Measurement of Primary Healthcare Resource Allocation Mismatch in China and Its Spatiotemporal Evolution Analysis Postprint

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Abstract

Background With population aging and an increasing proportion of chronic disease patients, public demand for primary healthcare resources is becoming increasingly diversified and complex. Demand for primary healthcare resources varies across different regions and populations, and some areas face shortages of primary healthcare resources, which severely constrains the coverage and quality of primary healthcare services and significantly impacts residents' medical experiences and health status. Objective To promote high-quality development of the primary healthcare service system, this study introduces a health distance model to analyze the spatiotemporal evolution of misallocation in primary healthcare resource allocation in China from 2011 to 2021, providing a reference for rational regional health planning, optimizing healthcare resource allocation schemes, enhancing primary healthcare service capacity, and promoting high-quality development of healthcare services. Methods An evaluation index system for misallocation of primary healthcare resources was established from three dimensions: physical, human, and supportive resources. Data were obtained from the China Health Statistics Yearbook and China Statistical Yearbook. A bi-level programming model and health distance model were employed to calculate the degree of misallocation in primary healthcare resource allocation from 2011 to 2021. Results From 2011 to 2021, the overall degree of misallocation in primary healthcare resources in China showed a significant downward trend; however, disparities in misallocation degrees between regions and provinces continued to widen. In 2011, the average misallocation degrees in the eastern, central, and western regions were 0.633, 0.624, and 0.754, respectively, corresponding to moderate misallocation, slight matching, and severe misallocation. In 2021, the average misallocation degrees in the eastern, central, and western regions were 0.479, 0.522, and 0.639, respectively, corresponding to moderate matching, slight matching, and moderate misallocation. Conclusion Although the overall degree of misallocation in primary healthcare resources in China is declining,

significant disparities persist, and the inequity in healthcare resource allocation continues to intensify. To continuously optimize primary healthcare allocation, promote high-quality development of the primary healthcare service system, and enhance the efficiency of China's healthcare system, attention must be paid to balancing resource allocation across regions, and differentiated policies should be formulated according to local conditions to further optimize healthcare resource allocation and improve the coverage and quality of primary healthcare services.

Full Text

Measurement of the Allocation Mismatch of Primary Medical Resources in China and Its Spatial and Temporal Evolution Analysis

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Abstract

Background: With population aging and increasing chronic disease prevalence, public demand for primary medical resources has become diversified and complex. Different regions and populations exhibit varying needs for primary medical resources, with some areas facing severe shortages that constrain both the coverage and quality of primary healthcare services, significantly impacting residents' medical experiences and health outcomes. **Objective:** To promote high-quality development of primary healthcare service systems, this study introduces a health distance model to analyze the spatiotemporal evolution of primary medical resource allocation mismatch in China from 2011 to 2021, providing references for rational regional health planning, optimizing medical resource allocation, improving primary healthcare service capacity, and advancing high-quality healthcare development. **Methods:** An evaluation index system for primary medical resource mismatch was established across three dimensions: material resources, human resources, and support resources. Data were obtained from the *China Statistical Yearbook of Health Statistics* and *China Statistical Yearbook*. A bi-level programming model and health distance model were employed to measure the allocation mismatch of primary medical resources from 2011 to 2021. **Results:** From 2011 to 2021, the overall mismatch degree of primary medical resource allocation in China showed a significant downward trend, yet disparities between regions and provinces continued to expand. In 2011, average mismatch values for eastern, central, and western regions were 0.633, 0.624, and 0.754, respectively, representing moderate mismatch, mild mismatch, and severe mismatch. By 2021, these values became 0.479, 0.522, and 0.639, corresponding to moderate matching, mild matching, and moderate mismatch. **Conclusion:** Although the overall mismatch degree of primary medical resource allocation in China is declining, significant disparities persist, and the imbalance in medical resource allocation continues to intensify. To continuously optimize primary medical resource allocation, promote high-quality development of primary healthcare service systems, and enhance the efficiency of China's medical and health system, attention must be paid to balancing resource allocation across regions, with differentiated policies formulated according to local conditions to further optimize medical resource allocation and improve the coverage and quality of primary healthcare services.

Keywords: Health resources; Resource allocation; Mismatch; Primary medical resource allocation; Bi-level programming model; Spatiotemporal pattern

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Primary medical resource mismatch refers to the deviation of various elements of primary medical resources from their optimal allocation state, while the degree of mismatch quantifies the extent and trend of this deviation. Since the 19th Party Congress, China has achieved remarkable accomplishments in its national development, with substantial progress in socio-economic development. Per capita GDP has grown steadily, infrastructure has continuously improved, per capita public service fiscal expenditure has increased, the social security system has gradually improved, and the basic public service system has been optimized, with the primary healthcare service system being basically established and achieving considerable development. However, due to factors such as economic system reform, accelerated industrialization, intensified population aging trends, expanded urbanization, and changes in national lifestyles, China faces imbalances between supply and demand of primary healthcare services, uneven distribution of medical and health resources, and mismatches between healthcare service development levels and development stages, resulting in severe primary medical resource mismatch.

