Empirical Analysis of the Impact of Regional Comprehensive Development Factors on Human Capital Accumulation

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Abstract. This study explores the relationship between regional development factors and human capital using Principal Component Analysis (PCA), focusing on the impact of regional economic activities and industrial innovation characteristics on human capital quality and labor market dynamics. The results show that regional economic activities (PC_X1) have a significant positive effect on human capital quality (PC_Y1), while industrial innovation characteristics (PC_X2) negatively impact human capital quality. Further panel regression analysis indicates that regional economic activities enhance labor force quality by promoting the expansion of educational resources, skill training, and employment opportunities. In contrast, industrial innovation may increase the demand for high-skilled labor, leaving low-skilled labor underserved, thus leading to labor market segmentation. The analysis of individual effects emphasizes the impact of long-term regional fixed factors such as educational resource allocation, infrastructure development, and policy environment on human capital disparities. This study provides theoretical foundations and practical recommendations for regional policymakers in promoting balanced economic development and optimizing human capital allocation.

Keywords: Regional comprehensive development; Industrial innovation; Human capital accumulation; Principal component analysis; Panel data analysis

1 Introduction

In the context of rapid economic development and increasing global competition, talent has emerged as a crucial driver of innovation-based economies. Brynjolfsson et al. (2023) conducted an empirical study highlighting the role of comprehensive talent management strategies in facilitating successful succession planning within enterprises[1, 2]. Their findings underscore that talent decisions are influenced not only by internal organizational practices, such as recruitment strategies and compensation schemes, but also by external macro-level factors, including regional development environments. Zhou et al. (2023) further emphasize the significance of regional development, industry

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environments, and income levels in attracting talent across Chinese provinces, demonstrating how economically advanced regions with favorable living conditions exert a stronger pull on talent resources[3].

The interplay between internal and external factors is particularly relevant in China's industrialization process, where the intrinsic relationship between regional development, talent mechanisms, and industrialization forms the backbone of its modernization model. Over the decades, China has transformed from labor-intensive to capital-intensive industries and has now entered a technology- and knowledge-intensive stage (Zhang & Li, 2011)[4]. This transition has concentrated economic resources and talent in core regions, creating imbalances in regional human capital accumulation. As highlighted by the Strategic and International Studies Center (2024), investing in human capital, such as STEM education and workforce training, is pivotal to sustaining China's competitive advantage[5]. Similarly, the IMF (2024) identifies human capital as a key driver for boosting labor productivity and ensuring sustainable economic growth, advocating for strategic investments in education and workforce skill development[6].

The importance of balancing regional innovation and talent distribution is further emphasized by the Global Times (2024), which argues that targeted education policies and talent development initiatives are critical for fostering technological advancement and industrial growth across the country[7]. Moreover, Lee and Chang (2024) stress the alignment of human resource strategies with regional factors, such as educational quality and infrastructure, to ensure effective talent attraction and retention[8]. Li and Zhang (2024) reinforce this perspective, asserting that regional opportunities, living standards, and development environments significantly influence talent mobility, especially in the context of globalization[9]. Finally, Sun and Chen (2024) note that industries, particularly in high-tech sectors, must account for both organizational strategies and external regional environments—such as innovation ecosystems and economic conditions—to effectively attract and retain talent[10].

As China enters a phase of high-quality and balanced regional development, understanding the dynamic relationship between regional comprehensive development factors and human capital accumulation becomes essential. This research aims to empirically examine these relationships to identify mechanisms driving talent aggregation, offering strategic insights into supporting China's next phase of economic growth and fostering innovative human capital strategies.

2 Statement of Problem

With the development of Chinese industrialization and regional economy, human resource have gathered into the central regions which influenced regional human capital accumulation. It is an important issue how the regional comprehensive development factors have impacts on human capital. Therefore, this research will focus on the empirical analysis of influence between the regional comprehensive development factors and human capital accumulation.

3 Research Methods

3.1 Research Framework

This study builds upon the cyclical characteristics of China's economic development, using annual data of Bureau of statistics from six representative regions between 2012 and 2019. The research investigates the impact of regional development factors (nine indicators) as independent variables on regional human capital (eight indicators) as dependent variables. By analyzing the relationships between these factors, the study identifies how different regional development aspects influence human capital.

