Research Topics

Multilevel medical security systems and big data in healthcare: trends and developments

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Multilevel medical security systems and big data in healthcare: trends and developments

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Editorial: Multilevel medical security systems and big data in healthcare: trends and developments

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Editorial on the Research Topic
Multilevel medical security systems and big data in healthcare: trends and developments

The medical security system has emerged and gradually developed since the 18th century to alleviate the social problems and contradictions caused by industrialization. However, in the past development of basic medical security, we found that it suffers from a low level of security, insufficient adaptability to resident mobility, and insufficient sustainability, which calls for the development of multilevel medical security systems. The construction of multilevel medical security systems requires the support of a large amount of statistical data. The development of big data makes the collection and analysis of those necessary statistics possible and makes breakthroughs in health economics. For example, The National Health Service (NHS) in the UK constructs an allocation model based on regional differences in population, age structure, economic status, labor cost, morbidity and mortality, and makes corrections and predictions through previous data, to achieve the purpose of allocating medical insurance funds according to needs. In this context, this Research Topic aims to disclose the driving role of big data in establishing multi-level medical security and introduce new relative findings.

The distribution of medical and health resources is an important indicator for measuring the adequacy of medical insurance. Ren et al. studied healthcare resource allocation in all provinces of China from 2010 to 2021 and found the allocation of healthcare resources in China's four major zones has undergone a process of change from "unbalanced quantity to relatively balanced quantity," but high-quality healthcare resources are highly concentrated in the eastern part of the country, and the problem of contradiction between people and doctors is prominent. It is recommended that the Internet plus healthcare technology be used to reshape the regional allocation of high-quality healthcare resources. Yu et al. analyzed the allocation of healthcare resources in Chinese centers for disease control and prevention from the perspective of population and spatial distribution, and to further explore the characteristics and influencing factors of the spatial distribution of healthcare resources.

Establishing a multilevel medical security system needs profound research on people with different characteristics. Dong focused on mobile populations and conducted studies on the impact of basic health insurance participation characteristics on the health of mobile populations and found that health insurance has a positive impact on health, public health services, and health service utilization among the mobile population, and that enrollment in local health insurance and Basic Medical Insurance for Urban Employees is more likely to be associated with higher levels of health and receive healthcare service utilization. Okechukwu et al. focused on female populations and explored the influences of Postpartum Medicaid eligibility extensions to puerperia. They evaluated associations between postpartum care visits and Medicaid insurance type and assessed effect modification by the delivery route and type of residence, and they found that women with pregnancy-related Medicaid insurance were less likely to attend postpartum visits and low-income women who lost their pregnancy-related Medicaid coverage after 60 days in Arizona experienced lower rates of postpartum care utilization. Zhou and Yang focused on poor populations and found medical insurance effectively mitigates household vulnerability to poverty and wealth inequality and made recommendations for government departments to establish health records for residents and to focus on compensating households that are on the cusp of escaping from poverty. Qiu and Zhang found that health shocks significantly increased the proportion of household spending on medical expenses and the effects were more pronounced in low-income households and those with health insurance. These findings offer strong support for the relative administrative department to promote public health, reduce the burden of medical expenses resulting from health shocks, and unlock the consumption potential.

Exploration of the influencing factors of medical and health development is necessary for a multilevel medical security system. Sun and Zhang found that donations have improved the overall medical level while widening the gap in medical security level between urban and rural areas and regions. The anomalous conclusion calls for an extension of donation policies. As the digital economy gets popular in China, Ding et al. conducted research on the impact of the digital economy on the high-quality development of the medical and health industry and found that the development of the digital economy has significantly promoted the high-quality development of the medical and health industry and has a better promotion in eastern and southern regions. Chen et al. explored the impact of regional healthcare development on medical collaborative innovation efficiency in the context of dual circulation strategy and found a significant positive spatial correlation.

It is also very important to discuss how big data can improve the medical security system from a practical perspective. Wang et al. developed a system for online assessment, which can be used to evaluate designated medical institutions in China. This has good implications for medical security system reform in other parts of China and in low and middle-income countries internationally.

In conclusion, the development of a multilevel medical security system is essential to address the limitations of traditional medical security frameworks, particularly in adapting to population mobility and ensuring sustainability. Leveraging big data is key to overcoming these challenges, as it enables the effective collection, analysis, and application of healthcare statistics. This Research Topic highlights significant advances in health economics, regional healthcare resource distribution, and the impact of healthcare policies on various populations. The above studies presented underscore the importance of using digital tools, such as big data and online systems, to enhance healthcare accessibility, efficiency, and equity, ensuring better medical security for diverse populations globally.

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Conflict of interest

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Spatial and temporal analysis of China's healthcare resource allocation measurements based on provincial data: 2010–2021

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Background: With the development of society, industrialization, urbanization, aging, lifestyle and social transformation, environmental degradation, global warming and other factors have had a great impact on the health of the population, and there is an urgent need to take a series of practical actions to promote the improvement of national health. Among them, healthcare resource allocation plays a key role in advancing the level of national health, treatment of chronic diseases, and leisure and healthcare.

Methods: This article collected panel data on healthcare resource allocation in all provinces of China from 2010 to 2021, and comprehensively applied Analytic Hierarchy Process, comprehensive scoring method, regional difference analysis and spatial autocorrelation analysis to reveal regional differences, spatial–temporal patterns and development characteristics of healthcare resource allocation in China.

Results: In terms of regional differences, intra-regional differences in healthcare resource allocation tend to narrow and inter-regional differences tend to widen. In terms of spatial pattern, the western provinces on the left side of the Hu Huanyong line generally have higher scores, while the central and eastern provinces on the right side of the Hu Huanyong line have lower scores, and healthcare resource allocation in the provinces on the left side of the Hu Huanyong line, such as Tibet, Xinjiang, Qinghai, Ningxia, Gansu, Inner Mongolia, Sichuan, have the spatial characteristics of HH clusters in terms of geographic location, while the southeast coastal provinces, such as Zhejiang, Fujian, Guangdong, Hainan, have the spatial characteristics of LL clusters in terms of geographic location. From the quadrant analysis, the 2010–2021 healthcare resource allocation in the first quadrant concentrates most of the provinces in the western and northeastern regions, while the third quadrant concentrates most of the provinces in the eastern region.

