



Analysis on the Balance of Health Care Resource Allocation Based on Improved Machine Learning

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Abstract. Health resource planning is an important means for the government to adjust resource allocation and achieve fair and efficient development of health. Its core is the balanced allocation of health resources. In order to solve the problem of low accuracy of health resource demand prediction, an analysis method of health resource allocation equilibrium based on improved machine learning was designed. Using the two-step mobile search method, combined with the Gaussian distance attenuation function and the search threshold set according to the classification of medical facilities, the spatial accessibility of weekday medical services is calculated. Based on the improved machine learning, the demand for health resources is predicted, and the change of resource characteristics and relevant policy variables leads to the change of health resource demand. According to the prediction results of the demand for health care resources, a supply-demand coordination model is constructed to measure the degree of coupling and coordination and the level of hierarchy. Lorentz curve was used to quantify the accessibility distribution of medical resources, Gini coefficient and global Moran index were calculated, and the equilibrium of health resource allocation was analyzed. The results show that this method can accurately predict the demand for health resources, and get the analysis results of allocation balance, which is conducive to the overall integration of medical resources.

Keywords: Improving Machine Learning · Medical Care · Health Resources · Allocation Balance

1 Introduction

Under the background of the basic establishment of the public health service system, the basic improvement of the national medical security system, and the deepening reform of the national health care system, the people's health level has significantly improved. The contradiction between residents' demand for healthy life and the current insufficient and unbalanced supply of medical facilities resources has become increasingly prominent, resulting in social phenomena such as "it is difficult and expensive to see a doctor". Health

resource planning is an important means for the government to adjust resource allocation and achieve fair and efficient development of health. The core of health resource planning is to optimize the allocation of health resources. China's central and local governments have carried out a lot of health resource planning work, which has played an important role in optimizing the allocation of health resources [1]. The comprehensive promotion of the equalization of regional health services has brought about a significant improvement in people's health. The analysis of the supply and demand framework of basic public services shows that China is about to enter a period of consolidation and improvement of the equalization of basic public services characterized by "comprehensive coverage, fairness and equality, and balanced burden". Objectively, there is an imbalance in the development of economic and social levels between regions, resulting in great supply differences in medical facilities between regions and between urban and rural areas, which has a negative impact on the health level of residents in some backward areas. Due to the lack of reasonable theoretical framework and model in the existing health resource planning, the allocation of health resources follows the feeling of health managers and is divorced from the actual needs of residents. The quality of health services is increasingly prominent, the supply of public health services is fragmented and other problems are prominent, health resources are divided into blocks, unreasonable structure and layout, shortage and waste of health resources coexist, and there is a lack of overall and comprehensive planning within and between regions [2]. This also leads to the unbalanced allocation of health resources in the health service system and the provision of health services cannot meet the health needs and other problems. The current medical and health management mechanism still has shortcomings, resulting in prominent problems such as the quality of medical and health services, unreasonable structure and layout, which are specifically manifested as the lack of medical means in hospitals in some areas and the lack of customers, while some hospitals are overcrowded, resulting in the coexistence of shortage and waste of medical resources [3]. How to use health resource planning to better deepen the reform of the medical and health system and promote the construction of "healthy China" still needs to make greater efforts in the scientificity of planning and the effectiveness of planning implementation. Based on improved machine learning, this paper analyzes the balance of the allocation of health care resources, which is of great significance for the overall planning of the distribution of health care resources within and between regions, and to solve the current imbalance and unfairness of distribution.

