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An Effective Study on Spatiotemporal Differentiation of Chinese Nursing Staff: Spatial Durbin Model

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Abstract: *The purpose of this article is to construct a nested matrix of "education economy" to study the spatial effects of Chinese nurses and further explore the influencing factors of the spatial distribution of Chinese nursing staff under the new healthcare reform. We use Monte Carlo simulation method to optimize and screen the nested matrix of "education economy". On this basis, we used Moran index, spatial Gini coefficient, and cold hot spot analysis method to analyze the spatial pattern of nurses in China. We construct a spatial Durbin model to analyze the main influencing factors and spatial spillover effects of nursing staff. The results indicate that the relative density area and relative average area of nursing staff in 31 provinces have significantly increased. The global Moran index has dropped from 0.523 in 2008 to 0.340. The distribution of personnel in hotspots spreads from economically developed areas to the central and western regions, with a significant contraction of cold spots. The level of provincial economic development (direct effect 0.493, indirect effect -1.519), unemployment rate (direct effect -0.118), education resource investment (direct effect 0.538, indirect effect 1.713), and per capita medical expenditure (direct effect 0.45 37) are the influencing factors on the spatial distribution of nursing staff. Therefore, it is more reasonable to use the nested matrix of "education economy" to study the spatial effects of Chinese nurses. After the new healthcare reform, the distribution of nursing staff in China has significantly improved. The health administrative department should pay attention to local economic development, reduce unemployment rate, increase investment in education resources, and reduce per capita medical expenses to ensure the healthy development of medical and health personnel.*

Keywords: *"Education economy" Nested Matrix, Spatial Durbin Model, Chinese Nurses, Spatial Spillover Effect, Partial Differential Decomposition*

1. Background

The number of nursing staff in China has significantly increased over the past decade through medical reform.[1,2] The talent cultivation of grassroots health teams and the strength of grassroots medical services have been continuously strengthened.[3,4] However, compared with developed Western countries, there is still a significant gap. The proposal of the "Healthy China 2030 Strategic Plan" and the "Global Health Human Resources Strategy (GSHRH)" has made active explorations to address the severe shortage of nursing teams. Domestic and foreign scholars mainly conduct research on nursing staff allocation through Gini coefficient, concentration index, and cross-sectional analysis.[5,6,7] A large number of scholars have conducted research on nursing staff management at the micro level.[8,9,10] However, traditional research hypotheses are derived based on prior probabilities, ignoring the objective connections and interactive effects between factors.[11,12] The first law of geography points out that there must be a certain spatial dependence between things, which is gradually widely used in the economic and environmental fields, but has not yet been promoted and popularized in the field of public health.[13] Therefore, scientifically evaluating the spatial distribution and dynamic changes of nursing staff in China, actively exploring the main factors and time-space effects that affect nursing staff mobility, incorporating spatiotemporal factors into the construction of relevant models in the health field, and constructing the optimal spatial matrix have important practical significance and foresight.[14,15]

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This article attempts to select appropriate indicators based on China's national conditions to construct the optimal spatial weight matrix, and evaluate the spatial mobility of provincial-level nursing staff in China from a macro perspective, in order to provide ideas and evidence-based basis for future related research and spatial model construction.

2. Methods

2.1 Research Area and Data Sources

This study covers 31 provinces (autonomous regions, municipalities directly under the central government) in China, excluding the Hong Kong Special Administrative Region, Macau Special Administrative Region, and Taiwan Province. 31 provincial-level administrative divisions in China from 2008 to 2018 were selected as the spatial basic units. The relevant data used in this study are all sourced from the China Statistical Yearbook from 2008 to 2018. Nursing staff are defined as registered nurses, i.e. practitioners who have obtained professional qualifications. According to survey data, the overall size of nursing staff in China has increased by 244% over the past 11 years, from over 1.67 million in 2008 to over 4 million in 2018, with an average annual growth rate of 22%. This study analyzes the spatial pattern of nursing staff in China based on two types of indicators: the total number of nursing staff and the number of nursing staff per thousand population, and performs logarithmic transformation on the relevant data to reduce statistical bias.

