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Designing Public Healthcare Resource Allocation Pathways in Hohhot Based on Spatial Resilience and Multi-source Data Optimization

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SUMMARY: *This study integrates spatial resilience with multi-source data to jointly design and optimize the allocation pathways of public healthcare resources. The Average Nearest Neighbor algorithm identifies spatial distribution patterns and agglomeration levels of medical facilities. Standard Deviation Ellipse Analysis captures spatial development trends and directional evolution. DBSCAN reveals spatial clustering characteristics of medical facilities. The 2SFCA algorithm calculates spatial accessibility of healthcare institutions. Particle Swarm Optimization determines optimal spatial locations for medical facility coverage. Experimental results demonstrate that the average spatial accessibility score improved from* 0.40×10^{-5} *to* 0.81×10^{-5} *under this methodology. In Qingshuihe County and Wuchuan County, spatial accessibility scores rose from approximately* 0.10×10^{-5} *to over* 0.72×10^{-5}*. The number of medical staff and hospital beds increased to 4.6 personnel and 6.3 beds, respectively. The average time spent seeking medical care decreased to 16 minutes, and the reserve rate for critical care beds rose to 18%. This holds significant implications for the scientific allocation of public medical resources in Hohhot. This project is based on the "Research on the Optimal Allocation of Public Medical Resources in the Urban Area of Hohhot Based on Multi-Source Data and Spatial Resilience Analysis - Planning Path under the Orientation of Healthy Inner Mongolia" (2025116006), a key school-level project of the College Students' Innovation and Entrepreneurship Training Program of Inner Mongolia University of Technology.*

KEYWORDS: *Spatial resilience; Multi-source data; Spatial distribution of medical facilities; Public healthcare; Scientific resource allocation*

1 Introduction

As urbanization continues to advance, the imbalance between supply and demand for urban healthcare resources is intensifying. Healthcare facilities, as key components of basic public service infrastructure, must be strategically located to ensure equitable access—enabling residents to enjoy balanced and equal healthcare services—while also guaranteeing high utilization rates to prevent waste of public resources [1, 2]. Optimizing healthcare facility layouts through multi-source data integration aims to explore distribution patterns more accurately from diverse perspectives. By synthesizing geographic information, government statistics, and behavioral data reflecting residents' daily lives, this approach enables more scientific analysis of resource allocation rationality. It strives to better balance residents' healthcare needs with facility utilization rates. As cities undergo continuous renewal and

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spatial expansion, healthcare facilities built alongside earlier urban development have become relatively outdated and largely concentrated in older districts. Coupled with the significant increase in private hospitals, spatial competition among hospitals has intensified. The development of medical facilities in urban sub-centers and new districts also necessitates more scientifically grounded layout planning. Therefore, optimizing the spatial allocation of urban medical resources is indispensable [3, 4].

Current scholarly research extensively addresses healthcare resource allocation. Wang, Y et al. proposed a multi-level spatial layout strategy integrating desert characteristics to optimize healthcare resource allocation. This approach synthesizes multi-source statistical data, including population metrics, and employs big data technology for spatial analysis of facility locations and transportation networks [5]. Hu, L and Cai, S used Taiyuan City as a case study, establishing a model to evaluate the rationality of spatial healthcare resource allocation from two dimensions: spatial distribution and supply-demand relationships [6]. Hu, J et al. constructed a multi-level evaluation system, employing network analysis to assess the services of high-quality hospitals and primary healthcare centers across multiple tiers, and further optimized multi-scenario configurations for various new multi-level healthcare facilities [7]. Wang, B and Sun, M introduced an innovative three-dimensional spatial elasticity assessment framework, employing an improved two-step Gaussian method to measure spatial accessibility and utilizing a geogewichted regression (GWR) model to analyze spatial heterogeneity factors [8]. Sun, T et al. proposed a comprehensive multi-source data-based sustainable development evaluation system framework to achieve settlement type identification principles and spatial principle optimization strategies [9]. Xiong, D et al. integrated multi-source data into evaluating and sustainably optimizing sports facility allocation in urban planning. By analyzing geographic information, road network topology, OpenStreetMap (OSM), population distribution, and social media points of interest (POI), they assessed public sports resource allocation in Xi'an's main urban area based on accessibility, equity, and spatial activity [10]. Zhang, S et al. proposed a logical framework integrating accessibility, resource allocation, and site optimization. They established a supply-demand coupling coordination model using Gini coefficients and Lorenz curves to evaluate the rationality of Tianjin's medical resource allocation [11].