2 Space Accessibility Calculation of Health Care Services

The research on the balance of medical resources involved in this study emphasizes the rational allocation of resources at the macro level, that is, using scientific planning means to enable residents in different locations to enjoy efficient and fair medical and health services, which should be reflected not only in geographical space, but also in quantity and quality. In this paper, the two-step mobile search method, combined with the Gaussian distance attenuation function and the search threshold set according to the classification of medical facilities, is used to study the spatial accessibility of weekday medical services. Accessibility impact mainly involves three factors: the attributes of medical

service institutions (facility scale, grade, number of health technicians, financial and material resources of institutions, etc.), the attributes of medical service demand points (population, consumption level, population composition, medical preference, etc.), and travel costs (traffic network direction, road grade, speed limit, time spent, etc.). The two-step mobile search method and the gravity model method are most widely used in the evaluation of spatial accessibility, but the two-step mobile search method is easier to understand, has strong operability, and takes comprehensive consideration of both supply and demand sides. Because of its scale, personnel, equipment, capital and other advantages, hospitals are actually the most important subject of medical and health facilities and the most important research object in related fields [4]. The first step of the two-step mobile search method is to calculate the supply-demand ratio. The specific method is to divide the opportunity quantity or supply quantity of each facility by the demand quantity within the respective search threshold in the defined search threshold. The formula is:

$$p_x = \frac{\sum_{x=1}^{m_1} \alpha_x d_{xy}^2}{\sum_{z=1}^{m_2} \beta_z d_{xy}} \quad (1)$$

In Eq. (1), p_x represents the ratio of the supply capacity α_x of the supply point x to the number of demanders served within the search threshold; d_{xy} is the distance cost between the supply point y and the supply point x ; m_1 and m_2 represent the total number of supply points and demand points; β_z refers to the demand quantity; z indicates the demand point. The second step of the two-step mobile search method is medical accessibility. Its concept is a decisive factor affecting the fairness of medical and health services. As an important indicator to judge the shortage area of medical services, it plays an extremely important role in the scientific layout and planning of medical services. Supply capacity α_x can be calculated by substituting the number of beds, licensed doctors, registered nurses, daily outpatient volume and other data in the study. When considering accessibility, only the medical institution points within the threshold range are considered, and the points beyond the threshold range are not considered, and for the points within the threshold, regardless of distance, each medical point has the same impact on the accessibility of demand points [5]. In real life, the travel distance and time cost of medical facilities with different travel distances are very different for residents, so simple summation fails to take into account the distance attenuation between supply points and demand points. According to the attenuation characteristics and actual needs of the distance attenuation function, this paper selects the Gaussian function as the distance attenuation function, and the formula is:

$$d_{xy} = \frac{e^{-\frac{1}{2} \left(\frac{d_{xy}}{d_0} \right)^2} - e^{-\frac{1}{2}}}{1 - e^{-\frac{1}{2}}} \quad (2)$$

In Eq. (2), e is the natural constant; d_0 indicates the search threshold. Then calculate the sum of the supply-demand ratio of all facilities in each demand area within the search threshold. According to the accessibility score of the demand point x calculated by the two-step mobile search method, the actual meaning is the average facility resources

that each demander can reach at the demand point x . Different from the original two-step mobile search method, the accessibility decay rate in the Gaussian distance decay function first accelerates and then slows down with the increase of distance, which is similar to people's expectations for the choice of medical facilities with the increase of travel distance or travel time in real life, and can more truly simulate the real decision-making state. The search scope selects the linear distance between the supply point and the demand point, Manhattan distance, great circle distance, or the actual road network distance according to the researchers' research purpose. The purpose of this paper is to study the medical accessibility of the actual situation, so the actual road network distance is selected for analysis. Associate the calculated spatial accessibility value to the residential population point data layer, use the point grid tool, select the spatial accessibility value as the generated value, turn the residential population point into a grid, and draw the spatial accessibility distribution diagram through the natural discontinuity method. Residents' access to ideal medical services is basically concentrated in urban areas or counties, and residents in areas with general spatial accessibility and below are mostly distributed in suburban or rural areas. The spatial accessibility is similar to the distribution characteristics of the traffic network. The regional accessibility of the dense traffic network also shows a high law. On the contrary, the regional accessibility of the sparse traffic network is also low.