2.2 Spatial autocorrelation analysis

Calculate the overall level of geospatial autocorrelation among nursing staff nationwide through the global Moran index.[16]The calculation formula is as follows:

$$I=\frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(\mathcal{X}_i-\bar{\mathcal{X}})(\mathcal{X}_j-\bar{\mathcal{X}})}{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\cdot\sum_{i-1}^{n}(\mathcal{X}_j-\bar{\mathcal{X}})^2} \tag{1}$$

Where $\mathcal{X}_{\mathrm{i}}$ ($\mathcal{X}_{\mathrm{j}}$) represents the number of caregivers per thousand population in regions i and j,n represents the number of provinces in the country,$\omega_{ij}$is the spatial weight matrix. I represents the number of nursing staff in each province of China per thousand people, which can effectively eliminate the mixed effects of population mobility.

2.3 Selection and Optimization of Spatial Weight Matrix

The construction methods of spatial matrices can be divided into three categories: adjacency space weight matrix, distance space weight matrix and nested space matrix. The current papers confirms that local income and educational resources are important factors in attracting the flow of nursing staff. Therefore, this article adopts the "Education Economy" nested space matrix(ω_{EE}) to analyze its spatial effects. As shown in Table 1.

Table 1: Estimated values and Monte Carlo simulations of the MORAN index for a single matrix in a certain year

Measurement indicators	matrix selection	MORAN value	Monte Carlo simulation (1000 times)		
			z value	SD.	P value
Nursing staff per thousand population	adjoin	0.1825	2.1045	0.1039	0.040
	Inverse distance power	0.0239	0.6518	0.0864	0.187
Per Capita GDP	KNN mean	0.4098	4.4065	0.0994	0.001
	Specify bandwidth	0.7681	3.8785	0.1520	0.006
Per capita education investment	KNN mean	0.422	4.7735	0.0949	0.001
	Specify bandwidth	0.4105	6.0539	0.0732	0.001

ω_{EE}(Education-Economic) matrix is defined as:

$$\mathrm{EE(i,j)}=\sum_{\mathrm{k=1}}^{\mathrm{n}}\mathrm{(i,k)}\otimes\mathrm{(k,j)},\mathrm{i=k=j} \tag{2}$$

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Where $A \in (i,k)$ represents the economic matrix, $r_{gdp} = \frac{\text{Local per capita GDP}}{\text{National per capita GDP}}$ as a measurement indicator.

$B \in (i,k)$ represents the educational matrix,

$r_{edu} = \frac{\text{Per capita investment in local government education resources}}{\text{Per capita investment in national government education resources}}$ as a measurement indicator.

We use the KNN algorithm, namely the K-nearest neighbor algorithm, to construct the spatial weight matrices of $A(i,k)$ and $B(i,k)$ respectively, and extract r_{gdp} and r_{edu} feature values form a feature space. The spatial distance between provinces is calculated using Euclidean distance and clustering is performed. Based on Monte Carlo simulation results, using the education economy nested space matrix(ω_{EE}) has the best convergence and is more suitable in this study.

The distance formula is as follows:

$$d(\chi_i, \chi_j) = \sqrt{\sum_{k=1}^{n} (\chi_{ik}, \chi_{jk})^2} \tag{3}$$

2.4 Cold and hot spot analysis

The local spatial autocorrelation is calculated and used to measure the correlation between adjacent spaces within a local area through cold hot spot analysis. The calculation formula is:

$$G_i^* = \frac{\sum_{j=1}^{n} \omega_{i,j} \chi_j - \bar{X} \sum_{j=1}^{n} \omega_{i,j}}{S\sqrt{\frac{[n\sum_{j=1}^{n} \omega_{i,j}^2 - (\sum_{j=1}^{n} \omega_{i,j})^2]}{n-1}}} \tag{4}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} \chi_j^2}{n} - (\bar{X})^2} \tag{5}$$

Where $\bar{X}$ is the average number of nursing staff in all regions,χ_j is the observed value of the number of nursing staff in region J,$\omega_{i,j}$ is the spatial weight of variables I and J,N is the number of variables.

2.5 Selection and construction of spatial econometric models

In order to select appropriate spatial econometric models, the Hausman test (5.31, $p>0.05$) and LM test (464.98, $p<0.01$) showed that the random effects model was superior to the fixed effects model and the mixed models.[17,18] In addition, further verify whether the SDM model can be simplified into an SLM model (110.01, $p<0.01$) or an SEM model (1120.36, $p<0.01$). The results indicate that SDM with random effects is the optimal model. The multicollinearity test shows that the VIF values of the explanatory variables are all less than 5. Therefore, there is no multicollinearity problem with the variables used in the study.