Given the small sample size—six regions over eight years, totaling 48 observations—direct regression analysis might overlook key influencing factors due to complexity and potential overfitting. Therefore, the study employs Principal Component Analysis (PCA) to reduce dimensionality, simplifying high-dimensional data into a manageable structure. Subsequently, a static panel model (fixed-effects FE and random-effects RE) is utilized to ensure robust statistical analysis, minimizing the reliance on dynamic panel models that require larger sample sizes.

STATA 18.0 served as a statistical tool in the analysis of data of this research.

3.2 Variables and Indicators

Based on Chinese National Bureau of Statistics, variables and indicators in the research are shown as Table 1:

Table 1. Variables and Indicators

Dependent Variables	y1	y2	y3	y4	y5	y6	y7	y8	
Indicators	Regional employee (ten thounsand people)	per capital education expenditure (RMB)	stuents in colleges (hundred million people)	Medical condition (hundred million medical bed)	R&D (ten thousand RMB)	Development funds (ten thousand RMB)	Per capita GDP (ten thounsand RMB)	per capital income (RMB)	
Independent variable	x1	x2	x3	x4	x5	x6	x7	x8	x9
Indicators	Sum of assets (100 million RMB)	foreign investment (hundred million dollar)	regonal GDP (hundred million RMB)	industry output ((hundred million RMB)	Relative economic ration	population (ten thounsand people)	employee in city (ten thousand people)	ration of citizen to population	Sum of patent (number)

3.3 Model Design

Principal Component Analysis (PCA): To reduce the dimensions of independent and dependent variables, the nine regional development factors are condensed into 1–2 principal components (explaining 70%–85% of total variance). Similarly, the eight regional human capital indicators are reduced to 1–2 composite indicators. The extracted principal components, PC_X1, PC_X2 (representing comprehensive development factors), and PC_Y1, PC_Y2 (representing human capital indicators), are used for subsequent modeling and analysis.

Panel Model: After extracting the principal components, a panel data model is employed to analyze the impact of comprehensive development factors (PC_X1, PC_X2) on comprehensive human capital (PC_Y1, PC_Y2). The Fixed-Effects (FE) model controls for time-invariant regional characteristics (e.g., regional economic foundations), while the Random-Effects (RE) model assumes individual differences as random. A Hausman test is conducted to select between the FE and RE models. The specific formula is:

$$PC\_Y_{i,t}=\alpha+\beta_1 PC\_X_{1i,t}+\beta_2 PC\_X_{2i,t}+\epsilon_{i,t} \quad (1)$$

4 Data Analysis

4.1 Principal Component Analysis

Principal component equations are derived and shown as below:

Principal Component Equations for Regional Development Factors (Independent Variables PC_X1 and PC_X2):

PC_X1 (First Principal Component):

$$PCX1=0.3883\cdot x1+0.3298\cdot x2+0.3904\cdot x3+0.3848\cdot x4+0.1615\cdot x5+0.3616\cdot x6+0.3785\cdot x7+0.0421\cdot x8+0.3716\cdot x9$$

PC_X2 (Second Principal Component):

$$PC\_X2=0.0986\cdot x1+0.2959\cdot x2+0.0347\cdot x3-0.1383\cdot x4-0.5944\cdot x5-0.2614\cdot x6+0.0323\cdot x7+0.6622\cdot x8+0.1458\cdot x9$$

From the above equations, it can be observed that PC_X1 is primarily influenced by economic scale (x1), industrial output (x3), infrastructure development (x4), population factors (x6), urbanization processes (x7), and innovation capability (x9). PC_X1 represents the overall level of regional economic activity and infrastructure, reflecting the vitality of regional economic development.

In contrast, PC_X2 is mainly determined by foreign investment (x5) and innovation capability (x8), capturing differences in regional industrial innovation capacity and technological levels. This dimension highlights the variations in industrial innovation characteristics within regional economies.

Principal Component Equations for Regional Human Capital (Dependent Variables PC_Y1 and PC_Y2):

PC_Y1 (First Principal Component):

$$PC\_Y1=0.4142\cdot y1-0.1584\cdot y2+0.4517\cdot y3+0.4480\cdot y4+0.4295\cdot y5+0.4200\cdot y6-0.1167\cdot y7-0.1551\cdot y8$$

PC_Y2 (Second Principal Component):

$$PC\_Y2=0.2101\cdot y1+0.5361\cdot y2-0.0550\cdot y3-0.0324\cdot y4+0.1948\cdot y5+0.2343\cdot y6+0.5459\cdot y7+0.5230\cdot y8$$

The results indicate that PC_Y1 is significantly influenced by y1, y3, y4, y5, and y6, representing the overall quality of regional human capital, such as education levels and workforce skills. In contrast, PC_Y2 is primarily driven by y2, y7, and y8, reflecting the specific characteristics of the labor market, such as participation rates and employment structures.