3 Prediction of Health Resource Demand Based on Improved Machine Learning

Accurate prediction of demand is the basis of health resource planning, and the core of health resource planning is the optimal allocation of health resources. Therefore, accurate prediction of demand is the basis of health resource allocation. Health needs are affected by many factors, including personal factors, such as age, gender, occupation, education level, behavior style, etc. at the same time, they are also affected by many macro factors, such as economic level, health-related policies, etc. [6]. Medical service facilities can be divided into four categories: hospitals, basic medical service facilities, special public health facilities and other facilities. Among them, hospitals are divided into three levels, namely, tertiary hospitals, secondary hospitals and primary hospitals. The basic medical system includes urban and township parts. The township system consists of village health stations and township health centers, and the urban part consists of outpatient clinics and community health service centers (stations). This paper predicts the demand for health care resources based on improved machine learning. The basic idea of health resource demand prediction is shown in Fig. 1.

First, according to the characteristics of people's health needs, the micro units were sampled to obtain data to form a data file. According to the real health needs of the population, build a model to simulate the changes in the parameters of demand influencing factors. The residential population point data is the center point of the pixel converted from the 1-km spatial resolution grid. Crop worldpop 100 m spatial resolution grid data using administrative boundaries. Resample the grid and resample the original data into 1km spatial resolution grid data. When resampling, select the superposition method to process the value of the grid. Use the administrative boundary to crop the 1km spatial

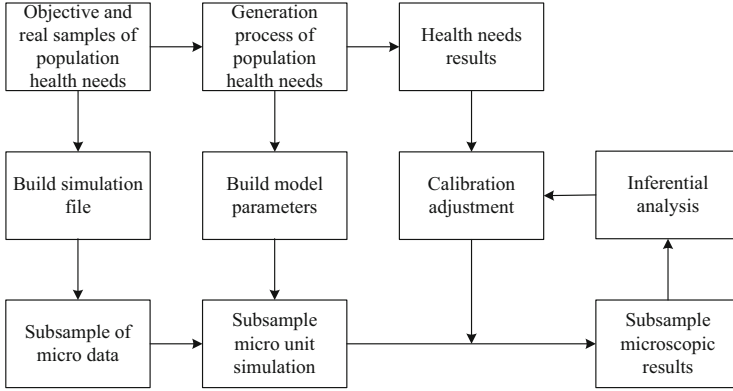


Fig. 1. Basic idea of health resource demand prediction

resolution grid, and then convert the grid data into the pixel center as the residential population point to participate in the calculation [7]. The kernel function of SVM can map low dimensional space to high dimensional space. In nonlinear problems, kernel functions can be used to add dimensions to the original data, thus transforming it into a linear problem in a higher dimensional space. The main function of Gaussian kernel function is composed of Euclidean distance equation, which is expressed as:

$$\vartheta(a, b) = \|a - b\| \quad (3)$$

In Eq. (3), ϑ represents Gaussian kernel function; a, b is the sample point. The traditional Gaussian kernel function can be expressed as:

$$\vartheta(a, b) = \exp\left(-\frac{\|a - b\|^2}{2\varepsilon^2}\right) \quad (4)$$

In Eq. (4), $\exp$ refers to exponential function; ε represents the width parameter. Computer programs are used to realize the changes of eigenvalues related to micro units due to the characteristics of micro units and the changes of relevant policy variables. Through the statistics, analysis, inference and synthesis of characteristic variables, the impact of policy changes on micro units can be obtained, and the implementation effects of policies at macro and all levels can be obtained. The population ratio is obtained by dividing the specific population allocated to each medical facility by the total service population of the corresponding medical facility, and then multiplying the population ratio by the number of resources of medical institutions within each range to calculate the number of medical resources of each medical facility occupied by each residential population. The main indicators in the database are individual health needs, needs and related influencing factors, including gender, age, marriage, education, urban and rural areas, healthy lifestyle factors, income, medical insurance, patient visits and hospitalization flow and other indicators. For the sample data of this study, each sample point is dense. When it is mapped to the high-dimensional space through the Gaussian kernel function, the sample points will become sparse. The way to alleviate this problem is to

attenuate the Gaussian kernel function to a certain extent when it is far away from the test point, so as to enhance the learning ability. According to this condition, this study deforms the Gaussian kernel function by adding two displacement parameters φ_1 and φ_2 on the basis of the traditional Gaussian kernel function. The improved Gaussian kernel function is as follows:

$$\vartheta(a, b) = \exp\left(-\frac{\|a - b\|^2 + \varphi_1}{2\varepsilon^2} + \varphi_2\right) \quad (5)$$