Conclusion: The allocation of healthcare resources in China's four major zones has undergone a process of change from "unbalanced quantity to relatively balanced quantity," but high-quality healthcare resources are highly concentrated in the eastern part of the country, and the problem of contradiction between people and doctors is prominent. It is recommended that Internet plus healthcare technology be used to reshape the regional allocation of high-quality healthcare resources.

KEYWORDS

healthcare resource allocation, regional differences, spatial–temporal pattern, spatial autocorrelation, China provinces

1 Introduction

The optimal allocation of healthcare resources is an important guarantee for achieving sustainable economic and social development, and is the key to enjoying basic healthcare services for all, meeting people's health needs, and promoting the construction of a healthy China (1). The level of healthcare resource allocation in a country or region is not only directly related to people's health, but also affects the smooth development of the economy and society (2). In the process of China's economic development from high-speed growth to high-quality development, the contradiction between the people's growing health needs and the imbalance and insufficiency of healthcare resource allocation remains prominent. Reasonable resource allocation can better meet the healthcare service needs of different groups of people, improve people's quality of life and health, reduce the gap in healthcare resource allocation between regions, between urban and rural areas, and between the rich and the poor, and realize the equity of healthcare resource allocation, which will in turn improve the stability and sustainability of the healthcare resource allocation system. From the perspective of geographic space, healthcare spatial distribution profoundly affects the health level and quality of life of residents in different regions, and is a problem of resource spatial allocation. Currently, academics mainly discuss healthcare resource allocation from two aspects.

First, healthcare resource allocation equity and efficiency research. Equity and efficiency have been important issues in healthcare resource allocation (3), and there is a value-oriented game (4). Academics have discussed the issue of healthcare resource equity and efficiency from several aspects of spatial equity, differential allocation, and measurement methods. First, spatial equity. The efficiency of resource allocation should take into account the interests of different groups and spatially balance efficiency and equity. Spatial equity-oriented healthcare resource allocation optimization can be achieved through the maximum accessibility parity model (5), and researchers have conducted healthcare resource allocation equity and efficiency studies from a spatial perspective in China (6, 7), the United States (8), Russia (9), and Thailand (10), respectively. The second is differential allocation. The prerequisite for effective healthcare resource allocation is differential allocation, so as to achieve equal rights, equal opportunities, procedural equality and fairness of results (11). Effective healthcare resource allocation is oriented to regional demand, providing differentiated supply and strengthening inter-regional exchanges so as to maximize efficiency (12). Third, the measurement method. Scholars use the Gini coefficient and the DEA-Malmquist index to comprehensively measure and characterize the efficiency and equity of spatial allocation of healthcare resources in China's provincial healthcare resource allocation, the county-level healthcare resource allocation in Hubei province (13), and the Xinjiang region (14), respectively, and explore their influencing factors. Using the concentration index, Theil index and comprehensive evaluation method, we analyze the equity of healthcare resource allocation at the grassroots level (15), the balance of spatial allocation of healthcare resources at each level and the changing status of healthcare resources in Shanghai, China, from 2012 to 2021 (16). Radial super-efficiency model and Kernel density estimation were used to analyze the trajectory of healthcare allocation efficiency changes (17) and dynamic evolution (18) in China.

Second, the study of regional differences in healthcare resource allocation and spatial distribution. The researchers studied regional differences in healthcare resource allocation from three spatial scales: the urban cluster perspective, the provincial perspective, and the municipal perspective. The first is the provincial scale. China's provincial healthcare resource allocation shows a rapid development trend. Quantitatively, the number of healthcare resources in China has increased, but the overall effective allocation has not been realized (19). In terms of regional differences, there are differences in the efficiency of healthcare resource allocation in different provinces, with the highest efficiency in the eastern region compared to the western region, followed by the central region. Healthcare resource allocation is uneven, but has shown a fluctuating and narrowing trend in recent years (20). In terms of measurement indicators, the number of primary healthcare institutions, the number of beds in primary healthcare institutions, and the number of primary healthcare personnel (21) are generally used to analyze the three dimensions. The second is city cluster scale. Healthcare resource allocation ownership decreases with decreasing city cluster level, and the difference in healthcare resource allocation increases with decreasing city cluster level (22). The spatial correlation of healthcare resource allocation in urban agglomerations and its convergence characteristics were measured by three dimensions of healthcare resource allocation supply, demand and efficiency (23). The study shows that the quality resources in the Yangtze River Delta, Beijing-Tianjin-Hebei, and the middle reaches of the Yangtze River urban agglomerations are higher than their average levels. The third is city scale. Scholars have analyzed the spatial pattern of healthcare resource allocation, influencing factors and its network evolution characteristics in Beijing (24), Wuhan (25), Zhengzhou (26), and Chongqing (27), respectively. A comparative study of the spatial distribution of healthcare resources between Beijing and London, Paris, New York and New Delhi is conducted through the dimensions of "proportion of healthcare land area in urban area" and "*per capita* area of healthcare land," and it is found that the center of the region has a high concentration of healthcare resources, which is the most important factor for the development of healthcare resources. The study found that the concentration of healthcare resources in urban areas is obvious, and the spatial distribution of resource allocation varies greatly, so the optimization of spatial distribution can be achieved by strengthening the management of control regulations, innovating healthcare models, coordinating the development of the region (28), and reinforcing the power of grassroots healthcare (29, 30).

In summary, the above studies provide an open idea for healthcare resource allocation measurement, but there are some areas that deserve further exploration. Healthcare resource allocation involves the dual considerations of equity and efficiency, but the two are often in conflict. As healthcare resources are always limited (doctors, hospitals, drugs, etc.), their benefits to different populations need to be weighed when resources are allocated. Different populations and regions have different needs for healthcare resource allocation, which also leads to the possibility of sacrificing efficiency while pursuing equity. In a remote rural area and a large city, the same investment in healthcare resource allocation may result in different health outcomes. Rural areas may require more resources to achieve the same health outcomes as urban areas due to poor infrastructure and low levels of education. Studies have been conducted to strengthen the measurement of equity and efficiency of healthcare resource allocation and to analyze healthcare resource allocation from the perspective of regional differences. In recent years, China has increased the investment and spatial allocation of healthcare resources in each region, but existing studies have not sufficiently analyzed the developmental characteristics of healthcare resource allocation in different regions, and have not sufficiently explored the regionality and regularity of healthcare resource allocation at the national level. Based on this, we will construct the panel data of healthcare resource allocation by province from 2010 to 2021, and comprehensively use the AHP method, comprehensive scoring method, Theil index, and Moran's I index to measure the regional differences, spatial–temporal characteristics, and spatial–temporal pattern of healthcare resource allocation in each province, in order to promote the optimal allocation of healthcare resources in China. Healthcare resource allocation, and provide empirical evidence for promoting the optimal allocation of healthcare resources in China.