Medical and health resources constitute an important component of basic public service resources, encompassing medical institution resources, healthcare human resources, medical facility resources, and other elements. To address the shortage of high-quality medical and health resources and the uneven distribution of primary medical resources in China, this study, based on the principle of "people-centered, unified fairness and efficiency," constructs a composite system bi-level optimization allocation model for primary medical resources and introduces the health distance model from ecological research to analyze the spatiotemporal evolution of primary medical resource allocation mismatch in China from 2011 to 2021 and explain its formation mechanism, aiming to provide relevant recommendations for primary medical resource allocation in China.

Literature Review

Current international research on medical resource allocation primarily focuses on healthcare system efficiency, medical institution service efficiency, influencing factors of medical resource allocation, and equity of medical resource allocation. Domestic research on medical resource allocation issues mainly addresses efficiency and equity. Xie Jinliang et al. utilized indicator data from 31 provincial regions in China, employing Data Envelopment Analysis (DEA) to construct a C2R model to evaluate the equity of medical resource allocation across provinces, finding relative fairness in inter-provincial allocation. Wei Kezhen measured and evaluated the efficiency of medical resource allocation in Chinese provinces in 2011 using the SBM model, revealing that eastern regions showed higher efficiency than western and central regions, with factors such as medical resource scale and policy support significantly influencing allocation efficiency. Chang Xiang et al. analyzed the efficiency and equity of medical institution resource allocation in China using Gini coefficient and Theil index methods, finding an upward trend in allocation efficiency in recent years, with equity primarily affected by intra-regional allocation differences.

Mismatch theory is an analytical framework applied to public resource allocation imbalances, focusing on the mismatch between resource demand and supply and its economic, social, and political impacts. First proposed by American scholar KAIN when studying urban employment spatial distribution, the theory suggests that severe employment mismatch within cities places workers at a disadvantage, making it harder to obtain high-quality job opportunities and causing resource allocation imbalances that increase spatial mobility costs, creating spatial mismatch phenomena in labor markets that adversely affect overall urban economic development and social equity. The theory has been widely applied to study relationships between urban residential and employment spaces. Orchal and LeGrand introduced mismatch concepts into economics, combining them with concepts such as "information asymmetry," "Nash equilibrium," and "Pareto optimality" to propose utility-maximization-based public resource allocation methods, attempting to explore issues of unfair public resource allocation. Domestic research on mismatch issues started relatively late, with Zhou Jiangping first introducing spatial mismatch theory to China to study urban employment mismatch. Currently, some domestic scholars have applied this theory to study mismatch issues in urban human settlements, industrial development, and basic public services, with scarce research on primary medical resource allocation mismatch.

Methodology

2.1 Indicator System Construction and Data Sources

Taking the primary medical resource allocation status of 31 provinces (autonomous regions, municipalities) as the research object and drawing on relevant research findings, this study fully considers the scientific nature and availability of indicator elements. Through systematic analysis, literature review, and expert consultation, an indicator system was constructed from three levels: health human resources, financial resources, and material resources to measure the mismatch degree of primary medical resource allocation in China. Indicator data were sourced from the *China Statistical Yearbook of Health Statistics* and *China Statistical Yearbook* from 2011 to 2021.

2.2 Model Construction

2.2.1 Data Standardization Different indicators may have different dimensions, making comparative analysis difficult. To reduce dimensional differences, indicator data require standardization using the range standardization method. The formulas are:

For positive indicators:

$$X'_{ij} = \frac{X_{ij} - \min X_{ij}}{\max X_{ij} - \min X_{ij}} \quad (1)$$

For negative indicators:

$$X'_{ij} = \frac{\max X_{ij} - X_{ij}}{\max X_{ij} - \min X_{ij}} \quad (2)$$

where $i(i = 1, 2, 3, \dots, m)$ represents regions, $j(j = 1, 2, 3, \dots, n)$ represents evaluation indicators, X_{ij} represents original data, $\max X_{ij}$ represents the maximum value of indicator j, and $\min X_{ij}$ represents the minimum value of indicator j.

2.2.2 Indicator Weighting The entropy weighting method was employed to determine indicator weights, which significantly reduces subjective factors in the weight determination process and makes indicator weights more objective. The calculation steps are as follows:

First, calculate the proportion P_{ij} of region i in indicator j:

$$P_{ij} = \frac{X'_{ij}}{\sum X'_j} \quad (i = 1, 2, 3, \dots, m; j = 1, 2, 3, \dots, n)$$

Second, calculate the entropy value e_j of indicator j:

$$e_j = -\frac{1}{\ln m} \sum_{i=1} p_{ij} \ln p_{ij} \quad (i = 1, 2, 3, \dots, m; j = 1, 2, 3, \dots, n)$$

Finally, calculate the weight w_j of evaluation indicator j:

$$w_j = \frac{(1 - e_j)}{\sum_{j=1} (1 - e_j)} \quad (j = 1, 2, 3, \dots, n) \quad (5)$$

2.2.3 Calculation of Ideal Allocation Level The ideal state of medical resource allocation refers to a condition where all elements within a region are at optimal allocation levels. In advancing primary healthcare service system construction, China must adhere to the principle of prioritizing fairness while balancing efficiency and fairness. Based on this principle, a bi-level programming model for medical resources (composite system bi-level optimization model) was constructed to calculate the optimal allocation level of medical resources for 31 provinces (autonomous regions, municipalities) from 2011 to 2021.