Next, we will establish a spatial Durbin model to analyze the impact of the spatiotemporal distribution pattern of nursing staff in China. The model settings are as follows:

$$\gamma_{it} = \alpha_0 + \rho\omega_{it} \ln \mathcal{Y}_{it}\, \varphi + \alpha_1 \ln \mathcal{X}_{1it} + \alpha_2 \ln \mathcal{X}_{2it} + \cdots + \alpha_9 \ln \mathcal{X}_{9it} + \rho' \omega_{it} \ln \mathcal{X}_{it} + \varepsilon_{it} \tag{6}$$

Where γ_{it} is the number of nursing staff, *I* represents spatial unit; *t* represents the time observation value; ρ is the spatial autocorrelation coefficient,ρ' is the spatial lag coefficient, ω_{it} is ω_{EE} spatial weight matrix,ε_{it} is a random perturbation term, which presents error value of spatial autocorrelation model.

The influencing factors of this study include four aspects: Economic factors: average resident salary, Salary ratio($\frac{\text{Average salary of medical staff}}{\text{Average salary of residents}}$),House price ratio($\frac{\text{Average House Price}}{\text{Average salary of residents}}$),unemployment rate these 4 indicators; Public service factors: Per capita medical expenses, per-capita education spending and Population growth these 3 indicator; Medical and health resources:Number of diagnosis and treatment personnel and per capita number of beds. This reflects the current supply and demand situation of local medical resources, all of which have become important considerations for nursing staff (Table 2).

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Table 2: Basic Statistical Information of Variables

variable	sample size	average value	standard deviation	minimum value	Maximum value
Nursing staff per thousand population	341	2.14	0.86	0.56	6.36
Per Capita GDP	341	10.60	0.52	9.19	11.85
unemployment rate	341	3.39	0.65	1.21	4.6
Number of diagnosis and treatment visits/logarithms	341	9.47	1.07	5.78	11.34
Per capita medical expenditure/logarithm	341	6.46	0.60	4.92	8.04
Average salary/logarithm of residents	341	10.78	0.39	9.95	11.89
Salary ratio	341	1.14	0.15	0.72	1.63
House price ratio	341	0.12	0.04	0.04	0.28
Per capita number of beds	341	4.66	2.13	2.19	38.21
Per capita education expenditure/logarithm	341	5.54	0.52	3.90	6.64
Population growth	341	28.55	64.12	-319	803

3. Results

3.1 Overall distribution of nursing staff

Based on existing literature and China's national conditions, the distribution of nursing staff in China is classified into three categories: relatively dense areas (number>3), relatively mean areas (2<number<3), and relatively sparse areas (0<number<2). (Table 3)

Table 3: Classification and Statistics of Nursing Personnel Spatial Distribution Based on Provincial Regions in China in 2008 and 2018

year	Distribution	Quantity/piece	Population ratio/%	Number of caregivers per thousand
2008	Relatively dense area	2	2.70	4.01
	Relative mean area	1	0.89	2.26
	Relatively sparse area	28	96.41	1.22
2018	Relatively dense area	13	38.28	3.40
	Relative mean area	17	61.47	2.69
	Relatively sparse area	1	0.25	1.62

The results showed the distribution of nursing staff in China in 2008 and 2018, with concentrated areas in Beijing and Shanghai in 2008. This is in line with the local developed economic development level and dense educational resources, and the distribution of nursing staff shows a significant imbalance. The average number of nursing staff in relatively dense areas is 4.01, while in relatively sparse areas it is only 1.22, a difference of 3.29 times. At the same time, 96.41% of the population is in areas with sparse nursing staff, only 2.7% of the population is in densely populated areas, and only Tianjin area has entered the average area. In 2018, there was a significant change in the distribution

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pattern of nursing staff in China. The average number of nursing staff in densely populated areas was 3.40, covering 38.28% of the population, an increase of nearly 14.18 times over the past 11 years. The number of nursing staff in the relative average area increased to 2.69, and the region increased to 17 provinces, covering 61.47% of the population. A large number of relatively sparse areas have become relatively average areas and relatively dense areas, gradually forming a multi center nursing human resource aggregation zone. The overall pattern shows a clear dispersion of agglomeration degree, and the distribution balance of nursing human resources has improved significantly.