In Eq. (5), φ_1 is the parameter that adjusts the amplitude of the function; φ_2 is the displacement bias of the adjustment kernel function. The improved SVM establishes a dynamic model of abstract system changes from discrete medical resource data to predict the demand for health care resources. After the model construction and test, the prediction results are analyzed and the fitting grade of the model is judged, and the prediction results of the original data are obtained. Reasonable allocation of community health service resources and Realization of the balance between supply and demand of community health services are the basic requirements for the optimal allocation of community health resources. The ultimate goal of the optimal allocation of health resources is to maximize the efficiency and benefits of community health services.

4 Build a Supply-Demand Coordination Model

In the process of using public medical resources, there may be inconsistencies between patients' personal needs and actual needs. When medicine believes that there is no need for medical services, but the actual utilization of medical services occurs, that is, there is "no need for demand", which will lead to the waste of medical resources. According to the prediction results of the demand for health care resources, a supply-demand coordination model is constructed, as shown in Fig. 2.

The essence of supply-demand coordination is to achieve dynamic balance between total supply and total demand, and to coordinate the proportion of supply and demand organically. Consistent with the actual needs, and based on this, we can obtain the expectation of effective medical services in medicine, that is, the reasonable expectation of public medical resources. The key factor is whether the individual on the demand side can obtain enough effective information. The supply system of medical and health facilities is divided into three primary indicators and six secondary indicators. The three primary indicators are economic input, facility allocation and medical efficiency. Among them, economic investment mainly reflects the strength of government capital investment and the level of regional economic development through medical financial investment and regional GDP; The facility allocation mainly reflects the facility scale, equipment scale and personnel scale through the building area, the number of beds and the number of health technicians; Medical efficiency mainly reflects the benefit efficiency of medical resources through the average number of daily diagnosis and treatment. The mismatch between supply and demand of public medical resources and the failure of graded diagnosis and treatment will cause great harm to patients and society. From the perspective of demand, the medical demand of outpatient services is calculated by