When constructing the fairness planning model, both a fairness objective function (Formula 6) and fairness constraints are included. To measure the ideal fairness state of regional medical resource allocation—where a certain proportion of the population is allocated the same proportion of medical and health resources—the Gini coefficient is introduced into the fairness objective function. On this basis, the minimum sum of Gini coefficients for indicators within primary medical resources is determined as the fairness objective function (Formula 7).

$$H_{mkj} = 1 - \sum_{i=1}(X_{ij} - X_{i-1,j})(Y_{mi} - Y_{m(i-1)}) \quad (6)$$

In Formula 6, mk represents each indicator within the primary medical resource mismatch evaluation index system, where $k = 1, 2, 3, \ldots, 4$. H_{mkj} is the Gini coefficient of medical and health resource m based on indicator j. X_{ij} represents the cumulative percentage of the jth indicator in the ith region, and Y_{mi} represents the cumulative percentage of the mth indicator's possession in the ith region. When $i = 1$, $X_{i-1,j}$ and $Y_{m(i-1)}$ are considered $(0, 0)$.

$$\min F(X_k) = \sum_{j=1} H_{mkj} \quad (7)$$

In Formula 7, $\min F(X_k)$ is the fairness objective function for regional medical resource allocation, with $F(X_k)$ ranging between 0 and 1. Values closer to 0 indicate fairer regional medical resource allocation.

During primary medical and health resource allocation, the sum of regional resource allocation must be controlled within the total regional resource scope, while ensuring that each region's allocation matches its demand index to reflect fairness in resource allocation among provincial regions. Therefore, fairness objective function constraints (Formula 8) must be established.

$$T_{kj} = T_{k0}$$
$$T_{kj} \leq DT_{kj}$$
$$\frac{U_{kj}}{U_{kz}} \geq 1 \,\|\!> \frac{T_{kj}}{T_{kz}} \geq 1$$

$$\alpha_{kjz}^{\min}\left(\frac{U_{kj}}{U_{kz}}\right) \leq \frac{T_{kj}}{T_{kz}} \leq \alpha_{kjz}^{\max}\left(\frac{U_{kj}}{U_{kz}}\right)$$
$$\sum_{i=1}(X_{ij} - X_{i-1,j})(Y_{mi} - Y_{m(i-1)}) \leq \beta$$
$$k = 1, 2, 3, \dots, 4; j, z = 1, 2, \dots, n; j \neq z$$

In Formula 8, T_{k0} represents the total primary medical and health resources in each province, including total health human, financial, and material resources; T_{kj} represents the allocation of each indicator of primary medical and health resources in each province; DT_{kj} represents the demand for k elements of indicator j in each province; $\alpha_{kjz}^{\min}(U_{kj}/U_{kz}) \leq T_{kj}/T_{kz} \leq \alpha_{kjz}^{\max}(U_{kj}/U_{kz})$ indicates that resource allocation in each province must fall within the demand interval; $\alpha_{kjz}^{\min}$ and $\alpha_{kjz}^{\max}$ represent the lower and upper demand coefficients for each province, respectively, with $\alpha_{kjz}^{\min} = 1$ and $\alpha_{kjz}^{\max} = 1$ in this study; and β represents the Gini coefficient value.

To balance efficiency and fairness principles, an efficiency planning model was constructed. Based on data envelopment theory and transformation dual programming theory, the efficiency objective function (Formula 9) was derived:

$$\min[\theta - \varepsilon(\epsilon G_s^- + \epsilon G_s^+)]$$
$$\sum_{i=1}\gamma_i A_i + s^- = \theta A_0$$
$$\text{s.t.} \sum_{i=1}\gamma_i B_i - s^+ = B_0$$
$$\frac{N}{n} \geq \theta(\theta = 1, s^-, s^+ = 0)$$
$$\sum_i \gamma_i = 1$$
$$\gamma_i \geq 0, i = 1, 2, \dots, 0, s^+ \geq$$

In Formula 9, A_i and B_i represent input and output indicator values; θ is the relative efficiency of decision-making unit DMU_0 (i.e., each indicator within the primary medical resource mismatch evaluation index system), with larger θ values indicating higher resource allocation efficiency levels; γ_i represents the indicator composition coefficient for each province; and s^+ and s^- are slack variables representing input excess and output deficiency values for each province.

