Journal of Asian Vocational Education and Training
Vol. 15-5, 2022

ISSN 2005-0550

Measurement and Comparison of Interprovincial Comprehensive Development Level of Higher Vocational Education in China —Based on the CIPP Evaluation Model

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ABSTRACT

In order to measure and compare the comprehensive development level of higher vocational education in different provinces, this study adopts the CIPP (Context, Input, Process, Product) evaluation model and uses cross-sectional data from the most recent year available, 2020, to analyze the development level of higher vocational education in 31 provinces and cities in mainland China. The research results reveal that there is a distinct spatial distribution pattern of "East > Central > West" in the development level of higher vocational education in various provinces in China. The comprehensive development index of higher vocational education in each province and city exhibits a global spatial positive correlation, with provinces that have similar levels of development being relatively concentrated spatially. From the perspective of the background, the development of higher vocational education shows a trend of "higher in the east, moderate in the central, and lower in the west." In terms of input, the development of higher vocational education demonstrates a trend of "central region decline." From the perspective of both input and output, it presents a pattern of "higher in the central and eastern regions, lower in the western region." To truly promote the all-round "index-style" high-quality development of higher vocational education in China, precise governance is required based on accurate understanding.

Keywords: Interprovincial; Higher Vocational Education; Development Level; CIPP Evaluation Model

The importance of higher vocational education in China's education system has gradually become more prominent. It has emerged as a crucial field for nurturing high-quality technical and skilled talents, providing significant support for the sustainable development of Chinese society and the economy. However, amid the rapid development of higher vocational education, we must confront a reality: there exists a notable imbalance in the development of higher vocational education among different provinces in China [1]. In this context, we need to delve into the current development levels of provincial higher vocational education in China. Are there significant disparities in the development of higher vocational education among different provinces? In which specific aspects do these differences in comprehensive development levels manifest? To measure and compare the comprehensive development levels of higher vocational education in different provinces, this study employs the CIPP (Context, Input, Process, Product) evaluation model and utilizes cross-sectional data from the most recent year available, which is 2020, to analyze the development levels and spatial distribution of higher vocational education in 31 provinces, autonomous regions, and municipalities directly under the central government in mainland China. It is important to note that in this context, higher vocational education specifically refers to full-time higher vocational education and does not include undergraduate vocational education programs.

Design of the Higher Vocational Education Development Index

1.The CIPP Evaluation Model

In China, the dimensions of higher education indicator systems are broadly categorized using structural classification, input-output classification, scale-quality classification, and scale-input-output classification methods (see Table 1). Worldwide, education development evaluation indicator systems are mainly divided into four categories, designed by the Organisation for Economic Co-operation and Development (OECD), the United Nations Educational, Scientific and Cultural Organization (UNESCO), the World Bank, and the National Center for Education Statistics in the United States. Among these, the OECD's education development indicator system is the most widely adopted. The CIPP evaluation model has been the consistent theoretical guidance for all education indicator systems since the OECD first published its education indicator system in 1992[2]. It was introduced by Stufflebeam in 1966 as an educational evaluation model that aimed to improve educational processes rather than merely prove their effectiveness in response to the limitations of Taylor's behavioral objectives model[3]. The CIPP model integrates four evaluation stages: Context, Input, Process, and Product, covering four decision types: Planning, Organizing, Implementing, and Recycling. This integration endows educational evaluation with scientific, comprehensive, and systematic attributes. The OECD, based on the CIPP evaluation model, has constructed its evaluation dimensions and indicator system, while UNESCO's World Education Indicators System also follows the four basic indicator dimensions of the CIPP model[4].

Many domestic studies have constructed education evaluation indicator systems based on the CIPP evaluation model. Zou Jiawen (2021) developed an indicator system for evaluating China's higher education development level based on the core design of the CIPP evaluation model[5]. Similarly, Li Dexian et al. (2021) referenced the CIPP model from the OECD education indicator system to create an evaluation indicator system for higher education based on the four dimensions: Context, Input, Process, and Results[6]. Pan Haisheng and Weng Xing (2021), inspired by the CIPP educational evaluation model, constructed an evaluation indicator system for higher vocational education, including teaching scale, teaching expenditure, teaching quality, and teaching outcomes[7]. A review of empirical research literature reveals that these studies have certain limitations in terms of the completeness and specificity of their indicator systems. In terms of completeness, due to restrictions related to data sources and data collection difficulties, some scholars have selected relatively limited variables related to higher vocational education. In terms of specificity, vocational education, as a type of education different from general education, should have indicators that reflect its unique characteristics when assessing its development. However, most studies have chosen broad indicators that do not capture the distinctive features of vocational education.