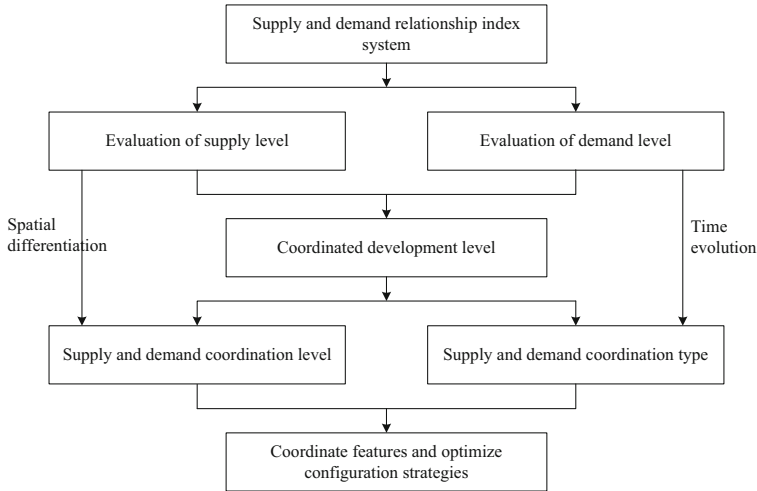


Fig. 2. Supply and demand coordination model

multiplying the number of people allocated to each medical facility by the annual per capita outpatient visits, and the resource supply is obtained by multiplying the number of health technicians by the medical ratio by the per capita daily visits of doctors by the number of doctor visits [8]. The residents' medical demand system is divided into three primary indicators and six secondary indicators. The three first-class indicators are population structure, economic level and traffic accessibility. Among them, the population structure mainly reflects the characteristics of population structure through the total population of each community, the proportion of floating population, the proportion of elderly population, and the proportion of population with high school education or above; The economic level is mainly reflected by the per capita income of residents; Traffic accessibility mainly selects the regional medical accessibility obtained from the previous analysis. After obtaining the supply-demand ratio between each residential population point and each medical facility, the Gauss distance attenuation function is used to modify the supply-demand ratio according to the time cost, and then the total number of residential population points on the assigned population ratio is multiplied by the supply-demand ratio to obtain the supply-demand ratio of each part of the population contribution. Finally, the probability of residents in each residential population point to obtain outpatient services is obtained by summarizing these supply-demand ratios according to the residential population points, Take this as the basis for evaluating the relationship between supply and demand. When it is considered that there is a need for medical services in medicine, but due to the high cost of medical treatment, inconvenient medical treatment, no corresponding medical resource supply or poor quality of medical resources and other conditions, the medical needs cannot be transformed into real needs, and the patients' diseases cannot be treated in a timely and effective manner. In order to quantitatively evaluate the coordinated development level of medical and health facilities, this paper constructs a coupling coordination degree model to judge its coupling coordination degree and level. The coupling coordination degree model

involves the calculation of three index values, namely, the coupling degree S value, the coordination index γ value, and the coupling coordination degree χ value. The coupling degree is calculated as follows:

$$S = \left[(\beta_1 \beta_2) \frac{(\beta_1 + \beta_2)^{-2}}{2} \right]^\mu \quad (6)$$

In Eq. (6), β_1 and β_2 are the comprehensive evaluation indexes of the supply and demand of medical and health facilities in the community respectively; μ refers to the adjustment coefficient, and the value is 2. The value of coupling degree S is used to reflect the relationship between supply and demand. The coordination index γ is used to reflect the overall synergy between facility supply and demand, and the formula is:

$$\gamma = \varpi_1 \beta_1 + \varpi_2 \beta_2 \quad (7)$$

In Eq. (7), ϖ_1 and ϖ_2 represent undetermined coefficients, both of which are taken as 0.5. The coupling coordination degree χ is an important index to evaluate the degree of supply-demand coordination. The formula is:

$$\chi = \sqrt{S\gamma} \quad (8)$$

When the value of coupling coordinated development degree is between 0–0.49, it is in the stage of supply and demand imbalance, and when the value of coupling coordinated development degree is between 0.50–1.00, it is in the stage of supply and demand imbalance. It is difficult for individual patients to do so because of information asymmetry; And in order to ensure good treatment effect, we often take adverse selection behavior according to our own cognition, giving priority to medical treatment with medical resources that we think are good brand, strong medical power, excellent equipment, good drugs, low risk and excellent quality, resulting in overcrowding in large hospitals and idle resources in small hospitals, which is mainly manifested in cross regional medical treatment. The current policies and allocation standards mostly take the service population and service radius as indicators to allocate medical and health facilities in the area. However, in the actual use process of residents, due to the different input-output ratio and use efficiency of various facilities, the supply level is also different; Even if the supply level is the same, residents' demand for medical and health facilities is different due to their own situation differences and external factors, indicating that the same supply can not meet the differentiated needs of residents.

5 Analysis on the Balance of Health Resources Allocation

The concept of health services is to serve citizens and ensure that residents in different areas of economic development and people of different income groups can enjoy equal health care services. In this study, Lorentz curve is used to quantify the accessibility distribution of medical resources. Lorentz curve refers to the curve formed by the point where the percentage of population “from the poorest population to the richest population” corresponds to the income percentage of each population percentage in a

