomeration, centered on Chongqing and Sichuan, stays around the national average level.

Liaoning is a special case in the northeast. It ranks first in that region. This may be because of its location in the south and its access to the coast. These factors make it more attractive to industrial digitalization talents in the northeast. Liaoning is also close to the Beijing-Tianjin-Hebei area.

Overall, the level of industrial digitalization talents agglomeration is closely tied to economic development. It shows strong regional features. Developed areas pull in relevant talents from surrounding regions through a strong siphon effect.

4. Influencing Factors of the Agglomeration of Industrial Digitalization Talents at the Provincial Level in China

The cultivation and attraction of talents is a complex social activity. After satisfying certain conditions, talent agglomeration will be formed. Through the above literature analysis, it can be considered that the external environment has a very important impact on talent agglomeration. The external environment includes many factors of social economy. The environment of a region can meet the spiritual and material needs of talents at the same time, so as to attract enough talents and promote industrial agglomeration. Therefore, based on this perspective, combined with the characteristics of industrial digitalization talents, this paper uses the panel data of 30 provinces and cities in China from 2011 to 2023 for regression analysis, and then discusses the overall impact of economic, industrial, cultural and life factors on the agglomeration of industrial digitalization talents.

4.1. Indicator Analysis and Variable Selection

In this paper, the industrial digitalization talents agglomeration (IDT) is used as the dependent variable. Based on the consideration of the actual needs of all aspects of talents, nine influencing factors in four categories of economy, industry, culture and life are selected as explanatory variables:

- Gross regional product (GDP): A region's economic prosperity tends to strengthen its ability to attract talent through a siphon effect. GDP serves as a direct proxy for this phenomenon.
- Per capita wage (pcw): When individuals decide where to work, wage levels rank among the most immediate considerations. A higher average wage in a region typically makes it more appealing to skilled workers.
- Level of digital economy (del): Drawing on the "center-periphery" framework, the concentration of resources within a region should correspond to its stage of economic development. Although agglomeration initially fuels rapid growth through economic spillovers, the primary engine of expansion gradually shifts from conventional resource inputs to gains in total factor productivity. Thus, advancing the digital economy can, to some extent, propel industrial digitalization and may also enhance the region's ability to draw in relevant talent.
- Economic structure (estr): This indicator is captured by the share of tertiary industry output in regional GDP. An evolving industrial mix—particularly a rising contribution from the service sector—can smooth the functioning of the socio-economic system and thereby attract more talent. However, the relocation of manufacturing activities may lead to industrial hollowing-out, posing a significant development challenge for the region.
- Population quality (pdl): We use the number of college students per 100,000 inhabitants as a measure; the presence and quality of higher education institutions partially reflect a region's cultural development. Whether by drawing in outside talent or by retaining local university graduates in the labor market, a better-educated population exerts a favorable influence.
- R&D expenditure input intensity (rd): Defined as the ratio of R&D spending to the GDP of industrial firms above a designated size, research and experimental development funding supplies the material foundation for technological innovation. Adequate financial support attracts innovative personnel, setting in motion a virtuous cycle of "rising investment → talent agglomeration → innovation output."
- Urbanization rate (urban): Calculated as the proportion of urban residents in the total population, the expansion of the urban population is a key marker of regional development [[18]]. National policies are primarily executed at the municipal level, and cities and towns act as hubs for talent, industry, and other resources. Nevertheless, excessive urbanization can generate crowding-related negative externalities—such as unequal access to development opportunities, elevated living costs, resource waste, and widening income disparities—which may ultimately impede economic growth [[19]] and dampen talent agglomeration.
- Medical level (med): Measured by the number of hospital beds per 10,000 persons, a higher standard of medical care generally signals better livability and stronger social safety nets, making a region more attractive for talent settlement.
- Public service level (psl): Captured by the share of public-sector employees in the total urban workforce, the quality of public services directly influences the comfort and convenience of daily life. A region's reputation in this regard also plays a non-negligible role in attracting talent.