The COVID-19 pandemic underscored the critical need for governments to prioritize existing urban medical spaces for major epidemic response. As a vital component of building spatial resilience in healthcare, medical spaces must exhibit multifunctionality, high adaptability, and flexibility during sudden public health emergencies—capable of rapid reconfiguration to generate new functions and meet emerging demands. Public healthcare in Hohhot exhibits significant resource allocation imbalances and underutilization. Therefore, this study proposes a path design for optimizing public medical resource allocation in Hohhot based on spatial resilience and multi-source data. This study integrates spatial resilience with multi-source data analysis. Utilizing the Average Nearest Neighbor (ANN), Differential Ellipse Analysis (DEA), DBSCAN, 2SFCA, and Particle Swarm Optimization (PSO) algorithms, it examines the spatial distribution patterns and clustering intensity of medical facilities. This approach reveals spatial development trends and directional evolution, identifies spatial clustering characteristics of medical facilities, calculates the spatial accessibility of medical institutions, and ultimately determines the optimal locations for medical facility coverage. This approach optimizes the spatial layout of public medical institutions. By scientifically allocating limited healthcare resources, it maximizes their effectiveness, enhances residents' access to medical services, and improves the efficiency and equity of the entire healthcare system.

2 Spatial Resilience Requirements for Healthcare Resource Allocation

2.1 Spatial Resilience

Spatial resilience considers the dynamic interactions and relationships within a system. It is a dynamic capacity that enables the system to cope with various disturbances and prevent external shocks from exceeding the critical threshold of what the space can withstand. Thus, spatial resilience embodies the fundamental properties of resilience theory—the capacity of an entire organization or system to maintain its structure, functions, and characteristics through absorption, adaptation, and transformation after experiencing external shocks. It reflects how relevant variables influence system resilience amid spatial variations within the system and its external environment.

Building upon resilience theory, spatial resilience focuses more specifically on how the attributes and variables of a system's spatial context influence its capacity for change and adaptation when confronting external shocks. To some extent, it reflects the impact of spatial planning and intervention strategies on urban systems. While a unified definition of spatial resilience has yet to emerge within the field of architecture, drawing analogies from concepts and definitions of spatial resilience in urban space and systems research, the spatial resilience of architecture can be understood as the capacity of its spatial attributes and variables to maintain original functions, structures, and characteristics when confronting external shocks. This study specifically examines the spatial resilience exhibited by healthcare architecture during pandemics, driven by its relevant spatial attributes [12].

2.2 Resource Allocation

Resource allocation is a fundamental prerequisite for the efficient operation of healthcare institutions. It involves optimizing the spatial and structural distribution of limited resources such as hospital beds, medical personnel, and equipment. This approach balances fairness in resource distribution with operational efficiency, ensuring residents receive equitable, high-quality services while maximizing resource value. Overall, resource allocation encompasses three dimensions: aggregate allocation, structural allocation, and spatial allocation. Aggregate allocation refers to the overall scale distribution of healthcare resources. Structural allocation involves resource distribution among different healthcare institutions. Spatial allocation pertains to the physical distribution of medical resources. By optimizing resource allocation within healthcare institutions, it is possible to build an efficient and resilient healthcare system capable of effectively responding to sudden outbreaks within extremely short timeframes.