whole (country, region). The drawing method is that the horizontal axis is the percentage of population and the vertical axis is the cumulative percentage of accessibility. The drawing is completed by connecting the corresponding points. The fairness of medical resource allocation between urban regions is an important goal that must be considered. The economic, geographical, demographic and traffic conditions of different regions of a city are different, so the fairness of resource allocation must be guaranteed, and spatial accessibility is also the key to urban medical resource allocation from a spatial perspective. The Lorentz curve accumulates the population data of social wealth and wealth from small to large, and connects the data points corresponding to the percentage of population and its percentage of social wealth [9, 10]. Assuming that the closer the gap between the allocated resources of each region and the population percentage (or geographical area percentage) of its city, the fairer the hospital medical resources allocated by each region will be. Draw the absolute fair line on the basis of Lorentz curve. The area between the curve and the absolute fair line is A_1 , and the area below the actual Lorentz curve is A_2 . Using $A_1(A_1 + A_2)$ can reflect the degree of unfair distribution. This calculated value is called Gini coefficient. The Gini coefficient is the percentage of all residents' income used for uneven distribution. The minimum Gini coefficient is equal to 0, representing the absolute average of income distribution; The maximum is equal to 1, indicating that the income distribution is absolutely uneven. The actual Gini coefficient is between 0 and 1. If the difference between the resource allocation of each region and its percentage in the city's population (or the percentage of geographical area) is closer, the more equitable the resource allocation will be considered. The calculation formula of Gini coefficient is:

$$g = 1 - \frac{\frac{1}{2} \sum_{i=1}^n (q_i + q_{i+1})\psi_{i+1}}{5000} \quad (9)$$

In Eq. (9), g represents Gini coefficient; i and n respectively represent the sequence number and collection sequence of residential areas; q represents the cumulative proportion of resources and represents the accessibility value of medical resources in this study; ψ represents the corresponding proportion of population, which is calculated based on the population data of residential areas in this study. The absolute fairness between regions that only pay attention to resource allocation will ignore the accessibility of residents at the regional boundary, and will also lead to the problem of allocation efficiency, while paying attention to the spatial accessibility of resource allocation will ignore the balance of development between regions, and lack of consideration for the coordinated development between different regions of the city in the future. The global Moran index is used to judge the aggregation state of accessibility data distribution and the degree of correlation between data, the global Moran index is the most commonly used spatial autocorrelation index, which is an important research index to study the potential interdependence between the observation data of variables in the same distribution area. In short, it is to determine whether there is a correlation between spatial

entities within a certain range, and its calculation expression is:

$$M = \frac{n \sum_{i=1}^n \theta(q_i - \bar{q})}{\sum_{i=1}^n q_i \sum_{i=1}^n (q_i - \bar{q})^2} \quad (10)$$

In Eq. (10), M represents the global Moran index; θ represents the spatial weight matrix; $\bar{q}$ represents the average of all study area data. For the specific model planning formula, the functional positioning of different levels of medical institutions, residents' medical behavior, regional balance, medical needs and other factors should be considered, and can be dynamically adjusted according to the future development of the city. Using the global Moran index, we can effectively obtain its spatial distribution equilibrium, and identify the corresponding data aggregation and dispersion state. For areas lacking medical resources or areas with waste and overflow of medical resources supply, it is also more accurate to identify, and then put forward planning suggestions for the scientific and reasonable allocation of medical resources and health facilities [11, 12]. If we want to achieve the goal of fairness of community health services, we need to have adequate protection in human resources, material resources and financial resources, eliminate the unfair factors of health services caused by geographical environment and economic conditions as far as possible, fully reflect the public interests of residents in the allocation of community health service resources, and ensure that residents can have fair access to community health services. Through continuous improvement, we will finally achieve a fair, reasonable and optimized allocation of community health service resources.