Through PCA of the eight human capital indicators (y1 to y8), two principal components were extracted: PC_Y1 (first principal component) and PC_Y2 (second principal component). Together, they explain 94.68% of the total variance, with PC_Y1 accounting for 57.06% and PC_Y2 contributing an additional 37.62%. This demonstrates that regional human capital can be effectively summarized by these two core dimensions.

From the structure of regional development factors (X), it can be concluded that they can be categorized into two key dimensions: overall economic activity (PC_X1) and industrial innovation characteristics (PC_X2). The first principal component contributes the most to the total variance, indicating that regional development is primarily driven by economic scale and infrastructure levels. Similarly, regional human capital (Y) is summarized into two primary dimensions: overall human capital quality (PC_Y1) and labor market characteristics (PC_Y2). The first principal component loads heavily on indicators related to educational levels and workforce skills.

In summary, PC_Y1 is significantly influenced by y1, y3, y4, y5, and y6, with loadings above 0.41, indicating that it represents the overall quality of regional human capital, including education levels, workforce skills, and overall development capabilities. This dimension reflects the concentrated strength of comprehensive regional human capital. Higher PC_Y1 values suggest regions with higher-quality labor resources and greater investments in education, providing a strong human capital foundation for regional economic development. Zhou et al. (2023) underscore that regions prioritizing education, workforce development, and overall capabilities are better positioned to attract talent, consistent with the finding that higher PC_Y1 values signify strong human capital foundations vital for regional economic growth[11].

Conversely, PC_Y2 is primarily driven by y2, y7, and y8, with loadings of 0.5361 and 0.5459 for y2 and y7, respectively. This dimension primarily reflects the dynamic characteristics of the regional labor market, such as employment structures, labor force participation rates, and alignment with market demand. PC_Y2 serves as a critical indicator for describing labor mobility and employment market characteristics, helping to understand the market adaptability of the regional workforce.

Finally, PCA distills regional human capital into two essential dimensions: overall quality (PC_Y1) and labor market characteristics (PC_Y2). These dimensions clearly describe the primary features of regional human capital. Subsequent analyses are recommended to use them as dependent variables, combined with regional development factors (e.g., PC_X1 and PC_X2) for regression analysis. Special attention should be paid to the significant effect of economic activity (PC_X1) on human capital quality (PC_Y1) and the potential impact of industrial innovation characteristics (PC_X2) on labor market dynamics (PC_Y2).

4.2 Panel Data Analysis

Using regional development factors (PC_X1 and PC_X2) extracted through PCA, this study further applies panel regression analysis to explore their dynamic effects on regional human capital (PC_Y1 and PC_Y2). The key focus of the panel model is the relationship between PC_X1 and PC_Y1, examining the positive impact of economic activity on human capital quality, and determining whether industrial innovation characteristics (PC_X2) significantly affect labor market dynamics (PC_Y2). A fixed effects model (FE) was adopted to evaluate the impact. Due to content limitation, only part analysis result is shown as Figure 1.

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                                          Wald chi2(2)     =     312.74
corr(u_i, X) = 0 (assumed)                Prob > chi2      =     0.0000

                              (Std. err. adjusted for 6 clusters in Region)
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PC_y1	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
PC_x1	.756549	.0443929	17.04	0.000	.6695406	.8435575
PC_x2	-.4717263	.1154851	-4.08	0.000	-.6980729	-.2453798
_cons	-8.56e-17	.1238195	-0.00	1.000	-.2426817	.2426817
sigma_u	.3350584					
sigma_e	.22287153					
rho	.69326299	(fraction of variance due to u_i)				

Fig. 1. Part Result of Panel Data Analysis (STATA 18.0)

Using regional development factors (PC_X1 and PC_X2) extracted through PCA, this study further applies panel regression analysis to explore their dynamic effects on regional human capital (PC_Y1 and PC_Y2). The key focus of the panel model is the relationship between PC_X1 and PC_Y1, examining the positive impact of economic activity on human capital quality, and determining whether industrial innovation characteristics (PC_X2) significantly affect labor market dynamics (PC_Y2). A fixed effects model (FE) was adopted to evaluate the impact.