Specific variable symbols and variable definitions are shown in Table 3:

Table 3 Indicators of Influencing Factors on the Agglomeration of Industrial Digitalization Talents

First-Level Indicators	Second-Level Indicators	Variable Symbols	Variable Definitions
Economic Environment	Gross Regional Product	gdp	Regional GDP (processed by logarithm)
	Per Capita Wage	pcw	Average wage of employees in urban units (processed by logarithm)
Industrial Environment	Digital Economy Level	del	Construct an indicator system and calculate the score using the entropy weight method

	Economic Structure	estr	Share of tertiary industry output in GDP
Cultural Environment	Population Quality	pdl	Number of college students per 100,000 people (processed by logarithm)
	R&D Investment Intensity	rd	The ratio of R&D spending by industrial firms above a designated scale to GDP
Living Environment	Urbanization Rate	urban	Urban population as a share of total population
	Medical Care Level	med	Number of medical institution beds per 10,000 people (processed by logarithm)
	Public Service Level	psl	Proportion of employees in the public service sector to the total urban employed population

We have four first-level indicators and nine second-level indicators. For the digital economy level (del), we build on earlier work. Several studies guide our approach: He Di et al. (2023) [[20]], Wu Jianhui and Guo Yongxin (2024) [[21]], and Shao Yingying, Hua Junguo, Li Bingbing et al. (2024) [[22]]. To measure this variable, we look at three aspects. They are digital infrastructure, the growth of digital industries, and the external digital environment. Then we use the entropy method. This gives us composite scores. These scores reflect digital economy development across provinces and cities from 2011 to 2023. For the other indicators, we take raw data from three sources. They are the National Bureau of Statistics' annual releases, the China Statistical Yearbook, and the China Labor Statistics Yearbook. Table 4 shows descriptive statistics for all these variables:

Table 4 Descriptive Statistics of Variables

Variable Names	Variable Symbols	Observations	Mean	Standard Deviation	Minimum	Maximum
Agglomeration Degree of Industrial Digitalization Talents	Idt	390	0.966	0.476	0.359	2.692
Gross Regional Product	Gdp	390	9.919	0.900	7.236	11.83
Per Capita Wage	Pcw	390	11.15	0.386	10.35	12.34
Digital Economy Level	Del	390	0.137	0.116	0.0145	0.747
Economic Structure	Estr	390	0.511	0.0892	0.333	0.852
Population Quality	Pdl	390	7.908	0.304	6.987	8.672
R&D Investment Intensity	Rd	390	0.0111	0.00600	0.00164	0.0324
Urbanization Rate	urban	390	0.606	0.120	0.350	0.896
Medical Care Level	med	390	4.015	0.232	3.323	4.492
Public Service Level	psl	390	0.122	0.0483	0.0280	0.274

4.2. Model Construction and Empirical Analysis

Then, combined with the research purpose, this paper analyzes the influence of multiple factors on the agglomeration degree of industrial digitalization talents, and constructs the following model:

$$idt_{it} = \beta_0 + \beta_1 gdp_{it} + \beta_2 pcw_{it} + \beta_3 del_{it} + \beta_4 estr_{it} + \beta_5 pdl_{it} + \beta_6 rd_{it} + \beta_7 urban_{it} + \beta_8 med_{it} + \beta_9 psl_{it} + \mu_{it} \quad (10)$$

In the above formula, idt_{it} is the industrial digitalization talents agglomeration level of region i in period t; gdp_{it} and pcw_{it} represent the economic environment of region i during period t; del_{it} and $estr_{it}$ represent the industrial environment of region i in period t; pdl_{it} and rd_{it} represent the cultural environment of region i in period t; $urban_{it}$,

med_{it} and psl_{it} represent the living environment of region i in period t; and μ_{it} is the random disturbance term in the formula.

We perform an F test and a Hausman test on the variable data. The F statistic is 89.81. This value is significant at the 1% level. The Hausman statistic is 296.92. It is also significant at the 1% level. As a result, we reject two null hypotheses. One is the null of the mixed effect model. The other is the null of the individual random effect model. Based on these test outcomes, we conclude that a standard individual-level fixed-effects model is appropriate for our regression analysis. We then use this model to examine what determines industrial digitalization talents agglomeration. Table 5 reports the corresponding regression estimates:

Table 5 Panel Data Regression Results

		idt
Gross Regional Product	gdp	-0.590^{***}
		(-7.68)
Per Capita Wage	pcw	0.526^{***}
		(6.44)
Digital Economy Level	del	-0.227
		(-1.91)
Economic Structure	estr	0.323
		(1.58)
Population Quality	pdl	0.102
		(1.79)
R&D Investment Intensity	rd	-8.547^{**}
		(-3.24)
Urbanization Rate	urban	-0.304
		(-0.81)
Medical Care Level	med	-0.00400
		(-0.06)
Public Service Level	psl	0.379
		(1.17)
	_cons	0.264
		(0.57)
	N	390
	R^2	0.31
	adj. R^2	0.23

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The regression results show that regional GDP (gdp_{it}), per capita wage (pcw_{it}), and R&D investment intensity (rd_{it}) have a significant impact on the agglomeration of industrial digitalization talents. The first two factors have the most obvious impact, but other factors have no significant impact on the agglomeration of such talents in the panel regression, which needs further analysis and verification.