2 Data and methods

2.1 Research methods

2.1.1 Analytic hierarchy process

In 1970, Saaty proposed Analytic Hierarchy Process (AHP), which is a systematic and hierarchical method of analysis that combines qualitative and quantitative. AHP method divides the evaluation objectives into an objective level (A), a criterion level (B), and a program level (C). By comparing two by two, the weight of each criterion on the objectives w_i be determined, which is characterized by subjective assignment.

AHP usually uses a 1–9 scale to judge the relative importance of each indicator in the system being evaluated, thus creating a judgment matrix. Let the evaluation element be $X = \{x_1, x_2, \ldots, x_i, \ldots, x_n\}$, x_{ij} denotes the result of the comparison of the importance of xi relative to x_j, and the 1–9 scale is used. Based on the meaning of the x_{ij} value scale, the Delphi method, that's taking the average scoring of experts, is used to compare the elements of the assessment element set X two by two, so as to obtain the judgment matrix P. The judgment matrix satisfies (31):

$$\mathrm{P} = \mathrm{X}_{\mathrm{n}\times\mathrm{n}} \tag{1}$$

The judgment matrix $\mathrm{X}_{\mathrm{n}\times\mathrm{n}}$ has $x_{ij} = 1/x_{ji}$. The eigenvector $\mathrm{M}_{\mathrm{n}\times 1}$ corresponding to the maximum eigenvalue λ_{max} is measured using the equation $\mathrm{PM} = \lambda_{max}$, and the weights w_i of each evaluation index are obtained using the normalized eigenvector M, which can be measured using the sum-product method.

In order to judge the scientific of the obtained weights, it is necessary to introduce the consistency indicator CI to test the consistency of the judgment matrix.

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{2}$$

The greater the value of consistency CI, the greater the degree of deviation of the judgment matrix from full consistency, the smaller the value of CI, the better the consistency of the matrix, when CI takes the value of 0, it indicates that the matrix has full consistency.

In order to test whether the judgment matrix has satisfactory consistency, it is necessary to define the test coefficient CR.

$$CR = \frac{CI}{RI} \tag{3}$$

If $CR < 0.1$, it means that the judgment matrix passes the consistency test, and vice versa, the judgment matrix needs to be adjusted until it passes the consistency test, where RI (Random Index) is the Random Consistency Indicator, and the RI can be obtained from the average Random Consistency Indicator lookup table.

2.1.2 Composite score method

The study used the composite score method to measure healthcare resource allocation in each province of China. The composite score of healthcare resource allocation was composed of Healthcare Facilities, Healthcare Personnel, and Healthcare Beds secondary indicators, and the secondary indicators were composed of nine tertiary indicators. Due to the differences in the magnitude of the raw data, the indicators were processed with data dimensionless by drawing on existing studies (32). The formula for measuring the composite score is as follows:

$$\begin{cases} d_{ij} = \dfrac{x_{ij} - x_{ij\min}}{x_{ij\max} - x_{ij\min}} (\text{Positive Indicator}) \\ d_{ij} = \dfrac{x_{ij\max} - x_{ij}}{x_{ij\max} - x_{ij\min}} (\text{Negative Indicator}) \end{cases} \tag{4}$$

$$\begin{gathered} Z = Z_{HF} + Z_{HP} + Z_{HB} \\ \sum_{n=1}^{h} w_i d_{ij} = \sum_{n=1}^{h_{HF}} w_i d_{HF_{ij}} + \sum_{n=1}^{h_{HP}} w_i d_{HP_{ij}} + \sum_{n=1}^{h_{HB}} w_i d_{HB_{ij}} \end{gathered} \tag{5}$$

In the above equation, Z is the comprehensive score of healthcare resource allocation, Z_{HF}, Z_{HP} and Z_{HB} are the scores of secondary indicators of Healthcare Facilities, Healthcare Personnel and Healthcare Beds, respectively, and x_{ij} denotes the raw data of healthcare resource allocation indicators. $x_{ij\min}$ and $x_{ij\max}$ denote the minimum and maximum values of the original data, respectively. Dij denotes the composite score of healthcare resource allocation after dimensionless processing, and w_i is the weight measured by AHP method.

2.1.3 Theil index

The Theil index examines inequality and variability from the concepts of informativeness and entropy, it decomposes the overall variability into variability between parts and variability within parts, and has a wide range of applications for analyzing and decomposing variability. The composite entropy index examines the variability between individuals from the concepts of informativeness and entropy, and it is the expected value of informativeness, i.e., the amount of expected information. The closer the relationship between individuals, the smaller the combined entropy index (33, 34).

$$GE = \begin{cases} \sum_{i=1}^{n} p_i \left[(y_i / u)^c - 1 \right], c \neq 0,1 \\ \sum_{i=1}^{n} p_i (y_i / u) \lg(y_i / u), c = 1 \\ \sum_{i=1}^{n} p_i \lg(y_i / u), c = 0 \end{cases} \tag{6}$$

In the above equation, the parameter c is used to determine the sensitivity of the index change. In general, it determines the sensitivity of the exponential change when $c < 2$. When $c = 0, 1$, it is well known as Theil index.