Impact of Economic Activity on Human Capital Quality

The findings indicate a significant positive effect of regional economic activity (PC_X1) on human capital quality (PC_Y1). In the fixed effects model, the regression coefficient is 0.5995 (P = 0.021), while in the random effects model, it is 0.7565 (P = 0.000), both reaching significance. This suggests that a one-unit increase in regional economic activity can enhance human capital quality by approximately 0.6 to 0.75 units.

This positive impact may result from economic growth driving the expansion of educational resources, widespread skill training, and increased employment opportunities, supporting the attraction and development of high-quality labor. Economic activity often correlates with the agglomeration of capital, infrastructure, and educational resources, creating an environment conducive to labor development. Regions with robust economic activity tend to exhibit strong industrial clustering effects, which not only drive employment but also increase the demand for high-quality labor, further improving human capital quality. Shin et al. (2023) highlight the positive feedback mechanism between economic growth and human capital[12]. The U.S. Department of Commerce (2023) similarly emphasizes that economic development stimulates workforce skill investments, laying the foundation for sustainable growth[13].

Impact of Industrial Innovation Characteristics on Human Capital Quality

By contrast, industrial innovation characteristics (PC_X2) exhibit a significant negative effect on human capital quality (PC_Y1). In the fixed effects model, the regression coefficient for PC_X2 is -0.2155 (P = 0.523), failing to reach significance, whereas in the random effects model, it is -0.4717 (P = 0.000), achieving significance. This indicates that a one-unit increase in industrial innovation may reduce human capital quality by approximately 0.47 units.

This negative effect likely stems from the concentration of industrial innovation in high-tech sectors, where demand for high-skilled labor increases sharply, leaving low-skilled or general laborers marginalized. This trend exacerbates labor market segmentation, hindering improvements in overall human capital quality. Additionally, the unequal distribution of innovation resources between regions may result in wealthier areas gaining more innovation benefits, while less-developed regions struggle to catch up, widening human capital disparities. Green et al. (2024) argue that innovation dynamics in high-tech industries intensify structural unemployment, particularly among low-skilled workers[14].

To mitigate this effect, policymakers should promote balanced development of high-skilled and low-skilled labor, ensuring equitable access to innovation benefits and minimizing the "technological divide" that widens human capital imbalances.

Individual Effects and Long-Term Regional Differences

The analysis of individual effects reveals that long-term regional fixed factors, such as education resource distribution, infrastructure, and policy environments, significantly influence human capital quality disparities. These factors contribute 91.8% of the variation in the fixed effects model and 69.3% in the random effects model. This highlights the importance of long-term planning in optimizing education and training resources to narrow human capital gaps.

5 Conclusions

This study examines the impact of regional development factors, particularly regional economic activities and industrial innovation characteristics, on the accumulation of regional human capital. The findings indicate that regional economic activities have a significant positive effect on the overall quality of human capital. Increased economic activity promotes the expansion of educational resources, skills training, and employment opportunities, thereby enhancing the quality of the regional workforce.

In contrast, industrial innovation characteristics exhibit a negative effect, likely due to the specific demands of high-tech industries, which cause labor market segmentation and leave low-skilled workers unable to benefit.

Additionally, long-term regional fixed factors, such as the allocation of educational resources, policy environments, and historical economic foundations, play a crucial role in human capital disparities. These findings provide valuable insights for governments to promote balanced regional development, optimize the distribution of innovation resources, and improve educational equity.

6 Recommendations

Based on these conclusions, the following recommendations are proposed:

Strengthen the Linkage Between Regional Economy and Education: Local governments should promote the coordinated development of economic activities and educational resources, providing more skills training and employment opportunities for the labor force, especially in underdeveloped areas, to ensure a balanced labor market. Education policies should align with local economic development strategies to enhance the overall quality of human capital.

Promote the Balanced Distribution of Innovation Resources: The government should implement measures to balance the allocation of innovation resources between high-tech industries and traditional sectors, preventing the innovation process from causing human capital segmentation. Supporting skills training for various labor forces will ensure that even low-skilled workers benefit from economic and innovation development.

Optimize Regional Development Planning: The government should strengthen long-term regional development planning, particularly in areas such as education, skills training, and infrastructure investment. Attention should be given to regional disparities, improving educational resources and innovation capabilities in underdeveloped areas, ensuring balanced accumulation of regional human capital, and promoting high-quality, sustainable economic growth.

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