Table 1 Division of Dimensions in Higher Education Indicator Systems

Classification Method	Author	Specific Dimensions
Structure	Jiang Lu (2018)	Hierarchy, Discipline, Layout
Input-Output	Yan Chaodong & Ma Jing (2017)	Input, Output
	Li Jing & Xie Shuqing (2015)	Input, Output
	Cai Wenbo & Zhao Zhiqiang (2021)	Resource Allocation/Input (Human, Material, Financial)
Quantity-Quality	Cheng Lanfang & Wang Yuanyuan (2009)	Quantity, Quality
	Pan Xingxia et al. (2020)	Resources, Benefits
	Wang Zhanjun et al. (2021)	Training Scale, Employment Scale
	Luo Si et al. (2019)	Number of Degree Programs, Quality of Degree Programs, Graduate Training Scale
Quantity-Input-Output	Song Meizhe & Li Mengsu (2019)	Quantity, Input, Output
	Shi Li & Chen Wanming (2015)	Input, Scale, Quality
	Xu Li et al. (2018)	Talent Agglomeration, Input, Output
	He Yiqing & Wu Zhengbo (2019)	Higher Education Agglomeration, Input, Output
	Xu Xue & Wang Zhanjun (2021)	Quantity, Input, Output
	Wang Jie et al. (2019)	Input Elements, Output Capability, Support Base
	Peng Shuolong & Wu Mingyang (2021)	Demand (Scale), Input, Environment (Support)

2.Indicator Design

As previously mentioned, the CIPP evaluation model has been widely applied in international education quality assessment. The OECD education indicators are based on the CIPP evaluation model, which explores and presents trends in the transformation and development of education systems using background indicators, input indicators, process indicators, and output indicators. It assesses the quality of education in various countries by comparing the development status of their education systems.Specifically, background indicators encompass aspects such as demographics, economics, and human capital. Input indicators include financial and human resources. Process indicators cover three key areas: participation levels across various educational stages, teacher quality, and educational equity. Output indicators encompass student learning achievements, graduation outcomes, and the labor market outcomes of education.

In line with the structured logic of the CIPP evaluation model and following the construction logic of "background, input, process, and output," this study has developed a comprehensive evaluation indicator system for higher vocational education, as shown in Table 2. The system consists of four dimensions, 13 primary indicators, and 25 secondary indicators. As indicated by the literature review in the previous section, existing research has paid significant attention to indicators related to input and process. Therefore, this study places emphasis on designing a substantial number of indicators within the input and process dimensions.

Table 2 Comprehensive Evaluation Indicator System for Higher Vocational Education System

System Level	Factor Level	Evaluation Indicator	Attribute	Weight
Background	Regional Economic Background	Per Capita GDP	+	0.0594
	Population Age Structure	Proportion of Population aged 15-64	+	0.0295
	Population Education Structure	Average Years of Education for Employed Population	+	0.0125
Input	Human Resources Input	Student-to-Teacher Ratio	-	0.0105
	Financial Resources Input	Proportion of Education Expenditure in Public Fiscal Education Expenditure	+	0.0136
		Proportion of Education Expenditure in Public Fiscal Expenditure	+	0.0140
		Proportion of Per Capita Education Expenditure in Per Capita GDP	+	0.0807
	Physical Resources Input	Per Capita School Building Area	+	0.0331
		Per Capita Number of Library Books	+	0.0427
		Per Capita Value of Teaching Instruments and Equipment	+	0.0916
Process	Overall Scale	Number of Schools	+	0.0316
		Number of Enrolled Students	+	0.0501
		Number of Enrolled Students	+	0.0551
	Teacher Quality	Proportion of "Double-qualified" Teachers among Full-time Teachers	+	0.0111
		Proportion of Senior Title Teachers among Full-time Teachers	+	0.0321
		Proportion of Graduate Degree Teachers among Full-time Teachers	+	0.0339
		Proportion of Awards in National Vocational College Teaching Ability Competition	+	0.0283
	Industry-Education Integration	Number of Modern Apprenticeship Pilot Programs	+	0.0223
		Number of Demonstrative Vocational Education Groups (Alliances)	+	0.0492
	Equal Opportunities	Enrollment Rate in Higher Vocational Education	+	0.0261
		Number of "Double-high" Institutions	+	0.0501
		Number of Higher Vocational Students per 100,000 People	+	0.1162
Output	Graduation Outcomes	Total Number of Graduates	+	0.0524
	Labor Market Outcomes	Cumulative Scale of Employment of Higher Vocational Graduates	+	0.0225
	Learning Achievements	Proportion of Award Winners in National Vocational College Skills Competitions	+	0.0313