Due to its property of dividing the overall variation into within-zone and between-zone variation, Theil index is widely used in empirical studies of overall spatial heterogeneity as well as spatial heterogeneity, and is calculated by the formula:

$$\text{Theil} = \sum_{i=1}^{n} T_i \ln(nT_i) = T_{WR} + T_{BR} \tag{7}$$

The Theil index can be further decomposed into intra-zonal and inter-zonal differences if the area under study is divided into groups according to a certain methodology.

$$T_{WR} = \sum_{i=1}^{n_{db}} T_i \ln\left(n_{db} \frac{T_i}{T_{db}}\right) + \sum_{i=1}^{n_d} T_i \ln\left(n_d \frac{T_i}{T_d}\right) + \sum_{i=1}^{n_z} T_i \ln\left(n_z \frac{T_i}{T_z}\right) + \sum_{i=1}^{n_x} T_i \ln\left(n_x \frac{T_i}{T_x}\right) \tag{8}$$

$$T_{BR} = T_{db} \ln\left(T_{db} \frac{n}{n_{db}}\right) + T_d \ln\left(T_d \frac{n}{n_d}\right) + T_z \ln\left(T_z \frac{n}{n_z}\right) + T_x \ln\left(T_x \frac{n}{n_x}\right) \tag{9}$$

In the above equations, Theil denotes Theil index; n is the number of provincial units within the sample region; T_{WR} is the difference within the four regional zones of the Northeast, East, Central, and West; T_{BR} is the difference between the four regional zones. n_{db}, n_d, n_z, and n_x are the number of provincial units within the Northeast, East, Central, and West regions, respectively; T_i is the ratio of the measured indicators within the region to the national average ratio T_{db}, T_d, T_z, T_x are the ratio of measured indicators to the national average in the Northeast, East, Central, and West regions, respectively.

The study covers 31 provinces, municipalities directly under the central government, autonomous regions and other provincial administrative units (Hong Kong SAR, Macao SAR and Taiwan Province are not included in the evaluation for the time being due to missing data). The four major zones measured in the article are: the northeastern region, which includes 3 provincial administrative units, namely Liaoning, Jilin and Heilongjiang; and the eastern region, which includes 10 provincial administrative units, namely Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Shandong, Fujian, Guangdong and Hainan. The central region includes 6 provincial administrative units, including Shanxi, Henan, Anhui, Hubei, Hunan and Jiangxi; the western region includes 12 provincial administrative units, including Inner Mongolia, Chongqing, Sichuan, Guangxi, Guizhou, Yunnan, Shaanxi, Gansu, Ningxia, Tibet, Qinghai and Xinjiang.

2.1.4 Spatial autocorrelation analysis

Spatial autocorrelation is the degree of correlation between a certain geographic phenomenon or attribute value on a regional unit and the same phenomenon or attribute value on a neighboring geographic unit (35), and is divided into global spatial autocorrelation and local spatial autocorrelation. Global spatial autocorrelation is mainly measured by Moran's I index, and its calculation formula is as follows:

$$I = \left(\frac{n}{\sum_i \sum_j W_{ij}} \right) \left(\frac{\sum_i \sum_j W_{ij} (x_i - \bar{x})(y_i - \bar{y})}{\sum_i (x_i - \bar{x})^2} \right) \tag{10}$$

Where: W_{ij} is the spatial matrix; n is the number of regional cells, x_i is the observation of the i^{th} cell; and$\bar{x}$is the mean value of the observation. The expected value of Moran's I index is:

$$E(I) = -1/(n-1) \tag{11}$$

Under the premise of passing the test of significance, a positive Moran's I index indicates that regions with higher composite scores of healthcare resource allocation show significant spatial clustering; a positive Moran's I index indicates that regions with their neighboring regions have significant spatial differences in their composite scores of healthcare resource allocation. Scores have significant spatial differences.

Local spatial autocorrelation is used to reveal the heterogeneous characteristics of geospatial differences to comprehensively reflect the trend of regional differences in the composite score of healthcare resource allocation in each province, and is usually measured by the Local Moran's I index. The degree of spatial difference between an attribute value and its neighboring regions and the significance of the difference. For spatial unit *i*, its Local Moran's I is defined as:

$$I_i = z_i \sum_i W_{ij} z_j \tag{12}$$

Where: z_i and z_j are standardized values of observations on district *i* and district *j*; W_{ij} is the spatial weight. The local spatial autocorrelation reflects the clustering characteristics of the district healthcare resourcing composite score through the LISA clustering map.

2.2 Evaluation indicators and weights

The AHP method was used to measure the weights of secondary and tertiary indicators (Table 1).

Firstly, the expert scoring of the secondary and tertiary indicators is done through the Delphi method. Secondly, the average score was obtained and the importance of the indicators was ranked to establish a judgment matrix. Thirdly, the sum and product method is used to measure the weights and verify the consistency of the judgment matrix.

TABLE 1 Weights established by analytic hierarchical analysis.

Secondary indicators	Weights of secondary indicators	Tertiary indicators	Weights of tertiary indicators
Healthcare facilities	0.3324	Number of hospitals per 10,000 people	0.1100
		Number of primary health-care institutions per 10,000 persons	0.1145
		Number of specialized public health institutions per 10,000 people	0.1079
Healthcare Personnel	0.3596	Ratio of health technicians to urban/rural	0.1114
		Number of practicing (assistant) physicians per 10,000 persons	0.1284
		Registered nurses per 10,000 population	0.1198
Healthcare Beds	0.3080	Number of hospital beds per 10,000 people	0.1050
		Number of beds in primary health-care institutions for 10,000 persons	0.0993
		Number of beds in specialized public health institutions per 10,000 people	0.1037

The judgment matrix for the secondary indicators was constructed as follows:

$$B = \begin{vmatrix} 1 & 0.9500 & 1.0500 \\ 1.0526 & 1 & 1.2000 \\ 0.9524 & 0.8333 & 1 \end{vmatrix}$$

Derive the judgment matrix weights:

$$w = \begin{vmatrix} 0.3324 & 0.3596 & 0.3080 \end{vmatrix}$$

Consistency tests were performed on the judgment matrix:

$$\lambda_{\max} = 3.000752$$

$$CI = \frac{\lambda_{\max} - n}{n-1} = \frac{3.000752 - 3}{3-1} = 0.000376$$

$$CR = \frac{CI}{RI} = \frac{0.00376}{0.58} = 0.000648 < 0.1$$

The judgment matrix passes the consistency test.

Similarly, the judgment matrices of the three levels of indicators were constructed separately, the judgment matrix weights were derived, and the consistency test was conducted.

