Research on the Influencing Factors of Chinese Healthcare Resource Allocation Problems Based on Principal Component Analysis

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Abstract: With the development of the social economy and the people's need for a better life, more and more people begin to pay attention to physical health. Consequently, the judicious allocation of healthcare resources has become paramount. This study utilizes 2022 healthcare indicator data from various regions of China. Before analysis, the data underwent Kaiser-Meyer-Olkin (KMO) and Bartlett's tests to confirm its suitability. Subsequently, a principal component analysis (PCA) was employed to construct a comprehensive evaluation model, facilitating an investigation into the allocation of healthcare resources across different regions. The findings revealed that factors such as population, economic conditions, and healthcare supply all positively influence the allocation of medical resources. Ultimately, this research aims to inform the development of a high-quality and efficient healthcare service system in China. Furthermore, it seeks to contribute to resource sharing among regions, reduce healthcare disparities, and ensure equitable access to medical care across all areas of China.

1 INTRODUCTION

The proper distribution of medical resources is related to the health of the people and the overall promotion of the construction of a healthy China (Liu, & Zhao, 2024). With the rapid socioeconomic development and accelerated population aging in China, the demand for high-quality medical services among the populace is increasing. However, significant are the disparities observed nowadays in health resource distribution across various regions. This makes the current allocation of medical and health resources in China still present an unfair situation of the dualistic structure system of urban and rural area (Dai et al., 2023).

Research on healthcare resource allocation has gained significant attention in recent years, leading to a proliferation of relevant studies. For instance, Zheng et al. (2018) applied principal component analysis to evaluate healthcare resource allocation, finding significant improvements over the past decade in service provision, utilization, and care delivery. Li (2023) applied factor analysis to show that there are regional differences in the rationality of medical resource allocation in China, and the overall situation is poor, with only a few provinces in a state of balanced supply and demand. Liu et al. (2024) used a three-stage DEA-Tobit model to analyze the efficiency of healthcare resource allocation and its influencing factors. The analysis concluded that there are obvious differences in the allocation of health resources in various regions. Therefore, in-depth research on the allocation of medical and health resources is important.

This study employs principal component analysis, which explores the factors influencing healthcare resource distribution. The findings aim to provide a scientific basis for optimizing government financial investment structures and guiding the allocation of high-quality resources to lower-level healthcare facilities.

2 METHOD

2.1 Data Sources and Indicator Selection

The data indicators for this study were obtained from China Statistical Yearbook (2023), China Health Statistics Yearbook (2023), and the National Bureau of Statistics of China. These indicators were

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integrated to create the dataset required for this analysis, as presented in Table 1. Due to data collection limitations, the regions of Macau, Hong Kong and Taiwan were excluded from the scope of this research. In this paper, the 31 provinces, municipalities and autonomous regions of Mainland China were categorized into three major regions: the eastern region, the central region and the western region.

Table 1: Description of Indicator Symbols

Name of the Indicator	Unit of the Indicator	Symbols of the Indicator
Population of the regions	Ten Thousand People	x_1
Number of public hospitals per region	PCS	x_2
The capability of hospital beds per 10,000 populations	PCS	x_3
Health technicians per 10,000 population	Person	x_4
Registered nurses per 10,000 population	Person	x_5
Hospital bed occupancy rate by region	%	x_6
Expenditures on health care by local finances	Hundred Million Yuan	x_7
Gross Domestic Product (GDP)	Hundred Million Yuan	x_8
Per Capita Disposable Income	Yuan	x_9

2.2 Method Introduction

Principal Component Analysis, a technique for reducing dimensionality, stands as PCA commonly that reconstructs the original variables into uncorrelated principal components by linear combination. The advantage of using this method is that it simplifies analysis complexity by removing redundant data and extracting key features. It also maximizes the preservation of the original data structure, further simplifying the data analysis process.

3 RESULT AND DISCUSSION

3.1 Data Preprocessing

In order to eliminate the difference in magnitude between different feature indicators, it is necessary to use Z-Score standardization to ensure that the contribution of each existing data to the model results is fair. After that, to verify the selected data's suitability and effectiveness, employed were the KMO and Bartlett's tests in this study. Shown in Table 2 are the obtained results. Reaching 0.662 was the KMO value, while the significance level $p = 0.000$ was observed. Thus, it can be seen that sufficiently reliable are the measurement outcomes obtained through these tests.

Table 2: The value of KMO and Bartlett's tests

KMO Value	Bartlett's tests		
	Approximate Chi-squared value	degrees of freedom	significance level
0.662	273.015	36	0.000

Indicator extraction

Following data validation and processing, PCA was employed for feature extraction and subsequent analysis. The results are presented in Tables 3.