2.3 Spatial Resilience Requirements for Healthcare Resource Allocation

The architectural spaces of large medical institutions form a critical component of the public health epidemic prevention system. However, their usage requirements often fluctuate significantly due to the persistence of pandemics. Consequently, the optimization of medical resource allocation is a dynamic process demanding ideal resilience in institutional spaces, healthcare personnel, and equipment. Following a pandemic, however, construction and operations at healthcare facilities rapidly contract. Under constrained building scales and operational budgets, effective design of medical spaces is essential. Such design must not only accommodate routine healthcare services and emergency pandemic response but also facilitate seamless transitions between the two. This prevents over-allocation of resources during routine care or insufficient provision during sudden outbreaks. Based on a deep understanding of medical procedures and institutional operations, resources must be rapidly reallocated to accommodate varying patient volumes across outpatient departments within short timeframes. This ensures swift containment of infectious diseases and enhances healthcare service quality [13, 14]. The spatial resilience requirements for healthcare resource allocation, as illustrated in Figure 1, reflect not only the rigid and resilient configurations of medical institutions but also the critical importance of their mutual transformation for the efficient operation of the healthcare system.

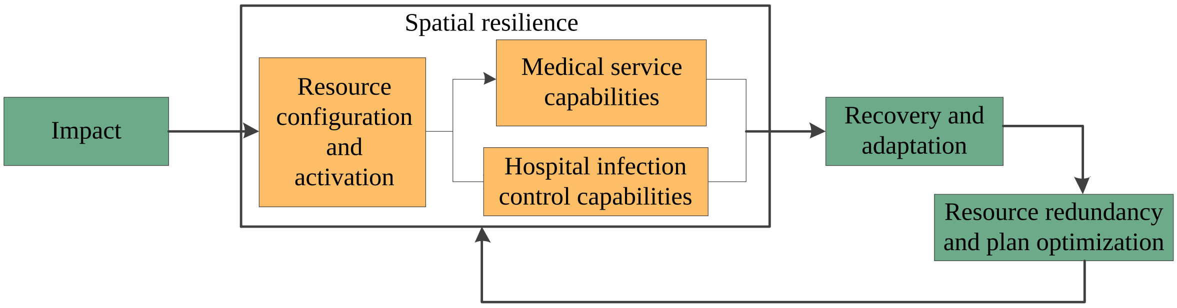

Figure 1: Medical resource allocation requirements based on spatial resilience

3 Spatial Resilience and Multi-Source Data Optimization Algorithms

Spatial accessibility serves as a crucial indicator for evaluating the rational distribution of healthcare resources. With accelerating urbanization, deepening population aging, shifts in lifestyle and ecological environment, as well as the occurrence of disasters and accidents, public medical institutions must possess ideal spatial resilience to respond to emergencies. The growing demand for healthcare services among residents further exacerbates the imbalance between scarce and unevenly distributed medical resources and the increasing needs of the population.

3.1 Average Nearest Neighbor Analysis

The average nearest neighbor is an analytical tool used to reflect the spatial distribution patterns and clustering levels of healthcare facilities. The formula for calculating the desired proximity distance between any two healthcare facilities is:

$$\overline{r}_e = \frac{1}{2\sqrt{n/A}} \tag{1}$$

Here, n denotes the number of facilities within all medical spaces within the study area, and A represents the area of the urban district where the hospital is located. The formula for calculating the actual average nearest distance of medical space facilities is:

$$\overline{r}_1 = \frac{1}{n}\sum_{i=1}^{n} r_i \tag{2}$$

The formula for calculating the average nearest neighbor ratio is:

$$R = \frac{\bar{r}_1}{\bar{r}_e} \tag{3}$$

When $R > 1$ indicates that medical facilities exhibit a dispersed spatial distribution pattern; when $R < 1$ indicates an agglomerated spatial distribution pattern; and when $R = 1$ indicates a random spatial distribution pattern.

Therefore, this section employs the average nearest neighbor algorithm to reflect the spatial distribution patterns and agglomeration levels of medical facilities.