Let γ_i, θ, s^+, and s^- be the optimal solution of the efficiency objective function. When $\theta = 0$ and $s^+ \neq 0$, $s^- \neq 0$, it indicates low medical resource allocation efficiency in the province, where $s^+ > 0$ indicates resource input excess and $s^- < 0$ indicates insufficient resource output. $N/n \geq \theta(\theta = 1, s^-, s^+ = 0)$ indicates that at least 90% of provinces in the n provinces achieve high-efficiency medical resource allocation, where N represents the number of provinces achieving this goal.

In summary, the medical resource bi-level programming model can be expressed as (Formula 10):

$$\text{Bi-level programming model for medical resources}\begin{cases}\text{Upper-level fairness planning model} & \begin{cases}T_{kj} = T_{k0} \\ T_{kj} \leq DT_{kj} \\ \frac{U_{kj}}{U_{kz}} \geq 1 \,\| > \frac{T_{kj}}{T_{kz}} \\ \alpha_{kjz}^{\min}\left(\frac{U_{kj}}{U_{kz}}\right) \leq \frac{T}{T} \\ \sum_{i=1}(X_{ij} - X_{i-} \\ k = 1, 2, 3, \ldots, 4;\end{cases} \\ \text{Lower-level efficiency planning model} & \begin{cases}\min[\theta - \varepsilon(\epsilon G_s^- - \\ \sum_{i=1}\gamma_i A_i + s^- \\ \text{s.t.} \sum_{i=1}\gamma_i B_i - \\ \frac{N}{n} \geq \theta(\theta = 1, s^- \\ \sum_i \gamma_i = 1 \\ \gamma_i \geq 0, i = 1, 2, \ldots\end{cases}\end{cases}$$

The bi-level programming model is a multi-objective programming model containing both fairness and efficiency planning models. Each level has decision variables and constraints, with decision variables at each level being interdependent. The upper-level decision variables and objective function directly affect those at the lower level. To determine the optimal allocation level of primary medical resources for 31 provinces (autonomous regions, municipalities) from 2011 to 2021—i.e., the optimal solution of the medical resource bi-level programming model—a master-slave hierarchical interactive algorithm was employed, as shown in Figure 1 [FIGURE:1].

According to the bi-level programming model, primary medical resource indicator allocation values are first substituted into the upper-level fairness objective function to obtain the H value. When the H value satisfies fairness constraints, it is substituted into the lower-level efficiency objective function; when the H value does not satisfy fairness constraints, new primary medical resource indicator allocation values are selected until the H value satisfies fairness constraints. Second, allocation values are substituted into the lower-level efficiency objective function to obtain target values including θ, s^-, s^+, and N. When target values satisfy efficiency constraints, the optimal solution is obtained; when target values do not satisfy constraints, variables are adjusted according to slack variable s^- and s^+ values. Finally, the optimal solution of the medical resource bi-level programming model can be determined.

2.2.4 Primary Medical and Health Resource Allocation Mismatch Value Medical resource allocation is influenced by multiple factors that exhibit dynamic trends within the system, making it difficult for medical resources to stabilize at optimal spatiotemporal allocation levels—i.e., no region satisfies the optimal solution of the medical resource bi-level programming model. The primary medical resource allocation mismatch degree refers to the relative comprehensive distance between primary medical and health resources and their ideal allocation state during development. A larger relative comprehensive distance indicates greater deviation from the ideal state, meaning a higher degree of medical resource allocation mismatch. To calculate the primary medical and health resource allocation mismatch value, the health distance model (Formula 10) was introduced:

$$HD(p,q) = \sum \left| \frac{[p(mpn) - q(mqn)]}{q(mqn)} \right| \quad (12)$$

In Formula 10, w_j is the weight of the jth indicator, $q(mqn)$ represents the optimal allocation value of each indicator of primary medical resources, $p(mpn)$ represents the actual allocation value of primary medical resource indicators in each province, and $HD(p,q)$ is the relative comprehensive health distance between P and q, i.e., the primary medical resource allocation mismatch degree.

2.3 Regional Difference Measurement of Mismatch Degree

The Dagum Gini coefficient is an upgraded version of the traditional Gini coefficient that addresses the limitation of other regional disparity measurement methods in handling overlapping data, enabling better identification of regional disparity sources. The Dagum Gini coefficient calculation formula is as follows:

$$G = \sum_{h=1}^{m} \sum_{j=1}^{m} \sum_{i=1}^{n_h} \sum_{r=1}^{n_j} \frac{|y_{h,i} - y_{j,r}|}{2n^2 \bar{y}} \quad (13)$$

In Formula 11, h and j represent different regions within a broad area, i and r represent different provinces within each region, l is the total number of inter-provincial units, and m is the total number of regions. According to subgroup decomposition methods, the Dagum Gini coefficient can be decomposed into intra-group coefficient, inter-group coefficient, and hypervariable density coefficient, i.e., Dagum = intra-group G_ω + inter-group G_{nb} + hypervariable density G_l. Intra-group G_ω reflects inter-provincial mismatch level gaps, inter-group G_{nb} reflects inter-regional mismatch level gaps, and hypervariable density G_l reflects cross-overlapping phenomena of regional mismatches, embodying relative disparity conditions of mismatch degrees.