For the background evaluation, background evaluation is an assessment based on the foundational conditions required for teaching. It focuses on various factors that could potentially influence teaching effectiveness. This study's primary indicators include economic development infrastructure, population age structure, and population educational structure, with their proxy variables as shown in the table.

For the input evaluation, input assessment typically assesses both subjective needs and objective resources, funding, manpower, materials, and methods that are available. In this study, while considering financial inputs and material inputs, we have also included manpower inputs as a factor, with their proxy variables as shown in the table.

For the process evaluation, process assessment serves the implementation of decisions by providing feedback through an analysis of the status of educational programs. This feedback information serves as a basis for improving educational programs. Primary indicators in this study include overall scale, teacher quality, industry-education integration, and equal opportunities.The participation of education at various levels can be reflected through the scale of each level of education. Therefore, in this study, the overall scale factor corresponds to the participation of education at various levels in the CIPP model. The proxy variables for overall scale, teacher quality, industry-education integration, and equal opportunities are as shown in the table.

For the output evaluation, output assessment serves the decision-making cycle by providing a value judgment on the effectiveness of educational programs. It involves measuring and analyzing the results of program implementation to determine whether to continue, modify, or terminate the program. Essentially, it constitutes a formative evaluation of educational plans. This study's primary indicators include graduation outcomes, labor market outcomes, and learning achievements, with their proxy variables as shown in the table. It should be noted that, following the design of cumulative scale indicators for graduate education by Li Liguo and Du Fan (2021), and considering that higher vocational education falls under academic education, this study uses post-employment data of higher vocational education to represent the cumulative scale of higher vocational education, specifically the number of individuals in the workforce holding higher vocational qualifications.

METHODOLOGY

1.Weight Calculation for Higher Vocational Education System

In this research, the entropy method[1] was applied to calculate the weights of various indicators in the higher vocational education system. The specific calculation steps are as follows:

(1) Dimensionless Transformation: Let X_j represent the original data of indicator j in 2020, $X_{j\max}$ denote the maximum value of indicator j, $X_{j\min}$ represent the minimum value of indicator j, and X'_j represent the data after standardization. The basic formulas are as follows:

$$X_j' = \frac{X_j - X_{jmin}}{X_{jmax} - X_{jmin}}$$, when the original data is a positive indicator (Equation 1)

$$X_j' = \frac{X_{jmax} - X_j}{X_{jmax} - X_{jmin}}$$, when the original data is a negative indicator (Equation 1)

[1] Note: Entropy is a thermodynamic quantity used to describe the degree of disorder in a system. In the context of this study, entropy is used as a method to assess the degree of data dispersion, which in turn helps determine the effectiveness and value of evaluation indicators. Specifically, higher data dispersion corresponds to larger information entropy values, leading to greater weights for the corresponding indicators, and vice versa. In contrast to widely used methods in existing research such as expert judgment, fuzzy comprehensive evaluation, and Delphi method, entropy-based methods eliminate the subjective arbitrariness in assigning weights during the calculation process, resulting in higher credibility of the calculated results. This makes entropy-based methods suitable for the comprehensive evaluation of multiple indicators.

(2)Entropy Calculation: Let E_j denote the information entropy of the *j*th indicator, and constant K=1/ln*m*. P_j represents the proportion of the 2020 value of the *j*th indicator to the total for that indicator, calculated as $P_j = X'_j / \sum_{i=1}^{m} X'_j$.Then, the entropy of the jth indicator is calculated using the formula:

$$E_j = -K \sum_{i=1}^{m} (P_j \ln P_j) \qquad \text{(Equation 3)}$$

To avoid missing data due to ln0, if P_j=0, we set P_j=0.000 000 1.