3.2 Standard Deviation Ellipse Analysis

Standard deviation ellipse analysis can precisely reveal the spatial distribution density, center of gravity, spatial extent, and directional variation of point-based geographic features. It primarily quantifies the spatial development patterns and directional evolution of point clusters through fundamental parameters such as the ellipse's center point, major axis, minor axis, and azimuth [15]. The center point of the standard deviation ellipse reflects the overall spatial distribution center of point features in two-dimensional space, i.e., the center of gravity. The deflection direction of the major axis indicates the overall spatial distribution orientation of point features, while the width of the minor axis displays their primary spatial distribution range. A larger difference between the major and minor axes signifies more pronounced spatial directionality of geographic features. The azimuth represents the angle formed by rotating clockwise from true north to the major axis of the ellipse.

The formula for calculating the ellipse center is as follows:

$$\begin{cases} SDE_X = \dfrac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \\ SDE_y = \dfrac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \end{cases} \tag{4}$$

Here, $\left(SDE_X, SDE_y\right)$ denotes the center coordinates of the ellipse, $\left(x_i, y_i\right)$ represents the coordinates of the medical facility, and w_i is the weight of the medical equipment. Therefore, the azimuth formula is:

$$tan\theta = \frac{\left(\sum_{i=1}^{n} w_i^2 \tilde{x}_i^2 - \sum_{i=1}^{n} w_i^2 \tilde{y}_i^2\right) + \sqrt{\left(\sum_{i=1}^{n} w_i^2 \tilde{x}_i^2 - \sum_{i=1}^{n} w_i^2 \tilde{y}_i^2\right)^2 + 4\left(\sum_{i=1}^{n} w_i^2 \tilde{x}_i \tilde{y}_i^2\right)}}{2\sum_{i=1}^{n} w_i^2 \tilde{x}_i \tilde{y}_i} \tag{5}$$

Among these, $\left(\tilde{x}_i, \tilde{y}_i\right)$ represents the deviation of the medical facility's coordinates from the center of the standard ellipse. The standard deviation formulas along the major and minor axes are:

$$\begin{cases} \sigma_x = \sqrt{\dfrac{\sum_{i=1}^{n}\left(w_i\tilde{x}_i cos\theta - w_i\tilde{y}_i sin\theta\right)^2}{\sum_{i=1}^{n} w_i^2}} \\ \sigma_y = \sqrt{\dfrac{\sum_{i=1}^{n}\left(w_i\tilde{x}_i sin\theta - w_i\tilde{y}_i cos\theta\right)^2}{\sum_{i=1}^{n} w_i^2}} \end{cases} \tag{6}$$

Here, σ_x and σ_y denote the standard deviations along the major and minor axes, respectively, corresponding to the values of the ellipse's semi-major axis and semi-minor axis.

This chapter employs standard deviation ellipse analysis to precisely reveal the spatial distribution density, center of gravity, spatial extent, and directional variation of point-based geographic features, enabling quantitative assessment of spatial development patterns and directional evolution within point clusters.

3.3 DBSCAN Algorithm

Density-based spatial clustering for noise applications (DBSCAN) algorithm, a density-based spatial data clustering path, the algorithm can divide high-density regions into clusters, divide the clusters into arbitrary shapes, and identify outlier points in space, which not only can effectively solve the problem of large amount of data and the overlapping and obscuring of the points of interest, but also can indicate the spatial distribution pattern from the macroscopic point of view and also preserve the details in the The positional accuracy of the data can also be preserved in details [16, 17]. In this paper, this algorithm is used to explore the distribution of urban medical facility clusters and to classify the clustering level in order to reveal the spatial agglomeration characteristics of medical facilities.

The DBSCAN clustering algorithm reflects the clustering status of point-like things by two parameters, Eps is the minimum distance radius of sample clustering, and MinPts is the minimum number of samples within the cluster scanning range. In this paper, the Eps and MinPts values are determined by the I-DBSCAN adaptive parameters, and the distance k-dist between each point and the kth neighboring point is calculated, and all the points to be sorted are plotted according to the k-dist in a k-dist plot sorted by size. The value of Eps is determined according to the value of the points in the sorted k-dist plot when the gradient of the curve varies greatly, and on the basis of the parameter Eps being determined, the expectation of the number of points within the scanning radius Eps is counted for each point in the set of points, and the optimal value of the minimum number of points MinPts for the clustering can be obtained:

$$MinPts = \frac{1}{n}\sum_{i=1}^{n} Count_i \tag{7}$$

where $Count_i$ is the number of points within the scanning radius Eps of point i.