2.3 Data sources

We fully consider the accessibility and continuity of the data sources of healthcare resource allocation by province, and all the nine three-level indicators of healthcare resource allocation are derived from the China Statistical Yearbook 2001–2022 compiled by the National Bureau of Statistics and published by China Statistical Publishing House, which corresponds to the panel data of the indicators of medical care, doctors, and beds of 31 provincial administrative units nationwide in the period of 2000–2021.

3 Results and analyzes

3.1 Analysis of regional differences in healthcare resource allocation

From 2010 to 2021, the composite score of healthcare resource allocation in the four major zones generally shows a fluctuating trend of growth, which is reflected in the composite score going through the process of "rising-declining-rising-declining." The average score of the four major zones increased from 0.3586 in 2010 to 0.3961 in 2013, then decreased to 0.3729 in 2015, then increased to 0.4179 in 2019, and then decreased to 0.3879 in 2021, with an average score increase of 8.17 percentage points from 2010 to 2021, indicating that healthcare resource allocation in the four major zones has increased to some extent. During the study period, the comprehensive score of healthcare resource allocation in the east, middle and west has obvious gradient characteristics. 2010–2018, the western region's comprehensive score of healthcare resource allocation was ahead of the other three regions, showing a spatial and temporal pattern of "western region > northeastern region > central region > eastern region." From 2019 to 2021, the Northeast region was ahead of the other three regions, showing a spatial and temporal pattern of "Northeast region > Western region > Central region > Eastern region" (Figure 1).

In terms of regional variation coefficients, the total variation in the composite score of healthcare resource allocation shows a narrowing trend, in which the intra-zone variation tends to narrow and the inter-zone variation tends to widen (Table 2). Theil index consists of the total variation, intra-zone variation, and inter-zone variation, which is equal to the sum of intra-zone and inter-zone variation, and is divided into the northeastern intra-zone, the eastern intra-zone, the central intra-zone, and the western intra-zone variations. The total variation was equal to the sum of intra- and inter-zonal variation, and intra-zonal variation was divided into northeastern intra-zonal variation, eastern intra-zonal variation, central intra-zonal variation, and western intra-zonal variation. The Theil index of the total difference in the composite score decreases from 0.0326 in 2010 to 0.0263 in 2021, a decrease of 19.45%. In terms of intra-zone differences, the Theil index decreases from 0.0296 in 2010 to 0.0165 in 2021, with a decrease of 44.20%, of which the changes in the Theil index of the differences within the Northeast region, the differences within the East region,

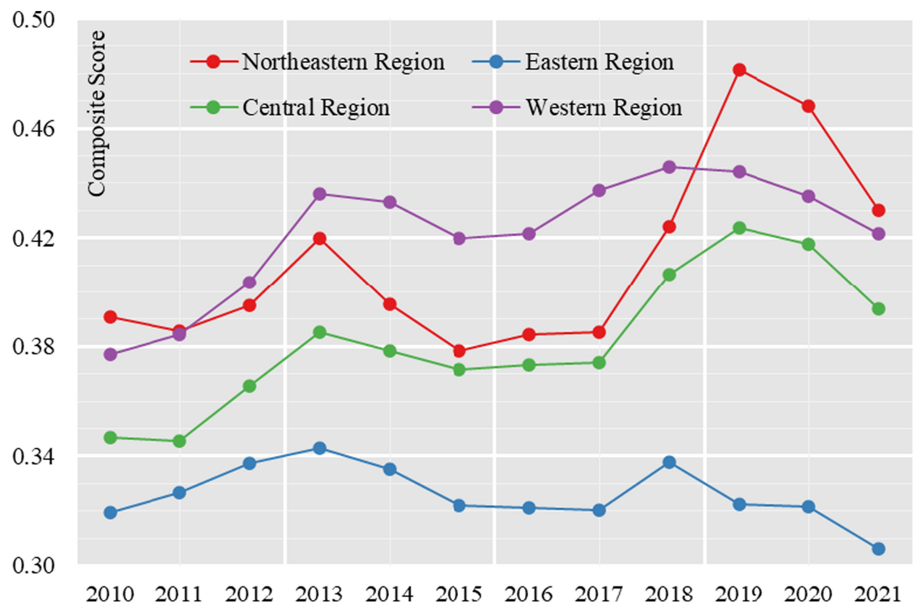

FIGURE 1
Healthcare resource allocation composite score of China (2010–2021).

TABLE 2 Theil index decomposition of healthcare resources allocation in China (2010–2021).

Year	T_{db}	T_d	T_z	T_x	T_{WR}	T_{BR}	T
2010	0.0002	0.0080	0.0075	0.0139	0.0296	0.0030	0.0326
2011	0.0003	0.0070	0.0049	0.0124	0.0246	0.0027	0.0273
2012	0.0003	0.0056	0.0039	0.0091	0.0189	0.0030	0.0218
2013	0.0002	0.0070	0.0032	0.0072	0.0176	0.0052	0.0228
2014	0.0006	0.0065	0.0043	0.0056	0.0170	0.0057	0.0227
2015	0.0005	0.0064	0.0055	0.0064	0.0187	0.0060	0.0248
2016	0.0003	0.0069	0.0060	0.0049	0.0181	0.0064	0.0245
2017	0.0010	0.0077	0.0051	0.0045	0.0183	0.0084	0.0267
2018	0.0003	0.0091	0.0055	0.0025	0.0173	0.0067	0.0241
2019	0.0004	0.0071	0.0048	0.0029	0.0152	0.0108	0.0261
2020	0.0001	0.0074	0.0025	0.0017	0.0118	0.0096	0.0214
2021	0.0002	0.0094	0.0018	0.0051	0.0165	0.0097	0.0263

the differences within the Central region, and the differences within the West region are −0.55, −17.48%, 75.81%, and 63.46 per cent. In terms of inter-zone variation, the Theil index increases from 0.0030 in 2010 to 0.0097 in 2021, a 2.29-fold increase.