When calculating G_ω and G_{nb}, G_{ij} (Gini coefficient between regions i and j) and G_{ii} (Gini coefficient within region i) must be calculated. Specific calculation formulas are as follows:

$$G_{ii} = \sum_{l=1}^{n_i} \sum_{m=1}^{n_i} \frac{|y_{i,l} - y_{i,m}|}{2n_i^2 \bar{Y}_i} \quad (14)$$

$$G_{ij} = \sum_{l=1}^{n_i} \sum_{m=1}^{n_j} \frac{|y_{i,l} - y_{j,m}|}{n_i n_j (\bar{Y}_i + \bar{Y}_j)} \quad (15)$$

$$G_{\omega} = \sum_{i=1}^{k} G_{ii} p_i s_i \quad (16)$$

$$G_{nb} = \sum_{i=2}^{k} \sum_{j=1}^{i-1} G_{ij} (p_i s_j + p_j s_i) D_{ij} \quad (17)$$

$$G_{l} = \sum_{i=2}^{k} \sum_{j=1}^{i-1} G_{ij} (p_i s_j + p_j s_i)(1 - D_{ij}) \quad (18)$$

D_{ij} represents the relative influence of primary medical and health resource allocation mismatch levels between regions i and j, and d_{ij} represents the difference in contribution rates of primary medical and health resource allocation mismatch levels between regions i and j. Specific calculation processes are:

$$D_{ij} = \frac{(d_{ij} - p_{ij})}{(d_{ij} + p_{ij})} \quad (19)$$

$$d_{ij} = \int dF_i(y)(y - x) dF_j(x) \quad (20)$$

$$p_{ij} = \int dF_i(y)(y - x) dF_j(x) \quad (21)$$

2.4 Regional Correlation Measurement of Mismatch Degree

Spatial autocorrelation analysis originated in the late 19th and early 20th centuries from studies on spatial distribution patterns of urban epidemics and ecological communities. The Moran index extends correlation coefficients to spatial dimensions by considering spatial weight matrices to evaluate correlation degrees among spatial units. The Moran index for primary medical and health resource allocation mismatch introduces spatial weight matrices to test whether the development index of inter-provincial mismatch degrees is correlated nationwide. The Moran index calculation formula is as follows:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(d_i-\bar{d})(d_j-\bar{d})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}} \quad (22)$$

In Formula 20, ω_{ij} represents the spatial weight matrix. Spatial weight matrices are typically divided into two categories: adjacency matrices and distance weight matrices. Distance weight matrices use specific numbers to represent distances between samples, where the distance refers to actual spatial distance.

For mismatch degrees, the Moran index I ranges between $[-1,1]$. Values greater than 0 indicate negative spatial correlation, where inter-provincial primary medical and health resource allocation mismatch degrees at the regional level show high mismatch levels adjacent to high values. Values less than 0 indicate positive spatial correlation, meaning mismatch degrees show high mismatch levels adjacent to low values. When I equals 0, no spatial correlation exists.

Results

3.1 Temporal Analysis of Primary Medical Resource Mismatch Degree

Using the health distance model, the mismatch degree values of primary medical resource allocation for 31 provinces (autonomous regions, municipalities) from 2011 to 2021 were calculated, as shown in Table 2 . According to the health distance model results, the overall mismatch degree of primary medical resource allocation in China showed a downward trend from 2011 to 2021. The extreme mismatch values were 0.904 and 0.193, corresponding to Tibet, which was in a state of severe mismatch in 2011, and Shandong, which was in a state of high matching in 2021.

Cluster analysis is a center-based clustering algorithm (K-means) that iteratively assigns samples to K classes to minimize the sum of distances between each sample and its class center or mean. Cluster analysis (K-Means) was used to classify China's medical resource allocation mismatch degree into five levels: $HD(p,q) \in [0.000-0.355)$ indicates high matching, $HD(p,q) \in [0.355-0.492)$ indicates moderate matching, $HD(p,q) \in [0.492-0.631)$ indicates mild matching, $HD(p,q) \in [0.631-0.719)$ indicates moderate mismatch, and $HD(p,q) \in [0.719-1.000)$ indicates severe mismatch. When the mismatch degree approaches 1, regional primary medical resource mismatch conditions worsen; when it approaches 0, conditions improve.

3.1.1 Temporal Changes In terms of average values, the average mismatch degree of primary medical resource allocation across 31 provinces decreased from 0.677 in 2011 to 0.552 in 2021, shifting from moderate mismatch to mild matching, gradually advancing toward the modernization goal of medical resource allocation capacity. Regarding the proportion of mismatch levels, in

2011, severe mismatch accounted for 45.1% of primary medical resource allocation mismatch levels, while moderate matching and above accounted for 12.8%. By 2021, severe mismatch accounted for 22.5%, while moderate matching and above accounted for 32.2%.