5. Conclusions

Turning to the regression findings, one observes that at the present stage, the clustering of industrial digitalization talents in China continues to be shaped predominantly by economic and environmental conditions—namely, only regional GDP, per capita wages, and R&D investment intensity exert statistically significant effects. Notably, the estimated coefficients for both regional GDP and R&D intensity carry negative signs. A plausible explanation is that while conventional economic growth and associated R&D funding still play discernible roles, the ongoing deepening of regional integration has largely stabilized large-scale talent flows. Industrial digitalization talents are now heavily concentrated. They cluster in several major urban agglomerations. These include the Beijing-Tianjin-Hebei region, the Yangtze River Delta, the Pearl River Delta, and the Chengdu-Chongqing area. At the same time, the economy keeps expanding. As it does, living costs in first-tier cities continue to rise. This increase gradually makes these cities less attractive to skilled workers.

Meanwhile, neither the level of digital economy development nor the economic structure variable shows a significant influence. This suggests that the linkage between industrial digitalization and digital industrialization remains relatively weak; a synergistic “conjugate effect” has yet to emerge, and thus the “1+1>2” payoff has not materialized. On the other hand, population quality is found to be significant at the 10% level, indicating a non-negligible effect. Consequently, strengthening investment in higher education and raising educational standards retain strong policy relevance. In contrast, the living-environment factors as a group are not significant, implying that across China’s regions—or at least among major provincial cities—socio-economic development and living costs may have approached a certain equilibrium, thereby further reducing the impetus for cross-provincial talent mobility.

Based on the literature reviewed and the empirical analysis above, we distill three policy implications from these findings:

First of all, the regional “economy-cost” balance mechanism should be optimized to suppress negative elasticity. The above empirical analysis shows that the high cost of living in first-tier cities may have weakened the economic pull. Policy should turn to “cost reduction and efficiency increase”: expand targeted support such as talent housing, taxation, and subsidies, and reduce living and business costs; at the same time, relying on the integration of metropolitan areas (Beijing-Tianjin-Hebei, Yangtze River Delta, Pearl River Delta, Chengdu-Chongqing), distribute incremental R&D projects to surrounding low-cost nodes to form a “headquarters + R&D enclave” model, which not only shares high-level infrastructure but also dilutes negative elasticity and maintains the continuous inflow of talents.

Secondly, we should open up the closed loop of “industrial digitalization-digital industrialization” and create a conjugate effect. The fact that the level of digital economy and economic structure variables are not significant indicates that the two have not been coupled and amplified. It is necessary to take scenarios as traction, with industry leaders building cross-enterprise and cross-regional “data-computing power-algorithm” sharing centers, embedding the achievements of digital industrialization into the digital transformation of traditional industries, and forming a scale market through policy package subsidies, data transaction pilots, and government procurement, so that talents can realize value multiplication in the flow of both ends, and truly produce a “1+1>2” synergistic dividend.

Finally, we should put more resources into higher education and lifelong learning. This will help unlock the dividend from population quality. Our results show that population quality is significant at the 10% level. This means that the existing stock of human capital still has a measurable influence on industrial digitalization talents agglomeration. In terms of policy, one option is to set up a joint training mechanism. This mechanism would involve universities, enterprises, and platforms. Such a system could amplify the positive marginal contribution of high-quality labor to agglomeration. It would also lay a long-term foundation for what we call “secondary talent attraction” at the regional level.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed

References

[1] Liu Shikun, Yao Yi. Measurement of City's Science and Technology Talent Flow and Its Impacton Green Total Factor Productivity: Based on Spatial Regression Model [J/OL]. JOURNAL OF NANJING NORMAL UNIVERSITY (Natural Science Edition),1-9[2025-10-21].DOI: 10.3969/j.issn.1001-4616.2025.02.001.

[2] Wang Fushi. Measurement of the Contribution of Talent Agglomeration and Human Capital to Economic Growth in Urban Agglomerations [J]. Statistics & Decision, 2023, 39(04): 71-74.DOI: 10.13546/j.cnki.tjyjc.2023.04.012.

[3] Sun Linjie,Sun Wanjun, Gao Ziqi. Research on the measurement and influencing factors of the agglomerationdegree of marine science and technology talents in China [J]. Science Research Management, 2022, 43(10): 192-199.DOI: 10.19571/j.cnki.1000-2995.2022.10.019.

[4] Park Sohyun, Lee Keumsook. The determinants of occupational distribution in Seoul metropolitan area: Comparison of high- and low-skilled occupations [J]. GEOGRAPHICAL RESEARCH, 2023. DOI: 10.1111/1745-5871.12612.