3.2 Spatial autocorrelation analysis of nursing staff

Global spatial autocorrelation analysis is used to measure the overall level of spatial autocorrelation among nursing staff nationwide. In 2008, the overall MORAN index of nursing staff in China was 0.523 (Z=5.028, p=0.001); In 2018, the global MORAN index of nursing staff in China was 0.340 (Z=2.170, p=0.018); The spatial agglomeration effect remains significant and forms the Moran index scatter plot based on it (Figure 1).

Among them, the horizontal axis represents the standard values of nursing staff in various regions, and the vertical axis represents their spatial lag. Most provinces and cities in China are located in the lower left and upper right quadrants, indicating that most areas of nursing staff have low and high concentrations in 2008 and 2018. However, the distribution in 2018 was more scattered and average compared to 2008, indicating a gradual decrease in the distribution differences among nursing staff in different regions.

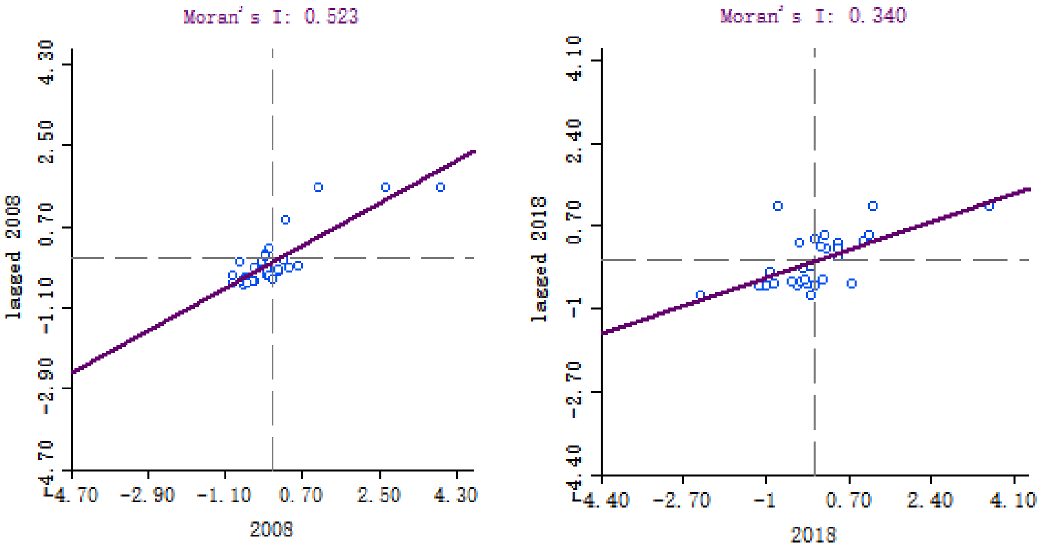

Figure 1: Scatter plot of Moran index for nursing staff in 2008 and 2018

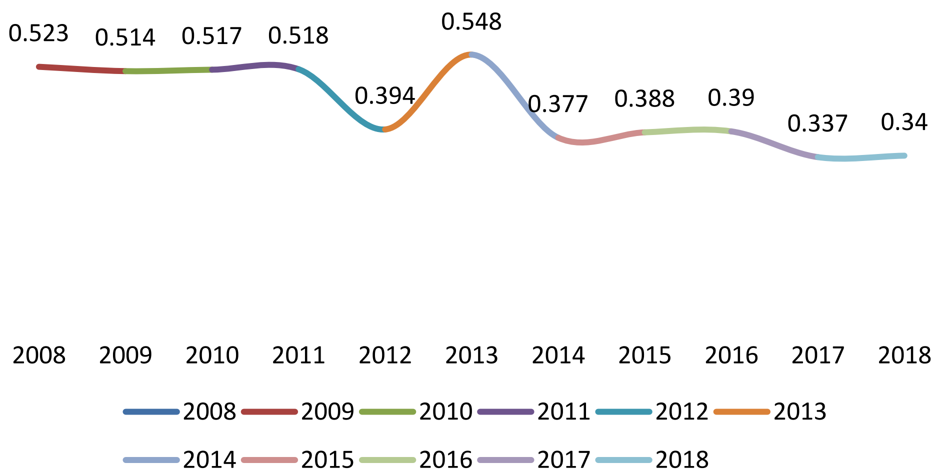

Figure 2: Global Moran's I values for Chinese nursing staff/1000 population from 2008 to 2018