From 2011 to 2018, optimization of medical resource allocation in some provinces stagnated, causing the proportion of severe mismatch to remain around 30.2% for an extended period. With the proposal of the "ensure basics, strengthen primary care, and establish mechanisms" principle in 2010, the medical and health system reform deepened, the tiered diagnosis and treatment system gradually advanced, rural doctor team construction developed toward higher quality and specialization, and primary healthcare policies were successively introduced. Regions with long-term severe mismatch levels all experienced varying degrees of reduction, with Xinjiang showing a significant decrease of 15.22%. Although some areas remained in severe mismatch for extended periods, overall, China's primary medical resource allocation mismatch degree showed a clear downward trend, with allocation levels steadily improving.

3.1.2 Temporal Characteristics Based on time series evolution analysis, China's primary medical resource allocation mismatch degree exhibited distinct phased characteristics, with 2014 and 2018 serving as turning points dividing three stages. From 2011 to 2014, China faced large gaps in primary medical resources, with allocation dominated by mismatch states, where mismatch status accounted for an average of 73.3% of cases, requiring relevant departments to increase resource investment and management to improve service quality and efficiency and meet people's high-quality health service demands. From 2015 to 2017, China gradually increased investment and management of primary medical resources, entering a stage of fluctuating decline in mismatch, where the proportion of mismatch status levels fluctuated downward while matching status levels rose hesitantly. Primary medical resource allocation optimization achieved initial results, but mismatch issues remained, requiring further improvement of policies and management mechanisms to enhance coverage and quality of primary healthcare services. From 2018 to 2021, China's primary healthcare service system continuously improved and perfected, entering a matching-dominated stage where matching status levels accounted for an average of 60.33% of cases. Primary medical resource allocation mismatch issues were initially resolved, but some mismatch remained, requiring continued strengthening of investment and management to promote expansion and balanced layout of high-quality primary medical resources and better meet people's healthcare needs.

3.2 Spatial Analysis of Primary Medical Resource Mismatch Degree

Based on primary medical resource allocation mismatch degree values and levels, spatial distribution maps of mismatch levels were drawn for 2011, 2014, 2018, and 2021, as shown in Figure 3 [FIGURE:3]. The spatial distribution pattern of China's primary medical resource allocation mismatch levels generally aligns with the "Heihe-Tengchong" line, showing that southeast regions have significantly lower mismatch degrees than northwest regions, and coastal regions have lower mismatch than inland regions. The pattern evolved from a severely mismatched unbalanced structure to a highly matched unbalanced structure. Overall, mismatch degrees increase from south to north and from east to west, with moderate and severe mismatch regions accounting for larger proportions and mostly distributed in western regions, where Qinghai and Tibet have long remained in severe mismatch states.

Qinghai is located on the plateau with cold climate, poor land resource quality, and inconvenient transportation, leading to insufficient social investment. Tibet possesses unique cultural tourism and water resources but lacks other natural resources such as energy and minerals, limiting agricultural and pastoral development due to water and fertilizer constraints and leaving economic development without support. Additionally, due to relatively small population size, generally low education levels among ethnic groups, insufficient labor market competitiveness, single industrial structure, and difficulties in logistics and material supply, these factors further result in Tibet and Qinghai having far fewer health human, material, and financial resources than other provinces.

Compared with western regions, eastern and central regions have larger proportions of mild and moderate-high matching areas with smaller internal differences. Moderate-high mismatch areas present a "semi-ring" pattern, with mild matching areas continuously expanding westward. Most provinces have entered mild matching status and gradually transitioned toward matching status. Most eastern provinces have entered transitional status, but Hainan remains in severe mismatch status, possibly due to brain drain from siphon effects and insufficient fiscal investment.

3.3 Spatial Difference Analysis

To analyze regional differences in primary medical resource allocation mismatch degrees among provinces, understand development trends in unbalanced mismatch level distribution, and explore causes of regional differences, the Dagum Gini coefficient was introduced. Using Stata 16.0 software, systematic analysis of regional differences in primary medical resource allocation mismatch degrees across China was conducted, with Dagum Gini coefficients and contribution rates presented in Table 3 .

According to Table 3, the overall Gini coefficient gradually increased from 2011 to 2021, indicating significant expansion of regional disparities in primary medical resource allocation mismatch degrees. Intra-group and hypervariable density Gini coefficients were significantly smaller than inter-group Gini coefficients, with inter-group contribution rates significantly larger than intra-group and hypervariable density contribution rates, indicating that overall differences in primary medical resource allocation mismatch degrees were primarily influenced by regional differences (i.e., differences among eastern, central, and western regions).