In this section, the DBSCAN algorithm is used to distribute and classify the clusters of healthcare facilities into clustering hierarchies, which finally reveals the spatial agglomeration characteristics of healthcare facilities.

3.4 The two-step moving search method (2SFCA)

In order to assess the rationality of the spatial layout of healthcare facilities, this paper uses accessibility for analysis. Studying the spatial accessibility of urban hospitals contributes to the fair and efficient distribution of medical resources and the equalization of medical resources [18]. In assessing the spatial accessibility paths of medical facilities, the two-step moving search path and the potential model are widely used in the spatial accessibility analysis of public service facilities due to the comprehensive consideration of the scale of demand. Compared with the potential model, the two-step moving search method can be easily and intuitively implemented, thus this paper adopts the 2SFCA method to calculate the supply-demand ratio and accessibility.

3.4.1 Calculation of supply/demand ratio

Centered on urban hospital supply point j, determine the distance threshold d_o based on the service radius of hospitals of different grades within the urban area. Establish the hospital service supply side based on urban road network data. Then search for all demand points k within the search radius d_o of j (in this study, demand points are urban residential points). Calculate the supply-demand ratio R_j:

$$R_j = \frac{S_j}{\sum_{i \in \{d_{ij} \le d_o\}}^{k} D_i} \tag{8}$$

In the equation, R_j represents the supply-demand ratio, which is the service capacity of urban hospital j and is expressed in this paper as the number of beds per capita. i denotes the demand point (i.e., residential area), j denotes the urban hospital supply point, and S_j denotes the supply service capacity of the urban hospital, represented in this paper by the number of beds in the urban hospital. D_i represents the scale of the demand point, expressed as the population of the residential area in this study. k denotes the number of residential areas within the search radius, while d_{ij} indicates the distance between demand point i and supply point j—measured using road network analysis distance in this study. d_o denotes the service radius, which is set according to the service radius of different tiers of hospitals in this study. The service radius for Level I hospitals is 2000 meters, for Level II hospitals is 5000 meters, and for Level III hospitals is 10000 meters.

3.4.2 Computational Accessibility

The accessibility value represents the relative ease with which residents of a given settlement can reach designated healthcare facilities. This metric reflects spatial barriers and competition for service provision. Therefore, the accessibility value for each settlement is calculated as follows:

$$A_i = \sum_{\in \{d_{ij} \le d_o\}}^{m} R_j \cdot f\left(d_{ij}\right) \tag{9}$$

In the formula, A_i represents the accessibility value for each settlement, m denotes the number of tertiary hospitals within the spatial scope centered at i with a search radius of d_o, and R_j is the supply-demand ratio calculated in the first step. $f\left(d_{ij}\right)$ is the distance decay function accounting for spatial friction, which can be further expressed as:

$$f\left(d_{ij}\right)=\begin{cases} e^{\frac{1}{2}*\left(\frac{d_{ij}}{d_o}\right)} & d_{ij} \leq d_o \\ 0^{1-e^{\frac{1}{2}}} & d_{ij} > d_o \end{cases} \tag{10}$$

This section ultimately completed the spatial accessibility analysis of healthcare facilities using the 2SFCA algorithm.

3.5 Particle Swarm Optimization Algorithm

The Particle Swarm Optimization (PSO) algorithm is a swarm intelligence algorithm within computational intelligence. Its solution process simulates a flock of birds searching for food. Each bird represents a particle in PSO. During their foraging journey, these birds alter their positions and velocities in flight. Initially dispersed across the sky, they gradually converge until they collectively locate food. Each particle in the PSO algorithm represents a solution within the search space. Adjusting position and velocity during flight aims to identify the optimal location experienced by each particle during its movement—this constitutes the particle's locally optimal solution, termed the particle best (pbest). The most suitable position collectively experienced by the entire swarm represents the globally optimal solution discovered by the swarm, known as the global best (gbest) [19].