(3) Weight Calculation: Let θ_j represent the entropy weight of the jth indicator. Then:

$$\theta_j = \frac{1-E_j}{\sum_{j=1}^{n}(1-E_j)} \qquad \text{(Equation 2)}$$

In this equation, a higher entropy weight θ_j indicates a greater impact of the indicator on the system, and vice versa. After calculation, the attributes and weights of various indicators in the higher vocational education system are presented in Table 2.

2.Global Spatial Autocorrelation Analysis

To investigate the interdependence of economic-geographic behaviors among different provinces, it is essential to consider the presence of spatial effects. Due to factors such as population mobility, technological diffusion, and trade interactions, relatively independent administrative regions exhibit a certain degree of correlation in socio-economic aspects[10]. Therefore, this study employs the method of global spatial autocorrelation analysis to characterize the spatial correlation characteristics of the coupling coordination degree among provinces.

Global spatial autocorrelation analysis can analyze the overall distribution of the comprehensive development level of higher vocational education across provinces in space, helping to identify whether there are spatial clustering characteristics. The degree of global spatial autocorrelation is measured using Moran's I index (global Moran's index), expressed by the formula:

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j\neq i}^{n} W_{ij}(\theta_i-\bar{\theta})(\theta_j-\bar{\theta})}{S^2 \sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}} \qquad \text{(Equation 5)}$$

In this equation, $S^2 = \frac{1}{n}\sum_{i=1}^{n}(\theta_i - \bar{\theta})^2$, $\bar{\theta} = \frac{1}{n}\sum_{i=1}^{n}\theta_i$. Here, θ_i and θ_j represent the comprehensive development index of higher vocational education in regions i and j, respectively. n is the number of spatial units. w_{ij} represents the spatial weight matrix between two regions. When the significance level is fixed, a positive Moran's I indicates a global positive spatial correlation in the comprehensive development index of higher vocational education in the region. Conversely, a negative value suggests a global negative spatial correlation.

3.Data Sources

The data sources for this research's indicators include the National Bureau of Statistics, provincial "Labor Statistics Yearbooks," "China Education Statistics Yearbooks," "China Population and Employment Statistics Yearbooks," "National Education Brief Statistics Analysis," "China Education Expenditure Statistics Yearbooks," "China Labor Statistics Yearbooks," "China Regional Innovation Capability Assessment Reports," and publicly available data materials from the Ministry of Education.

Overall Measurement and Comparison of Interprovincial Higher Vocational Comprehensive Development

1. Overall Measurement of Interprovincial Higher Vocational Comprehensive Development

Based on the CIPP research framework, this study constructed a comprehensive evaluation index system for higher vocational education. Using the entropy method, appropriate weights were assigned to each indicator, and the Higher Vocational Education Comprehensive Development Index for each province was calculated to reflect the overall level of higher vocational education in each province (see Figure 1).

The calculation results indicate that in 2020, Shandong had the highest level of development in higher vocational education, while Hainan had the lowest. Among the top 10 provinces in the overall index ranking, 7 were from the eastern region, 3 from the central region, and none from the western region. Among provinces ranked 11-21 in the overall index, 4 were from the eastern region, 2 from the central region, and 5 from the western region. For provinces ranked 22-31 in the overall index, 2 were from the eastern region, 1 from the central region, and 7 from the western region, showing a clear pattern of "eastern > central > western."[2]

Further observation and comparison reveal that Jiangsu and Zhejiang scored higher than the national average in all four aspects: background, input, process, and output. There are no apparent weaknesses in their overall performance. Conversely, Guizhou, Hainan, Shanxi, Jilin, and Xinjiang scored lower than the national average in all four aspects, indicating overall weaker capabilities.