To analyze intra-group differences across regions, intra-group Gini coefficient decomposition diagrams for eastern, central, and western regions were drawn (Figure 4

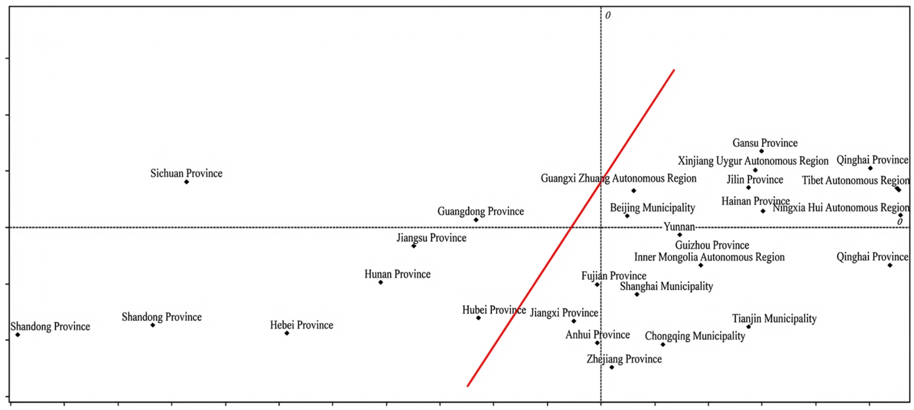

Figure 1: Figure 4

). In terms of trends, all three regions showed mismatch degree trends consistent with the overall Gini coefficient, exhibiting varying degrees of increase. Central region intra-group mismatch differences showed the largest increase, rising from 0.122 in 2011 to 0.169 in 2020, an increase of 38.52%.

Although central region medical resource allocation levels showed upward trends, internal analysis reveals that the "strong provincial capital" policy implementation in central regions created siphon effects, causing population and resources in non-capital cities and counties to concentrate in provincial capitals. Population inflow into provincial capitals further intensified their medical and health service pressure. Externally, central region policy support lagged behind eastern regions and was affected by natural conditions, forming a "central collapse" phenomenon. In contrast, eastern regions, driven by economically strong provinces (municipalities) such as Beijing, Shanghai, and Shandong, experienced rapid economic development, advanced industrial structure, high local fiscal medical expenditure proportions, and strong talent attraction. This further intensified population and resource loss in surrounding cities in central regions. Under dual internal and external environmental influences, intra-group mismatch differences in central region primary medical resources continued to expand.

3.4 Spatial Correlation Analysis

Global spatial autocorrelation values describe the overall distribution of attribute values across regional units, reflecting the average clustering degree of similar attributes within regions. To measure whether spatial correlation exists in primary medical resource allocation mismatch levels at the inter-provincial regional level, the Moran index was introduced as an indicator for measuring spatial correlation, with results presented in Table 4 .

According to Table 4, from 2011 to 2021, global Moran index P values were all less than 0.05 and significantly positive at the 1% level, indicating that primary medical resource allocation mismatch degrees during this period had significant positive spatial correlation. The global Moran index showed a fluctuating upward trend with small variation amplitude, indicating obvious spatial clustering effects in primary medical resource allocation mismatch degrees, with certain stability and long-range effects.

The Moran scatter plot is a two-dimensional visualization of spatial data correlation, where the slope of the trend line intuitively reflects the degree of global spatial autocorrelation, and better matching between scatter point distribution and the trend line indicates better autocorrelation fitting relationships. Based on Moran index results, Moran scatter plots of primary medical resource allocation mismatch degrees were drawn for 2011, 2014, 2018, and 2021 (Figures 5-8 [FIGURE:5], [FIGURE:6], [FIGURE:7], [FIGURE:8]).

Moran scatter plots divide 31 provinces (autonomous regions, municipalities) into four quadrants. The first and third quadrants show negative spatial correlation, while the second and fourth quadrants show positive spatial correlation. The first quadrant represents high observation value regions and high lag value regions (high-high regions), indicating that both the region and its surrounding areas have high mismatch levels, with surrounding regions having negative impacts on the region's mismatch level. The second quadrant represents low observation value and high lag value regions (low-high regions), indicating low mismatch levels in the region but high mismatch levels in surrounding areas. The third quadrant represents low observation value and low lag value regions (low-low regions), indicating that both the region and its surrounding areas have low mismatch levels, with surrounding regions having positive impacts on the region's mismatch level. The fourth quadrant represents high observation value and low lag value regions (high-low regions), indicating high mismatch levels in the region but low mismatch levels in surrounding areas.

From 2011 to 2021, provinces consistently in the low-low quadrant include Jiangsu, Shandong, Hubei, Hunan, and other central and eastern provinces, where primary medical resource allocation mismatch levels are low and positively influenced by surrounding provinces and municipalities, showing local complementarity in mismatch levels. Provinces consistently in the high-high quadrant include Jilin, Heilongjiang, Qinghai, Xinjiang, and other western provinces, where primary medical resource allocation mismatch levels are high and significantly negatively influenced by surrounding provinces and municipalities. With the advancement of western development and the "Belt and Road" economic belt policies, mismatch degrees in western regions have decreased year by year in recent years. However, due to historical reasons, western regions are mostly ethnic minority poverty-stricken areas with economic development levels below the national average, backward primary medical and health facility construction, serious brain drain of primary talent, and severe lack of medical and health resources. Consequently, primary medical resource mismatch degrees in western regions remain higher than those in eastern and central regions for extended periods.