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In addition, in 2008, the four regions of Beijing, Tianjin, Shanghai, and Zhejiang, which were located in high and high concentration areas, moved closer to low and low concentration areas in 2018. The number of low and low concentration areas has significantly decreased. In 2008, low and low concentration areas in China have disappeared in 2018, while Qinghai and Tibet have become low concentration areas, indicating a significant loss of nursing staff in Qinghai and Tibet. The Tianjin area became a low high concentration area in 2018, demonstrating the siphon effect of Beijing on nursing staff, leading to the loss of health human resources in the Tianjin area. Therefore, the spatial effect and dependence of the distribution of nursing staff are influenced not only by local economic development but also by neighboring regions.

At the same time, the MORAN index of nursing staff in China showed a decreasing trend year by year from 2008 to 2018, indicating a weakening of the spatial agglomeration of nursing staff and a preliminary improvement in the supply balance of health human resources (Figure 2).

3.3 Analysis of cold and hot spots in the distribution of nursing staff

Evaluate the similarity and dissimilarity of adjacent regions by calculating the Gi * index of the distribution of nursing staff in China in 2008 and 2018. The hot spots are mainly concentrated in four regions: Beijing, Tianjin, Shanghai, and Zhejiang, while the other regions were cold spots in 2008. The developed economic and educational resources in these four regions have attracted a large number of medical staff, while also driving the rapid flow of nursing human resources in the surrounding areas. The attractiveness of nursing staff in the southwest and central regions is relatively low. Zhejiang Province has become a non hot spot area, and the old cold spot area disappeared in 2018. Qinghai and Ningxia have become new cold spots, indicating a diffusion trend in the spatial distribution of nursing staff. There is still a concentration trend in certain regions such as Beijing and Shanghai.

3.4 Factors influencing the spatial distribution of nursing staff

Table 4: SDM econometric model estimation results

variable	coefficient	standard error	P value	variable	coefficient	standard error	P value
Per Capita GDP	0.839***	0.22	0.000	Wx* Per Capita GDP	-1.17***	4.52	0.001
unemployment rate	-0.122**	0.06	0.033	Wx* unemployment rate	0.092	0.10	0.461
Number of diagnosis and treatment visits/logarithms	0.118	0.09	0.197	Wx* Number of diagnosis and treatment visits/logarithms	-0.136	0.09	0.210
Per capita medical expenditure/logarithm	0.535***	0.17	0.001	Wx* Per capita medical expenditure/logarithm	-0.517***	0.21	0.019
Average salary/logarithm of residents	-0.028	0.33	0.934	Wx* Average salary/logarithm of residents	0.285	0.43	0.504
Salary ratio	-0.136	0.26	0.596	Wx* Salary ratio	-0.250	0.54	0.608
House price ratio	0.005	1.18	0.997	Wx* House price ratio	0.353	1.90	0.856
Per capita number of beds	<0.001	0.01	0.912	Wx* Per capita number of beds	0.011	0.02	0.534
Per capita education expenditure/logarithm	0.128	0.15	0.389	Wx* Per capita education expenditure/logarithm	0.591*	0.22	0.056
Population growth	<0.001*	<0.001	0.058	Wx* Population growth	<-0.001	<0.001	0.883
_cons	-2.130	1.86	0.016	Wx* Nurses per thousand population	0.686***	0.05	0.000

Notes:*p<0.1, **p<0.05,***p<0.01.Wx*pgdp, Wx*ur, Wx*lnpmn, Wx*lnpme, Wx*lnaw, Wx*awr, Wx*hw, Wx*beds, Wx*lnpe,Wx*pu Respectively represent the spatial lag of each explanatory variable. Wx*nurse represents the spatial lag of the outcome variable.