In terms of the contribution rate of regional difference coefficients, the contribution rate of intra-zone differences shows a decreasing trend during the study period, from 90.93 per cent in 2010 to 62.99 per cent in 2021 (Figure 2). The contribution rate of inter-zone differences shows an increasing trend, from 9.07% in 2010 to 37.01% in 2021, which indicates that the differences between the four major zones tend to expand, while the differences within the zones tend to decrease. The contribution rates of intra-zone differences among the four major regions, in descending order, are: Eastern region > Western region > Central region > Northeastern region. The contribution rate of intra-zone differences in the eastern region rises rapidly from 24.66% in 2010 to 35.96% in 2021, indicating that healthcare resource allocation tends to cluster in the eastern region; the contribution rate of intra-zone differences in the western region falls rapidly from 42.73% in 2010 to 19.38% in 2021, indicating that the western region tends to flatten the change in healthcare resource allocation. The contribution rate of difference within the western region drops rapidly from 42.73% in 2010 to 19.38% in 2021, indicating a clear trend of flattening of resource allocation in the western region. The contribution rate of intra-zone variance in the Central Region also shows a rapid decline, with the contribution rate of intra-zone variance in the Central Region rapidly declining from 22.94% in 2010 to 6.89% in 2021, indicating that the trend of flattening the allocation of healthcare resources in the Central Region is also obvious. The Northeast region has the lowest intra-zone variance contribution (only 0.76 per cent) and the variation over the study period is very small.

Characterizations of changes in regional differences in healthcare allocation:

First, the trend of regional healthcare resource allocation and inputs increasing at different speeds is obvious. Since 2012, the Chinese government has continuously improved the new mechanism for the operation of grassroots healthcare organizations, pushed forward the reform of public hospitals and a series of other efforts, greatly promoting the development of the healthcare cause, and putting forward the institutional framework of healthcare with Chinese characteristics in the form of a public healthcare service system, a healthcare service system, a healthcare guarantee system, and a drug supply and guarantee system. The institutional framework of healthcare with Chinese characteristics, and promoting the process of equalizing the spatial allocation of healthcare resources, thereby significantly increasing the number of hospitals in the northeast, east, central and west regions from 2,306, 7,303, 4,982 and 6,327,

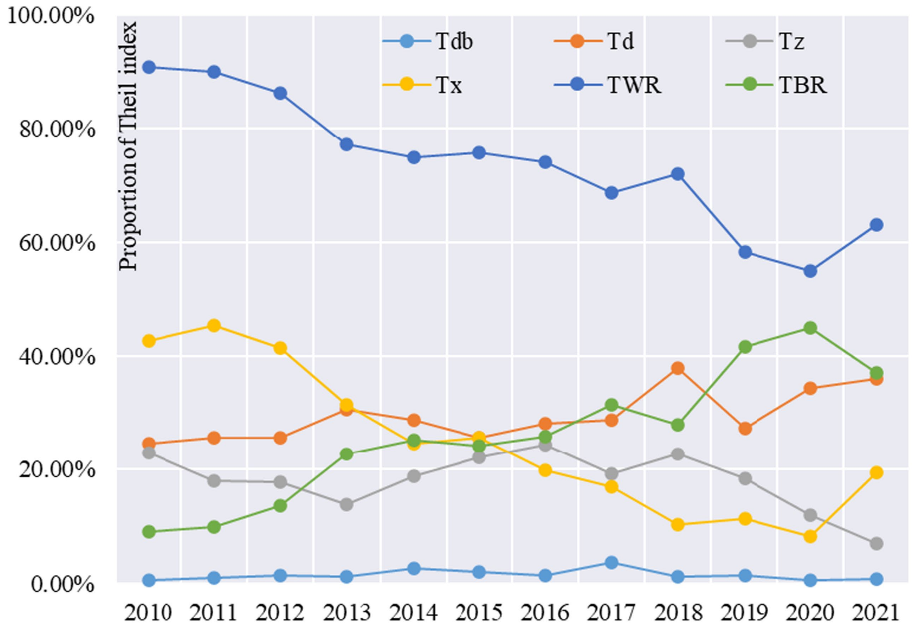

FIGURE 2
Contribution of Theil index to healthcare resource allocation in China (2010–2021).

respectively, in 2010 to 3,456, 12,808 and 9,042, respectively, 11,309, an increase of 1,150, 5,505, 4,060 and 4,982, respectively.

Second, the number of regional healthcare resource allocation tends to be balanced. The rise in the overall score of healthcare resource allocation in the western region has narrowed the difference in the quantity of healthcare resource allocation between the eastern and western regions, indicating that during the period under study, the allocation of healthcare resources in China's four major zones went through the process of "unbalanced quantity - relatively balanced quantity," which reflects that the level of equalization of public services in healthcare resources in the four major zones is constantly taking a new step forward.

Third, there are obvious differences in the quality of regional healthcare resource allocation. Due to historical reasons, differences in the level of economic development and other reasons, regional differences in the allocation of high-quality healthcare resources in the east, center and west still exist and are large, with the eastern region having 1,810,879 practicing (assistant) doctors in 2021, which is 5.73, 1.71 and 1.64 times that of the northeastern, central and western regions, respectively. In this regard, in 2020, the Chinese government issued the Opinions on Deepening the Reform of the Medical Security System, which aims to provide opinions on deepening the reform of the healthcare security system in order to comprehensively establish a healthcare security system with Chinese characteristics, and endeavor to solve the problem of imbalance and insufficiency in the development of medical security. Healthcare insurance is a major institutional arrangement that reduces the burden of medical treatment on the public, enhances people's well-being, and maintains social harmony and stability; by 2030, China will have fully established a medical insurance system with basic medical insurance as the mainstay, medical assistance as the backbone, and supplemental medical insurance, commercial health insurance, charitable donations, and medical mutual aid as co-development.

3.2 Spatial pattern of healthcare resource allocation

Using AHP and comprehensive score method to measure the comprehensive score of healthcare resource allocation and the score of secondary indicators of 31 provincial administrative units across the country in 2010, 2015, 2018 and 2021, and visualize them through GIS to reveal their spatial–temporal pattern and spatial differentiation law.