Discussion

Various elements of China's primary medical resources are interlinked, exhibiting not only bidirectional interactive relationships but also complex multi-directional interactions that collectively influence medical resource allocation mismatch degrees during interaction processes. Human, financial, and material resources in medical institutions gradually form strong and stable internal driving forces through coordination and operation, orderly promoting continuous optimization of medical resource allocation structure and levels. While forming internal cohesion, various resource elements in medical institutions continuously gather external forces from multiple parties to obtain funding, talent, management experience, and policy support, thereby forming resource agglomeration advantages. In addition to interactive relationships between internal and external elements and medical resource allocation mismatch degrees, external environmental elements also have dynamic correlations, waxing and waning during interaction processes to form comprehensive forces that affect medical resource allocation efficiency levels. Economy and finance mutually support each other: better economic levels yield more fiscal revenue, while reasonable fiscal policies and improved fiscal allocation structures provide policy support for economic development. The interaction mechanism between the two can provide a solid economic foundation and favorable policy environment for primary healthcare.

4.1 Enhance Regional Economic Development Levels and Promote High-Quality Regional Economic Development

Regional economic development levels, industrial structure, and openness to the outside world constitute the basic material drivers for optimizing China's primary medical resource allocation. Improved regional economic development means more fiscal resources and social capital will flow into the medical and health field, thereby strengthening material guarantees for medical resources. These guarantees are reflected not only in the renewal of medical facilities and equipment but also in the training of medical service personnel, research and development, and application of medical technology. Meanwhile, optimization and upgrading of regional industrial structure will provide new opportunities and space for the development of the medical industry, promoting deep integration between the medical industry and regional economy. Additionally, higher openness facilitates the introduction of international advanced medical management concepts and technical means, promoting cross-border flow and sharing of medical resources. Therefore, localities should fully consider the impact on primary medical resource allocation when promoting regional economic development, actively exploring development paths suitable for themselves. They can develop characteristic industries based on unique advantages such as geographical location, natural resources, and cultural heritage, while strengthening international exchanges and cooperation, introducing advanced medical management concepts and technical means, and promoting high-quality development of the medical industry.

4.2 Improve Local Government Administrative Capacity and Optimize Local Fiscal Expenditure Structure

Improving government administrative capacity and optimizing fiscal expenditure structure are key to alleviating contradictions between supply and demand of primary medical resources and promoting balanced distribution of medical resources. Enhanced government administrative capacity means not only improved policy formulation and execution efficiency but also precise control and effective supervision of medical resource allocation. This capacity helps ensure rational allocation of medical resources, avoiding the coexistence of resource waste and shortage, thereby promoting construction and development of medical and health institutions at all levels. Additionally, adjusting fiscal expenditure structure can promote coordinated development of medical and health institutions at all levels, achieving effective 下沉 of medical resources. This can not only improve the accessibility and quality of primary healthcare services but also promote balanced distribution of medical resources, achieving a combination of efficiency and fairness.

4.3 Optimize National Macro Policies and Formulate Rational Health Planning

National macro policies play multidimensional and far-reaching roles in regional development, particularly in promoting local economic growth, optimizing resource allocation, and enhancing local government public health service capacity. Policy implementation promotes balanced distribution of medical and health resources by increasing investment in primary medical resources, effectively reducing the mismatch degree of primary medical resource allocation in China. This improvement not only enhances the accessibility and fairness of medical and health services but also lays a solid foundation for establishing a sound medical and health system and achieving universal health coverage.

This study introduced the health distance model to construct an evaluation index system for primary medical resource mismatch from three dimensions: material resources, human resources, and support resources. Using relevant yearbook data from 2011 to 2021, bi-level programming and health distance models were employed to measure the mismatch degree of primary medical resource allocation in China. Results show that from 2011 to 2021, the overall mismatch degree of primary medical resource allocation in China exhibited a clear downward trend, yet disparities between regions and provinces continued to expand. Specifically, in 2011, average mismatch degrees for eastern, central, and western regions were moderate mismatch, mild mismatch, and severe mismatch, respectively, while by 2021 they became moderate matching, mild matching, and moderate mismatch. This indicates that although overall mismatch is declining, regional imbalances continue to intensify.

To continuously optimize primary medical resource allocation, promote high-quality development of primary healthcare service systems, and enhance the efficiency of China's medical and health system, attention must be paid to balancing resource allocation across regions, with differentiated policies formulated according to local conditions to further optimize medical resource allocation and improve the coverage and quality of primary healthcare services.

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