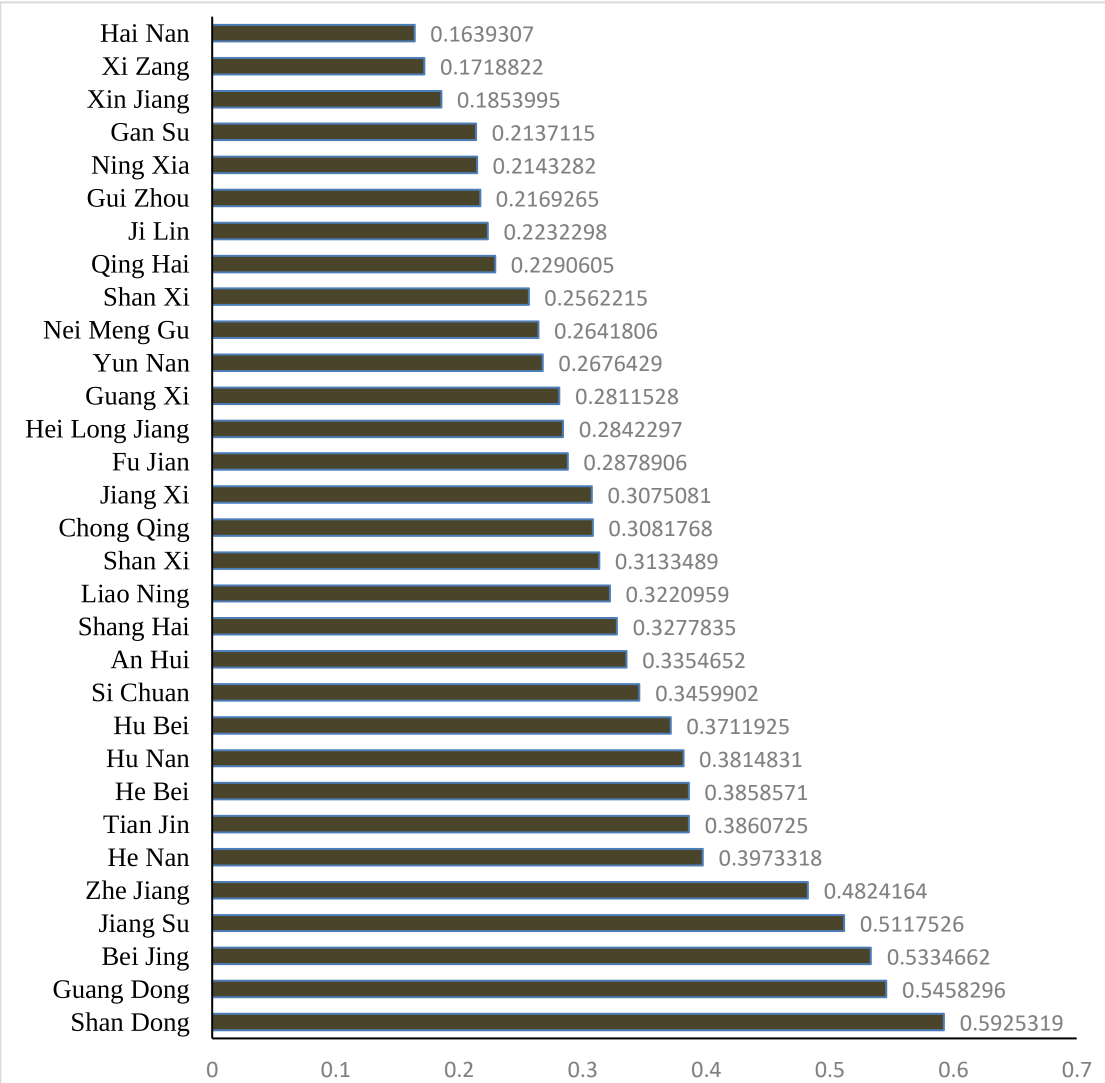

Figure 1: Higher Vocational Education Comprehensive Development Index of 31 Provinces and Cities in China in 2020

[2] Note: According to the 2018 statistical consultation response from the National Bureau of Statistics, China's eastern region includes 10 provinces and municipalities: Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes 6 provinces: Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western region includes 12 provinces, autonomous regions, and municipalities: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The northeastern region includes 3 provinces: Liaoning, Jilin, and Heilongjiang. This study categorizes the northeastern region as part of the eastern region and adopts the classification method of dividing China into three major regions: eastern, central, and western.

2. Spatial Comparison of Interprovincial Higher Vocational Comprehensive Development

To explore the spatial clustering characteristics of the Higher Vocational Education Comprehensive Development Index among the 31 provinces and municipalities in China, the global Moran's Index was calculated using STATA 16.0 software (see Table 4). In 2020, the estimated values of the global Moran's Index ranged from 0.039 to 0.427. Although there was some fluctuation, the values consistently exceeded 0 and largely passed the 1% significance test. This indicates a positive global spatial autocorrelation feature in the comprehensive development index of higher vocational education among provinces and municipalities. Provinces with similar levels of vocational education development tend to be spatially concentrated, meaning that provinces with higher development levels are relatively adjacent, while those with lower development levels also cluster together. There is significant spatial influence between neighboring provinces, emphasizing the relevance of geographic spatial distribution in enhancing vocational education development.