First, the spatial pattern of healthcare resource allocation composite scores by province was analyzed. The study found that the healthcare resource allocation composite scores of Chinese provinces are distributed along both sides of the Hu Huanyong line (the Heihe-Tengchong line, east of which more than 90% of China's population is concentrated, is the Hu Huanyong line). Provinces to the left of the Hu Huanyong line generally have higher healthcare resource allocation composite scores, while provinces to the right of the Hu Huanyong line have lower healthcare resource allocation composite scores (Figure 3). Among the top 25% of provinces ranked by the composite score, the Northeast region slipped from 2 to 1 province, the Eastern region had only 1 provincial administrative unit, the Central region rose from 1 to 2 provinces, and the Western region experienced a rise from 4 to 6 provinces and then slipped to 4 provinces. Among the bottom 25% of provinces in terms of overall score, the eastern region rises from 5 to 6 provinces, the central region varies between 1 and 2 provinces, and the western region declines from 2 to 1. In 2010, the top 5 provinces were Tibet, Xinjiang, Shanxi, Beijing, and Heilongjiang, and the bottom 5 provinces were Jiangsu, Anhui, Chongqing, Guangdong, and Fujian, in that order. 2021, the top 5 provinces are Tibet, Qinghai, and Fujian, in that order. In 2021, the top 5 provinces are Tibet, Qinghai, Gansu, Inner Mongolia and Heilongjiang, and the bottom 5 provinces are Guangdong, Tianjin, Fujian, Shanghai and Zhejiang (Table 3).

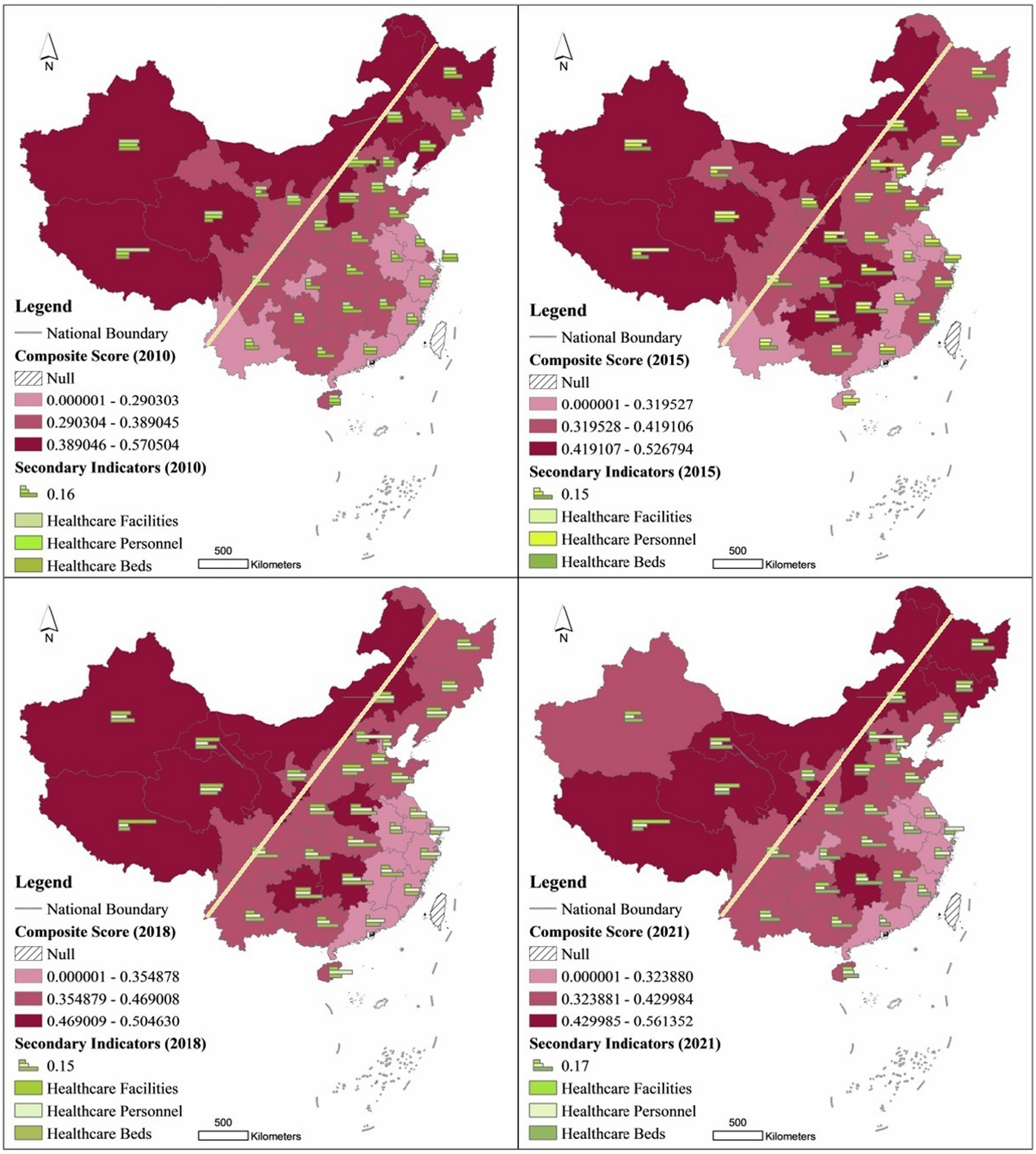

FIGURE 3
Spatial pattern of healthcare allocation scores by province in China.

Second, the spatial pattern of healthcare resource allocation secondary indicator scores by province is analyzed. In terms of Healthcare Personnel's secondary indicator scores, the top 5 provinces in 2010 were Beijing, Xinjiang, Qinghai, Shanxi, and Liaoning, and the bottom 5 provinces were Chongqing, Gansu, Anhui, Jiangxi, and Guangxi, in that order. In 2021, the top 5 provinces were Beijing, Shanghai, Shanxi, Inner Mongolia, and Zhejiang, and the bottom 5 provinces were Guangdong, Chongqing, Jiangxi, Fujian, and Guizhou, in that order. In terms of the Healthcare Facilities secondary indicator scores, the top 5 provinces in 2010 were Tibet, Shanxi, Xinjiang, Qinghai, and Inner Mongolia, and the bottom 5 provinces were Shanghai, Guangdong, Anhui, Jiangsu, and Hubei, in that order. The top 5 provinces in 2021 were Tibet, Qinghai, Shanxi, Gansu, and Inner Mongolia, and the bottom 5 provinces were Zhejiang, in that order, Jiangsu, Anhui, Guangdong and Shanghai. In terms of the Healthcare Beds secondary indicator scores, the top five provinces in 2010 were Xinjiang, Shandong, Shanxi, Hunan, and Heilongjiang, and the bottom five provinces were Fujian, Hainan, Guizhou, Jiangsu, and Qinghai, in that order. In 2021, the top five provinces were Hunan, Hubei, Guizhou, Jiangxi, and Sichuan, and the bottom five provinces were Tibet, Guangdong, Shanghai, Beijing, and Tianjin, in that order. The next five provinces were Tibet, Guangdong, Shanghai, Beijing, and Tianjin.