Further analysis based on the data in Table 3. Employing the Kaiser-Harris criterion, factors with eigenvalues exceeding 1 were retained. This study extracted three principal components using PCA. The eigenvalue for Component 1 was found to be 3.844, while Component 2 showed a value of 2.556. As for Component 3, it was only 1.348. These three components collectively accounted for 86.086% of the variance. Overall, the information loss from the original indicators was minimal, indicating a satisfactory outcome from the PCA.

Table 3: Explained Variance

Component	Initial Eigenvalue			Sum of Squares of the Factor Loadings		
	Initial Eigenvalue	Percentage of Variance	variance contribution rate%	Total Eigenvalue	Percentage of variance	variance contribution rate%
1	3.844	42.710	42.710	3.844	42.710	42.710
2	2.556	28.395	71.105	2.556	28.395	71.105
3	1.348	14.980	86.086	1.348	14.980	86.086
4	0.710	7.886	93.971			
5	0.266	2.960	96.931			
6	0.137	1.518	98.449			
7	0.059	0.654	99.103			
8	0.053	0.593	99.696			
9	0.027	0.304	100.000			

3.2 Principal Component Analysis

From Table 4 can be observed the component matrix, which emerges after principal components extraction procedures. This matrix elucidates the correspondence between each indicator and the extracted principal components. Employing an absolute factor loading coefficient threshold of 0.5, it observes that indicators x_1, x_2, x_6, x_7 and x_8 correspond to component 1; indicators x_4,x_5 and x_9 correspond to component 2; and indicator x_3 corresponds to component 3. Consequently, the linear combinations of the principal component factors can be expressed as in equation (1).

Table 4: Component Matrix

Indicator	Component 1	Component 2	Component 3
x_1	0.938	-0.271	0.063
x_2	0.759	-0.397	0.253
x_3	-0.036	-0.241	0.922
x_4	-0.059	0.911	0.209
x_5	0.098	0.858	0.439
x_6	0.652	0.191	0.215
x_7	0.969	0.065	-0.090
x_8	0.940	0.044	-0.203
x_9	0.354	0.811	-0.313

$$F_i = \sum_{j=1}^{9} A_i * Zx_j \, , (i = 1,2,3) \qquad (1)$$

$$A_i = \frac{B_i}{\sqrt{C_i}}, (i = 1,2,3) \qquad (2)$$

From equation (2) where A_i denotes the eigenvectors, B_i represents the i-th column vector of the component matrix for the three extracted principal components, C_i signifies the eigenvalues of the three extracted principal components and Zx_j is the variable matrix after Z-score standardization of the data for each province.

Substituting A_i yields three linear combinations of F_i regarding Zx_j. Subsequently, substituting the Zx_j data into equation (1) allows for the derivation of principal component scores for each province. This process effectively transforms the initial nine indicators into three composite indicators, F_1, F_2, and F_3, which represent the allocation of regional healthcare resources. To be more specific, a comprehensive principal component evaluation model is generated. The specific model is shown in equation (3).

$$F = \frac{C_1}{C_1+C_2+C_3} F_1 + \frac{C_2}{C_1+C_2+C_3} F_2 + \frac{C_3}{C_1+C_2+C_3} F_3 (3)$$

By substituting the data for F_1, F_2, and F_3 into equation (3), a comprehensive score (F) is calculated for each province. The results of this analysis are presented in Table 5. It shows the top regions for medical resource allocation. Beijing ranks first, followed by Guangdong Province and Zhejiang Province. Conversely, Tibet Autonomous Region, Qinghai Province, and Ningxia Hui Autonomous Region, occupying the bottom three positions. These areas are all located in China's western part. All in all, the result reveals that medical and health resources are predominantly concentrated in the eastern region, gradually decreasing as one moves westward.