Meanwhile, the overall Moran's Index is relatively low, suggesting that the spatial autocorrelation level of vocational education development between regions is not very high. In other words, the spatial impact on vocational education development levels among provinces is relatively small.When examining individual dimensions, the global Moran's Index for background, process, and output is relatively high, with values ranging from 0.209 to 0.427, indicating stronger spatial autocorrelation and overall spatial clustering in these dimensions. However, the global Moran's Index for input did not pass the significance test.

Table 4 Moran's I for Higher Vocational Comprehensive Development Index in 2020

Dimension	Background	Input	Process	Output	Total Score
Moran's I	0.209	0.039	0.255	0.427	0.261
Z	2.333	0.762	2.691	4.224	2.724
P	0.010	0.223	0.004	0.000	0.003

Due to the global Moran's Index's limitation in revealing the dependence of spatial phenomena and its lack of visual significance in depicting the intuitive differences between provinces and their surrounding regions, which only characterizes the overall spatial agglomeration characteristics without indicating specific clustered regions, local spatial autocorrelation analysis serves to complement the shortcomings of global spatial autocorrelation analysis. Therefore, in this study, we employed the Local Getis-OrdGi index to identify spatial agglomeration patterns of high or low values in the development of vocational education in China. These patterns were categorized into diffusion effect zones ("High-High Agglomeration"), transitional zones ("Low-High Agglomeration"), slow-growth zones ("Low-Low Agglomeration"), and polarization effect zones ("High-Low Agglomeration") based on their nature.[10]

"High-High Agglomeration" indicates that provinces with high levels of vocational education development are surrounded by other provinces with similarly high levels of development, signifying a concentrated spatial distribution of high levels of vocational education development. On the other hand, "Low-High Agglomeration" suggests that provinces with low levels of vocational education development are surrounded by neighboring provinces with relatively high levels of development, indicating that provinces with low levels of vocational education development are surrounded by provinces with relatively higher levels of development in space. "Low-Low Agglomeration" implies that provinces with low levels of vocational education development are surrounded by other provinces with similarly low levels of development, with only a few provinces falling into this category. Lastly, "High-Low Agglomeration" signifies that provinces with high levels of vocational education development are surrounded by neighboring provinces with relatively lower levels of development. The specific distribution of agglomeration types is presented in Table 5.

Table 5 Distribution of LISA Agglomeration Types in 31 Provinces and Regions of China

Agglomeration Type	Provinces
High-High	Shandong, Jiangsu, Henan, Anhui, Hubei
Low-Low	Qinghai, Tibet, Xinjiang
Low-High	Hainan
High-Low	-
Not Significant	The other 22 provinces

Note: The significance level of agglomeration types is 5%.

From the table, it is evident that in 2020, the "High-High" agglomeration pattern was distributed predominantly in the Huai River Basin, spanning the eastern and central regions of China. Provinces such as Shandong, Jiangsu, Henan, Anhui, and Hubei exhibited generally high levels of vocational education development. These provinces not only had high levels of vocational education development themselves but also had a relatively high level of vocational education development in their surrounding provinces. They played a significant role in radiating and stimulating vocational education development in their neighboring areas.

Meanwhile, the "Low-Low" agglomeration pattern was primarily concentrated in the western regions, with provinces such as Qinghai, Tibet, and Xinjiang being the main representatives. These provinces lagged behind in terms of vocational education development and faced similar challenges or limitations. They can be considered as "low-lying areas" in the national vocational education landscape. Not only did they have relatively low levels of vocational education development, but they also had a somewhat negative impact on the surrounding provinces.The "Low-High" agglomeration pattern was observed in Hainan Province, indicating that vocational education resources and development opportunities in this region were still at a relatively low level. However, neighboring provinces, such as Guangdong, had better vocational education development levels. This reflects the uneven distribution and development of vocational education in the region.For the remaining provinces that did not reach a significant level of agglomeration, no further discussion is provided.

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