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Table 5: Direct and indirect effects results estimated by the SDM econometric model

variables	direct effect	p-value	indirect effect	p-value
Per Capita GDP	0.493**	0.014	-1.519**	0.038
unemployment rate	-0.118**	0.029	0.024	0.925
Number of diagnosis and treatment visits/logarithms	0.091	0.219	-0.149	0.343
Per capita medical expenditure/logarithm	0.437***	0.001	-0.397	0.276
Average salary/logarithm of residents	0.138	0.620	0.692	0.316
Salary ratio	-0.320	0.203	-0.824	0.431
House price ratio	0.212	0.847	0.881	0.814
Per capita number of beds	0.008	0.317	0.031	0.409
Per capita education expenditure/logarithm	0.538***	0.000	1.713**	0.011
Population growth	0.001***	0.002	0.001	0.363

Note:*p<0.1, **p<0.05, p<0.01

The results indicate that there is a significant correlation between per capita GDP, unemployment rate, per capita medical expenditure, and the spatial distribution of nursing staff (Table 4). Due to the spatial lag effect of both explanatory and outcome variables in the construction of the model, it is not possible to objectively measure its elasticity coefficient. Therefore, the direct and indirect effects of the relevant variables are obtained through partial differential decomposition to test the spatial spillover effect of the relevant indicators. Direct effects represent the interrelationships between local variables, while indirect effects represent the extent to which local outcome variables are influenced by adjacent regional independent variables (Table 5).

Specifically, every 1% increase in per capita GDP in the local area will increase the number of local nursing staff by 0.493%, while every 1% increase in per capita GDP in adjacent areas will reduce the number of local nursing staff by 1.519%. This indicates that the flow of nursing staff is more inclined towards areas with higher levels of economic development. In addition, every 1% increase in local unemployment rate will result in a loss of 0.118% of nursing staff, and no impact of changes in unemployment rates in adjacent areas on the flow of local nursing staff has been observed. The rapid development of medical technology has increasingly raised the demand for nursing professional knowledge. Therefore, nursing staff pay more attention to learning professional skills and career advancement resources. For every 1% increase in local education resource investment, the number of local nursing staff will increase by 0.538%, while for every 1% increase in education resource investment in adjacent areas, the number of local nursing staff will decrease by 1.713%. Although the net inflow of population in urban development has little impact on attracting nursing staff, it also has a positive promoting effect.

4. Conclusion and Discussion

The construction of spatial weight matrix is a key step in spatial effect analysis, and the selection of spatial matrix directly affects the results of spatial effect analysis. *Lee* et al. studied the errors of different spatial weight matrices in panel dynamic models.[21] Stakhovych et al. simulated the spatial weight matrix.[22] Scholars used adjacency matrices to study the dynamic changes of plant invasion.[23] This study randomly simulated geographic matrix, education nested matrix, economic nested matrix, and "education economy" nested spatial matrix when constructing spatial weight matrix. It was found that the use of nested spatial weight matrix resulted in more obvious spatial dependence, making more use of the spatial effects of analyzing the distribution of nursing personnel.

Since the new healthcare reform in 2009, the nursing team in China has continued to develop and grow, with a significant increase in the number of thousands of nurses in various regions and a more balanced distribution at the provincial level. This result shows that the global MORAN index is positive and showing a decreasing trend year by year, but there is still room for improvement in the total number of nursing staff, and there is still a spatial agglomeration pattern in some economically developed regions. Therefore, it is necessary to further consider the mobility of medical personnel, comprehensively consider the current situation of medical personnel allocation in local and similar

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regions, and improve the efficiency of health human resource allocation in building a high-quality and efficient medical service system.

The results of this study suggest that there is a significant spatial spillover effect in the distribution of nursing staff in China. The level of local economic development, unemployment rate, and per capita medical expenses are the main factors determining the distribution of nursing staff. No significant impact was found on housing prices and income levels. This is because the main group of nursing staff mobility is younger, and they pay more attention to the improvement of public service levels and personal abilities in cities, which is consistent with Western equilibrium theory and related research.[19,20] Therefore, urban development not only needs to increase the absolute value of personal income, but also the comprehensive improvement of educational resources and public service capabilities is crucial for attracting and retaining talents.

This article uses a spatial econometric model to explore the dynamic changes in nursing human resources at the provincial level. We construct a multidimensional spatial weight matrix of "education economy" to objectively evaluate the "siphon effect" of nursing human resources between regions, which can provide new ideas for similar researchers to construct spatial matrices.

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