[5] Bieri, David S. Booming Bohemia? Evidence from the US High-Technology Industry [J]. INDUSTRY AND INNOVATION, 2010.17(01):23-48. DOI: 10.1080/13662710903573828.

[6] Shi Dandan, Han Shenggui, Li Xuelin, Ye Zongxiang. Research on Qinghai's Innovation-Driven Development fromthe Perspective of Talent Contribution Rate [J]. QINGHAI SCIENCE AND TECHNOLOGY, 2024, 31(01): 41-50.DOI: CNKI: SUN: QKKJ.0.2024-01-005.

[7] Lyu Yiqing, Tong Yao. Calculation of the Development Efficieney of Scientific andTechnological Talents and Analysis of Temporal and Spatial Differences [J]. Science and Technology Management Research, 2023, 43(05): 117-126.DOI: CNKI: SUN: KJGL.0.2023-05-014.

[8] Huang Xin, Zhang Shuiping, Zhang Jin, Yang Kun. Research on the impact of digital economy on Regional Green Technology Innovation: Moderating effect of digital talent Aggregation [J]. ENVIRONMENTAL SCIENCE AND POLLUTION RESEARCH, 2023.30(29):74409-74425.

[9] Sun Jian, You Wen. A Study on the Interactive Relationship between Talent Agglomeration and Industrial Agglomeration [J]. Journal of Management World, 2008(03):177-178. DOI: 10.19744/j.cnki.11-1235/f.2008.03.025.

[10] Bramwell Allison, Wolfe David A. Universities and regional economic development: The entrepreneurial University of Waterloo [J]. RESEARCH POLICY, 2008.37(08):1175-1187. DOI: 10.1016/j.respol.2008.04.016.

[11] KRUGMAN P. Increasing returns and economic geography ［J］. Journal of Political Economy, 1991，99(3): 483—499.

[12] Gao Bin, Zhang Naiwen. Comprehensive evaluation of urban talent development environment based on entropy weight-topsis method [J]. JOURNAL OF INTELLIGENT & FUZZY SYSTEMS, 2023.44(05):7577-7587. DOI: 10.3233/JIFS-222889.

[13] Shi Mengyu, Shen Kunrong. Research on Eeonomie Growth and Spatial Spillover Effeet of Talent Introduction Policy ToolsA Case Study of Yangtze River Delta [J]. Inquiry into Economic Issues, 2022(01):32-49.

[14] China. Research Report on China's Digital Economy Development (2023) [R]. China Academy of Information and Communications Technology (CAICT), 2023.

[15] Li Baoyu, Zhang Jing. A Study of Methods for Updating and ForecastingIOTs Consistent with the GDP Accounting Caliber [J]. Journal of Quantitative & Technological Economics, 2012, 29 (11): 149-160. DOI ： 10.13653/j.cnki.jqte.2012.11.011.

[16] Zhang Hongxia, Xia Ming, Su Rujie, Lin Chen. The Compilation of the Time Series Input-outputTables in China: 1981-2018 [J]. Statistical Research, 2021, 38 (11): 3-23. DOI: 10.19343/j.cnki.11-1302/c.2021.11.001.

[17] Zhao Yuhan, Yang Feiyang, Song Xuguang, et al. Measurement of China's Industrial Digitalization Scale and Path Analysis [J]. Macroeconomics, 2024, (05): 74-88. DOI: 10.16304/j.cnki.11-3952/f.2024.05.003.

[18] United Nations． World urbanization prospects: the 2009 revision[R]． New York: UN, 2010．

[19] BUHAUG H，URDAL H． An urbanization bomb? Population growth and social disorder in cities［J］． Global Environmental Change，2013，23(1) : 1-10． DOI: 10.1016/j.gloenvcha.2012.10.016.

[20] He Di， Zhao Xuanzhuo，Qi Qi. Measurement, Spatial Pattern and Regional Difference ofDigital Economy Development in China [J]. Journal of Industrial Technological Economics, 2023, 42 (03): 54-62. DOI: 10． 3969 /j ．issn．1004－910X．2023．03．006.

[21] WU Jianhui. GUO Yongxin. Digital economy boosts the development of new urbanization:An analysis based on spatial Durbin model and Threshold model [J]. Resource Development & Market, 2024, 40(09):1350-1361. DOI: 10.3969/i.issn.1005-8141.2024.09.009.

[22] Shao Yingying, Hua Junguo, Li Bingbing. Research on the enabling eftect and mechanism of digital economy on urban-rural integrated development [J]. Research of Agricultural Modernization, 2024, 45(03):477-487. DOI: 10.13872/j.1000-0275.2024.0047.