6 Experimental Study

6.1 Overview of the Study Area

Taking the allocation of health care resources in a city as the research object, the data of population distribution and medical resource distribution in the region were collected, and the balance of resource allocation was analyzed. The total population of the city is 2036528, and the regional population distribution is uneven. There are 43 medical and health institutions in the city, including 16 first-class hospitals, 14 s-class hospitals and 13 third-class hospitals. There are 58 township health centers and community health service centers. The distribution of medical and health institutions is relatively concentrated and mostly distributed in urban areas, with less distribution in township areas. Township health centers and community health service centers are evenly distributed, and each township and street has at least one health center or community health service center. On the whole, the spatial accessibility level of the southern region is higher than that of the northern region, and the spatial accessibility level of the central region is higher than that of the eastern and western regions. More than 85% of the residents are located in areas with good spatial accessibility and excellent grade, which shows that most of the population can enjoy better medical services. After the data collection in the study area is completed, the data are statistically analyzed and sorted out, and the obtained data are

visually expressed by using Excel chart tools. And the final visualization is reflected in the demand forecast of health resources and the equilibrium analysis of health resource allocation. Combined with the data published in the statistical yearbook of the city, the general situation of medical resource allocation in each administrative region in the study area is summarized.

6.2 Prediction and Analysis of Health Resource Demand

In order to verify the prediction effect of this method on the demand for health care resources, the prediction accuracy is calculated. The test results are compared with the resource allocation equilibrium analysis method based on GM (1,1) grey prediction model and ARIMA model. The test results of the accuracy of demand forecast results are shown in Table 1.

Table 1. Accuracy of demand forecast results

Number of tests	An improved machine learning based equilibrium analysis method for health care resource allocation	Analysis method based on GM (1,1) grey prediction model	Analysis method based on ARIMA model
1	0.692	0.584	0.524
2	0.755	0.561	0.511
3	0.693	0.542	0.582
4	0.756	0.575	0.595
5	0.742	0.526	0.597
6	0.781	0.513	0.614
7	0.724	0.502	0.601
8	0.748	0.551	0.625
9	0.765	0.584	0.642
10	0.782	0.567	0.616

According to the results in Table 1, this paper predicts the demand for health resources based on improved machine learning, with an accuracy of 0.744, which is 0.193 and 0.153 higher than the analysis methods based on GM (1,1) grey prediction model and ARIMA model. Therefore, the data prediction effect of this method is good, and it can effectively evaluate the demand for health care resources. The number of health institutions, licensed (Assistant) doctors, registered nurses and beds were analyzed by using the prediction results of improved machine learning.

6.3 Analysis of Resource Allocation Balance

The equilibrium of health resource allocation was analyzed from two aspects: Gini coefficient and global Moran index. The Gini coefficient of health resources is calculated according to population distribution and regional area distribution, and the results are shown in Table 2 and Table 3.

Table 2. Gini coefficient of health resources by population distribution

Particular year	Health institutions	Practicing (Assistant) doctor	Registered nurse	Bed
2012	0.2920	0.1832	0.2051	0.1788
2013	0.2762	0.1915	0.1934	0.1550
2014	0.2878	0.1858	0.1862	0.1632
2015	0.2853	0.1627	0.1825	0.1563
2016	0.2745	0.1546	0.1707	0.1449
2017	0.2686	0.1783	0.1618	0.1355
2018	0.2631	0.1455	0.1556	0.1256
2019	0.2360	0.1624	0.1585	0.1262
2020	0.2164	0.1567	0.1149	0.1036
2021	0.2412	0.1564	0.1426	0.1154

If the Gini coefficient is less than 0.2, it means that the degree of unfairness is very low, and the height in the region is average; If the value is 0.2–0.29, it means that the degree of unfairness is low and the region is relatively average; If the value is 0.3–0.39, it means that the degree of unfairness is moderate and the region is relatively reasonable; If the value is 0.4–0.59, it means that the degree of unfairness is high and the regional gap is large; If the value is above 0.6, it means that the degree of unfairness is very high, and the gap within the region is wide. According to the results in Table 2, from 2012 to 2021, the average Gini coefficients of health institutions, licensed (Assistant) doctors, registered nurses and beds were 0.2641, 0.1677, 0.1671 and 0.1405 respectively. The Gini coefficient of health institutions does not exceed 0.29, indicating that the imbalance of resource allocation is low; The Gini coefficient of the number of licensed (Assistant) doctors, registered nurses and beds is less than 0.2, and its resource allocation has a very low imbalance and is in a fair state. When the health resources are distributed according to the population, the Gini coefficient shows a downward trend with the increase of years, indicating that the balance is improving, and the allocation of health resources is becoming more and more equitable.