This paper employs the particle swarm optimization algorithm to optimize the spatial selection for medical facility coverage. Within the algorithm, each particle continuously updates its solution based on two extremes. Velocity and position updates form the core of the particle swarm algorithm, with its principle expression and update method as follows:

$$V_{ij}=V_{ij}+C_1\cdot rand\left(0,1\right)\left(P_{ij}-X_{ij}\right)+C_2\cdot rand\left(0,1\right)\left(P_{gj}-X_{ij}\right) \tag{11}$$

Among these, X_{ij} and V_{ij} represent the optimal location for medical facility coverage between demand point i and current supply point j and the speed at which demand point i reaches supply point j respectively. P_{ij} represents the optimal location of the medical facility coverage space between demand point i and current supply point j after iteration, while P_{gj} denotes the globally optimal location of the medical facility coverage space after evaluation. C_1 and C_2 represent the individual cognition coefficient and social learning coefficient, respectively, while $rand\left(0,1\right)$ denotes a random number.

This section employs the particle swarm optimization algorithm to ultimately determine the optimal siting plan for the medical facility coverage space.

4 Analysis of Public Healthcare Resource Allocation Pathways

4.1 Overview of Public Medical Institutions in Hohhot City

As the provincial capital, Hohhot boasts convenient transportation and abundant medical resources. It ranks first in the region for the number of Grade III Class A hospitals within its jurisdiction, houses the nation's sole Grade III Class A Mongolian medicine hospital, and possesses world-leading instruments and equipment. Currently, Hohhot has 46 public hospitals. The population, area, and public medical institutions across Hohhot's districts are shown in Table 1. Among these hospitals, there are 9 Class A tertiary hospitals, 5 Class B tertiary hospitals, 1 traditional Chinese medicine hospital, and 2 Mongolian medicine hospitals. Hohhot encompasses 4 districts—Xincheng, Huimin, Yuquan, and Saihan—and 5 county-level cities: Tumed Left Banner, Tuoketo County, Helinger County, Qingshuihe County, and Wuchuan County. Specifically: 5 in Yuchuan District, 7 in Saihan District, 4 in Tumed Left Banner, 4 in Tuoketo County, 4 in Helinger County, 4 in Qingshuihe County, and 3 in Wuchuan County. The 46 hospitals collectively offer approximately 8,483 beds, equating to 2.8 beds per thousand residents, indicating a severe shortage of hospital beds. The total medical staff numbers around 10,365, translating to 3.5 healthcare professionals per thousand residents. Specifically, there are 1.6 physicians and 1.7 nurses per thousand residents, reflecting a significant shortage of medical personnel. In 2023, these hospitals treated 457,000 outpatient visits and admitted 25,000 inpatients, achieving an 88.8% bed occupancy rate with an average hospital stay of approximately 10.5 days. They not only serve Hohhot residents but also extend care to surrounding prefectures and neighboring countries, annually treating nearly 20,000 international patients from Mongolia, Russia, South Korea, Japan, and others. Consequently, Hohhot's public healthcare system faces significant challenges: structural imbalances in resource allocation, information technology infrastructure failing to meet current demands, suboptimal healthcare service quality, and a critical shortage of medical personnel.

Table 1: Population, area and public medical institutions in each district of Hohhot

District Name	Population (10000 people)	Area(km^2)	Public hospital (home)	Tertiary hospital (home)	Secondary hospital (home)	First-level hospital (home)
Xincheng District	69.97	700	8	5	3	0
Huimin District	39.58	175	7	2	4	1
Yuquan District	45.30	213	5	0	2	3
Saihan District	87.87	1013	7	2	3	2
Tumd Left Banner	27.85	2712	4	0	1	3
Tokto County	15.71	1313	4	0	1	3
Holinger County	15.08	3401	4	0	1	3
Qingshuihe County	6.76	2859	4	0	1	3
Wuchuan County	8.63	4885	3	0	1	2

4.2 Data Sources

Table 2 serves as the data source. The data for this study primarily includes three components: supply points, demand points, and road traffic data for public healthcare in Hohhot.