Table 5: Region Comprehensive Score

Region	Province	F_1	F_2	F_3	F	Comprehensive Ranking
Eastern Region		0.999	0.875	-0.781	0.648	1
Central Region		0.065	-0.740	0.614	-0.105	2
Western Region		-0.959	-0.309	0.306	-0.524	3
Eastern Region	Beijing	-0.055	6.555	0.539	2.229	1
	Tianjin	-1.990	1.191	-2.061	-0.953	27
	Hebei	1.125	-1.604	-0.370	-0.035	14
	Shanghai	1.041	3.318	-0.591	1.508	5
	Liaoning	-0.780	-0.499	0.660	-0.437	19
	Fujian	0.106	-0.332	-1.769	-0.365	18
	Guangdong	5.207	-0.957	-2.546	1.825	2
	Hainan	-2.309	0.182	-0.873	-1.237	28
	Jiangsu	3.242	0.399	-0.838	1.594	4
	Zhejiang	2.403	1.888	-0.912	1.656	3
	Shandong	2.996	-0.512	0.174	1.348	6
Central Region	Anhui	0.345	-0.761	0.117	-0.060	15
	Jiangxi	-0.134	-1.315	-0.399	-0.570	20
	Heilongjiang	-1.204	-1.192	1.347	-0.756	25
	Henan	2.392	-1.319	1.029	0.931	8
	Hubei	0.826	-0.456	0.811	0.400	10
	Hunan	0.953	-0.750	1.262	0.445	9
	Shanxi	-0.814	-0.650	-0.233	-0.659	22
	Jilin	-1.847	0.528	0.981	-0.571	21
Western Region	Chongqing	-0.663	-0.146	0.740	-0.248	17
	Sichuan	2.305	-0.788	1.667	1.173	7
	Guizhou	-0.610	-0.359	1.363	-0.184	16
	Yunnan	0.225	-0.045	1.072	0.283	12
	Tibet	-3.307	-2.091	-2.733	-2.806	31
	Shaanxi	-0.145	0.570	1.054	0.300	11
	Gansu	-1.680	-0.502	0.802	-0.860	26
	Qinghai	-2.792	-0.047	0.143	-1.376	30
	Ningxia	-2.598	0.564	-0.906	-1.261	29
	Xinjiang	-0.789	-0.938	0.100	-0.683	24
	Inner Mongolia	-1.534	0.267	-0.028	-0.678	23
	Guangxi	0.084	-0.197	0.400	0.047	13

3.3 Discussion

Through the above analysis, it highlights uneven medical resource allocation across China's eastern, central, and western regions, aligning with findings by Liu (2023). And the Economic development levels and demographic factors further shape this disparity, corroborating research by Liu et al. (2024).

Based on the above research, this paper makes the following recommendations:

The eastern region requires optimized healthcare resource allocation to address its concentration in urban hubs. It should be comprehensively evaluated based on the coverage of existing primary care organizations, the scope of the population served, and other factors (Feng, 2019). And policies should promote the coordinated, balanced and sustainable development of medical resources within the region (Guo, Li, &Wu, 2024). Furthermore, telemedicine and routine expert consultations can further support central, western, and less-developed regions, enhancing overall healthcare quality. For example, Peking University First Hospital has assisted many county hospitals by sending experts. They have promoted the development of local medical care.

As a bridge between east and west, the central region should establish provincial healthcare centers to integrate advanced eastern resources and technologies, extending their benefits westward for improved resource-sharing efficiency. Meanwhile, through implementing a concurrent construction and training approach can upgrade infrastructure and elevate local medical capabilities. For instance, the collaboration with the Second Affiliated Hospital of Xi'an Jiaotong University to establish a national regional medical center aims to leverage Xinjiang as a base, radiate to the northwest and Central Asia, and achieve coordinated development in regional healthcare.

As health human resources are converging to developed regions (Lei, Yan, Hu, Xi, &Xiao, 2023), the western region needs policies incentivizing talent mobility. The government needs to establish long term retention mechanisms to attract skilled professionals, measures to encourage experts to relocate westward, and strategies to reduce local talent outflow. As the same time, the government should redistribute funds from developed to underdeveloped provinces to balance regional financial burdens (Li, Yang, &Chen, 2025). This could equalize medical resource allocation.

4 CONCLUSION

Based on 2022 data encompassing population, economic indicators, and healthcare supply, this paper analyzes the factors influencing healthcare resource allocation of China. Overall, the comprehensive scores for the eastern region exceed zero, indicating a positive trajectory for the future development of healthcare resources. Conversely, the central and western regions exhibit comprehensive scores below zero, suggesting significant challenges and slower progress in healthcare resource allocation. Further analysis of F1, F2, and F3 reveals a notable disparity in the F3 score for the eastern region compared to other areas. This suggests a higher population density in the eastern region, leading to a sustained high demand for hospital beds and chronic operational strain on healthcare facilities. However, the eastern region maintains advantages in terms of hospital quantity, quality of medical resources, economic factors, and healthcare demand. In contrast, the central and western regions, characterized by lower population densities, experience significantly reduced healthcare demand compared to the eastern region. These regions also face lower government economic investments, leading some areas to lagging development and facing the challenge of underutilized medical resources.

Based on these findings, The paper proposes several recommendations. These recommendations aim to provide a reference for the development of a Healthy China. Implementing these policies can facilitate resource sharing among regions, reduce healthcare disparities, and ensure equitable access to medical services for the population. Ultimately, the goal is to establish a high-quality and efficient healthcare service system, significantly improving the health of the population and achieving the long-term objective of building a healthy nation commensurate with a modern socialist country.

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