According to the results in Table 3, when medical and health resources are distributed by regional area, the average Gini coefficients of health institutions, licensed (Assistant) doctors, registered nurses and beds during 2012–2021 are 0.3792, 0.3344, 0.3090 and 0.2998 respectively. The number of health institutions, licensed (Assistant) doctors and registered nurses is between 0.3–0.39, indicating that the imbalance of the above three

Table 3. Gini coefficient of health resources distribution by regional area

Particular year	Health institutions	Practicing (Assistant) doctor	Registered nurse	Bed
2012	0.4133	0.3651	0.3425	0.3292
2013	0.4026	0.3586	0.3215	0.3145
2014	0.3895	0.3548	0.3288	0.3025
2015	0.3974	0.3434	0.3146	0.3186
2016	0.3826	0.3359	0.3143	0.3058
2017	0.3768	0.3285	0.3058	0.2954
2018	0.3648	0.3215	0.3072	0.2835
2019	0.3615	0.3176	0.2964	0.2902
2020	0.3521	0.3167	0.2837	0.2811
2021	0.3516	0.3023	0.2751	0.2772

medical resources is moderate, relatively reasonable in the region, and generally fair. The Gini coefficient of the number of beds is less than 0.3, indicating that the imbalance of resource allocation is low, which shows a relatively fair state. With the change of time, the Gini coefficient of the distribution of health resources by regional area shows a downward trend, indicating that the balance of resource allocation is improving year by year. Compared with the Gini coefficient of population distribution, the resource allocation balance of geographical distribution is relatively poor. There are certain differences between the two, which is relatively unfair. The global Moran index of various health care resources is calculated according to the population distribution, and the results are shown in Table 4.

Table 4. Global Moran index of health resources by population distribution

Particular year	Health institutions	Practicing (Assistant) doctor	Registered nurse	Bed
2012	0.0814	0.1406	0.1863	0.0935
2013	0.0951	0.1512	0.1752	0.0867
2014	0.1135	0.1455	0.1628	0.0854
2015	0.1268	0.1334	0.1586	0.0781
2016	0.1126	0.1268	0.1465	0.0748
2017	0.0953	0.1451	0.1554	0.0925
2018	0.0842	0.1243	0.1377	0.0856
2019	0.0984	0.1372	0.1441	0.0663
2020	0.0827	0.1285	0.1313	0.0792
2021	0.0865	0.1256	0.1292	0.0634

According to the results in Table 4, the global Moran index mean values of the number of health institutions, licensed (Assistant) doctors, registered nurses and beds are 0.0977, 0.1358, 0.1527 and 0.0806 respectively, indicating a high balance of resources. With the growth of time, the overall Moran index shows a downward trend, so the allocation equilibrium is also improving year by year.

In conclusion, the data prediction effect of the method presented in this paper is good, and it can effectively evaluate the demand for health care resources. The balance is improved and the allocation of health resources is more and more fair. Compared with the Gini coefficient of population distribution, the balance of resource allocation of geographical distribution is relatively poor, and there are some differences between the two, showing a more unfair performance. With the increase of time, the global Moreland index decreased, and the allocation balance also improved year by year.

7 Conclusion

At present, the spatial service scope defined by the 3000 m medical service circle used in the planning of medical facilities in China is often difficult to meet the actual medical needs of residents in reality. In order to match the actual medical needs, we need to give priority to policy guidance and further expand the medical service circle. Expand the service scope of various medical service resources, integrate various medical resources and facilities at all levels, and promote the establishment of medical consortia. Based on improved machine learning, this paper proposes an analysis method for the balance of health care resource allocation. This method can accurately predict and evaluate the resource demand, and is helpful to improve the accessibility and balance level of high-quality medical services. In this paper, the supply of medical services only considers the number of licensed (Assistant) doctors and registered nurses, without a comprehensive evaluation of the overall service capacity of the hospital, which can be considered in future research.

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