Table 2: Data sources

Data Type	Data Name	Data Source	Specific Data
Supply Point	Public medical service institutions	Hohhot Health Commission	Basic information on public medical service institutions (location, number of ambulances)
		Baidu Map API Technology	Geographic location of supply points (latitude and longitude)
Demand Points	Population data	WorldPop	Raster data, 1000m × 1000m resolution
Road traffic	Transportation network	National Geographic Information Center	Transportation network, road types
	Administrative district planning		Administrative division names and shapes

4.3 Analysis of Accessibility to Healthcare Facilities

This study obtained average spatial accessibility data for nine districts and counties in Hohhot based on public hospital-related data from 2019 to 2023. In January 2024, it employed a path for optimizing public medical institution resource allocation designed based on spatial resilience and multi-source data. The average spatial accessibility data for the nine districts and counties was obtained, and the spatial accessibility of medical institutions before and after optimization is shown in Figure 2. Prior to resource allocation optimization, Hohhot's overall average spatial accessibility score for public medical institutions was 0.40×10^{-5} points. Among these, Xincheng District, Huimin District, Yuquan District, and Saihan District demonstrated relatively high spatial accessibility scores of 0.67×10^{-5} points, 0.60×10^{-5} points, 0.60×10^{-5}, and 0.64×10^{-5}, respectively. However, public medical institutions in Qingshuihe County and Wuchuan County scored lower at 0.12×10^{-5} and 0.10×10^{-5}, representing 70.0% and 75.0% below Hohhot's overall average. However, following the resource allocation path optimization design proposed in this paper, Hohhot's overall average spatial accessibility score for public medical institutions reached 0.81×10^{-5}. Due to the larger resident populations in Xincheng, Huimin, Yuquan, and Saihan districts, their public medical institutions maintained relatively high spatial accessibility scores of 0.87×10^{-5}, 0.85×10^{-5}, 0.90×10^{-5}, and 0.92×10^{-5}, respectively. The remaining five counties—Tumed Left Banner, Tuoketo County, Helinger County, Qingshuihe County, and Wuchuan County—had lower scores due to smaller populations and the presence of only primary-level hospitals. Thus, their spatial accessibility to public medical institutions is slightly lower than the four districts, yet all exceed 0.72×10^{-5} points—11.1% below Hohhot's overall average spatial accessibility for public medical facilities. Results indicate that this paper's healthcare resource allocation approach, optimized through spatial resilience and multi-source data, significantly improves the overall spatial accessibility of public medical institutions.

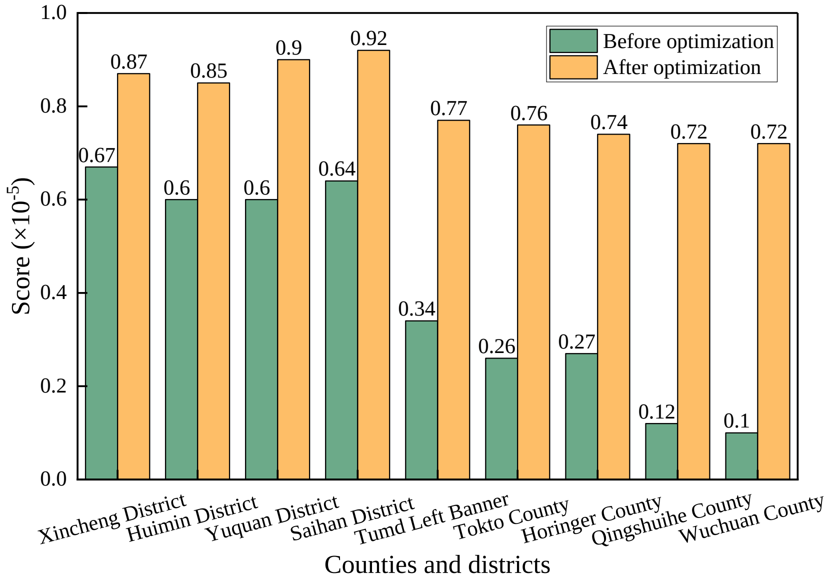

Figure 2: Spatial accessibility of public medical institutions before and after optimization

4.4 Analysis of Resource Allocation Efficiency

By obtaining relevant data on Hohhot's public healthcare resources from 2019 to 2023, we derived metrics including total resource volume, spatial accessibility, redundancy, and fitness. Using this data as the baseline for the city's current public healthcare resource allocation, we redistributed resources among Hohhot's public medical institutions through three approaches: traditional standard quotas, administratively balanced allocation, and the proposed spatial resilience and multi-source data optimization method. The resource allocation results are presented in Table 3.

Both the traditional standard quota and administrative equilibrium allocation paths, as well as the proposed spatial resilience and multi-source data optimization path, can address the current issues of scarce medical resources, poor spatial accessibility, insufficient redundancy, and suboptimal fitness. The traditional allocation increases the number of healthcare workers and hospital beds per thousand residents from 2.3 and 3.8 to 3.1 and 5.0, respectively. In contrast, the proposed approach directly elevates these figures to 4.6 and 6.3. Moreover, while the traditional approach reduces medical service time from 27 minutes to 22 minutes, the proposed approach further lowers it to 16 minutes, significantly enhancing service efficiency and daily patient throughput. The severe shortage in critical care bed reserve capacity has also been significantly alleviated. While the traditional resource allocation approach increases the critical care bed reserve rate to 8%, the approach proposed in this paper raises it to 18%, effectively easing the medical pressure caused by insufficient beds for critically ill patients. Following the reallocation of medical resources, backup designated hospital pre-designation points have been established to enable rapid response to pandemic outbreaks.

Table 3: Resource allocation results

Indicator Classification	Indicator Details	Status quo	Traditional standard quotas and administrative balance allocation paths	Optimize configuration paths based on spatial resilience and multi-source data
Total resources	Number of doctors per 1,000 residents	2.3	3.1	4.6
	Number of hospital beds per 1,000 residents	3.8	5.0	6.3
Spatial accessibility	Average time spent in hospital (minutes)	27	22	16
	Gini coefficient for accessibility	0.48	0.36	0.24
Redundancy	Critical care bed reserve rate (%)	4	8	18
Fitness	Number of designated backup hospitals (units)	0	1	3

5 Conclusion

This paper integrates multi-source data with spatial resilience to jointly optimize the allocation pathways of public healthcare resources, analyzing outcomes from both healthcare accessibility and resource allocation efficiency perspectives. Results indicate that the designed allocation pathways elevate Hohhot's overall public healthcare accessibility score from 0.40×10^{-5} to 0.81×10^{-5}. spatial accessibility scores for Xincheng, Huimin, Yuquan, and Saihan districts improved from 0.67×10^{-5}, 0.60×10^{-5}, 0.60×10^{-5}, and 0.64×10^{-5} to 0.87×10^{-5}, 0.85×10^{-5}, 0.90×10^{-5}, and 0.92×10^{-5}, respectively. The spatial accessibility scores for Qingshuihe County and Wuchuan County rose from 0.12×10^{-5} and 0.10×10^{-5} to over 0.72×10^{-5}. The traditional resource allocation pathway increases the number of healthcare personnel per thousand residents to 3.1 and the number of hospital beds to 5.0, reduces the average time spent seeking medical care to 22 minutes, and raises the reserve rate of critical care beds to 8%. In contrast, the pathway proposed in this paper increases healthcare personnel to 4.6 per thousand residents and hospital beds to 6.3 per thousand residents, reduces the average time spent seeking medical care to 16 minutes, and raises the reserve rate of critical care beds to 18%. Therefore, the public healthcare resource allocation pathway proposed in this paper—optimized through spatial resilience and multi-source data—holds significant importance for enhancing residents' healthcare efficiency, optimizing resource allocation, and establishing a more scientific, equitable, and efficient healthcare system.

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