Characterizations of the evolution of the spatial pattern of healthcare resource allocation in each province:

First, the number of hospitals and the number of hospital beds increased significantly. The number of hospitals in the northeastern,

TABLE 3 Ranking of healthcare resource allocation composite scores by province in China.

Year	Sorting	Northeastern Region	Eastern Region	Central Region	Western Region
2010	Top25%	2	1	1	4
	Middle50%	1	4	4	6
	Bottom25%	0	5	1	2
2015	Top25%	0	1	1	6
	Middle50%	3	4	3	5
	Bottom25%	0	5	2	1
2018	Top25%	0	1	1	6
	Middle50%	3	3	3	6
	Bottom25%	0	6	2	0
2021	Top25%	1	1	2	4
	Middle50%	2	3	3	7
	Bottom25%	0	6	1	1

eastern, central and western regions increased from 2,306, 7,303, 4,982 and 6,327 in 2010 to 3,456, 12,808, 9,042 and 11,072 in 2021, respectively. The number of hospitals per 10,000 people in the Northeast, East, Central and West regions increased from 0.211, 0.165, 0.153 and 0.206 in 2010 to 0.356, 0.240, 0.259 and 0.321, respectively, in 2021, beds in primary healthcare institutions were 9.471, 7.737, 15.041 and 12.967, respectively.

Second, the comprehensive score of healthcare resource allocation shows a spatial pattern of "west high, east low." The reason for the "west-high-east-low" composite score by province is closely related to population density. Our study focuses on reflecting the level of healthcare resource allocation between regions, and uses the average volume indicator to measure the total resources of hospital facilities in the eastern region may not be inferior to those in the western region, but the western region is sparsely populated and the eastern region has a high population density, which leads to the spatial phenomenon of "west high, east low" in the average volume indicator of the two regions. In 2021, the population density of Tibet Autonomous Region, which ranked first in terms of Healthcare Facilities secondary indicator score, was 2.5 people per square meter, while the population density of Shanghai, which ranked last in terms of Healthcare Facilities secondary indicator score, was 3,900 people per square meter, which is a difference of 1,560 times. In 2010, the number of hospitals per 10,000 people in Tibet was 0.337, and the number of hospitals per 10,000 people in Shanghai was 0.133, with a difference of 2.53 times, while in 2020 the number of hospitals per 10,000 people in the former was 0.489, and the number of hospitals per 10,000 people in the latter was 0.171, and the gap between the two widened to 2.86 times. In 2010, the number of professional public health institutions per 10,000 people in Tibet and Shanghai was 1.140 and 0.592 respectively, and in 2020, the number of beds in professional public health institutions per 10,000 people in Tibet and Shanghai changed to 1.366 and 0.522, respectively. The former's *per capita* amount of healthcare was expanding, while the latter's *per capita* amount of healthcare is growing slowly or even declining, due to the high population density in developed eastern regions such as Shanghai, and the size of the population greatly dilutes healthcare resources in developed regions.

Third, the allocation of high-quality healthcare resources presents a spatial pattern of "high in the east and low in the west." The western region scores higher in healthcare facilities but lower in doctor resources. The opposite is true for the eastern region, which scores lower in terms of hospitals *per capita* and hospital beds *per capita*, but higher in terms of physician resource allocation. 2021 Healthcare Personnel rankings for secondary indicators show that cities such as Beijing and Shanghai are in the top two, while regions such as Chongqing and Xinjiang are at the bottom of the rankings. In addition to the impact of population density on the indicator of the number of doctors per 10,000 people, population migration factors are also playing a huge role. Regions such as Beijing and Shanghai are national center cities with the most advanced healthcare resources in China, bringing together the best doctors in the country. In fact, the concentration of healthcare professionals and technicians is closely related to economic development, with talents tending to concentrate in more developed regions, which also provide healthcare professionals and technicians with considerable salaries, a platform to help the world and the people, and a platform to show their skills, which is in line with the law of migration of talents.

3.3 Spatial and temporal analysis of healthcare resource allocation

Using spatial autocorrelation analysis to test the distribution of high and low concentrations of healthcare resource allocation, we calculated and tested the global Moran's I statistic for the composite scores of healthcare resource allocation in 31 provincial administrative units in China. As shown in Table 4, the global Moran's I statistic of healthcare resource allocation composite score of each province in China from 2010 to 2021 passes the significance test at the 0.01 confidence level, and the global Moran's I statistic is greater than zero, that's the healthcare resource allocation composite score of each province in China is in the global distribution of high and low agglomeration. Resource allocation composite scores in China's provinces have positive spatial correlation at the global level. This suggests that at the national level, provinces with higher healthcare resource allocation composite scores are geographically adjacent to

TABLE 4 Moran's I statistics by Province, China, 2010–2021.

Variables	2010	2015	2018	2021
Moran's I	0.4500**	0.3742**	0.4120**	0.5250**
variance	0.0063	0.0062	0.0062	0.0062
Z-statistic	6.0680	5.1337	5.6293	7.0421

**Moran's I statistic for each year passed the significance test at the 0. 01 significance level.

provinces that also have higher healthcare resource allocation composite scores, and provinces with lower healthcare resource allocation composite scores are geographically adjacent to provinces that also have lower healthcare resource allocation composite scores.

The global Moran's I statistic shows a "decreasing-increasing-increasing" trend over the sample period of 2010–2021. This indicates that, globally, the spatial agglomeration effect of provinces with similar healthcare resource allocation scores shows a development trend of "weakening and then strengthening." From the specific period, there is a significant decline in 2010–2015, with the global Moran's I statistic decreasing from 0.4500 to 0.3742, and then a slow increase from 2015 to 2018, with the Moran's I statistic increasing sharply from 2018–2021 to 0.4120. 0.4120 to 0.5250 sharply.

In order to deeply explore the spatial agglomeration of the composite score of healthcare resource allocation and its spatial–temporal evolution in each province of China, further spatial statistical analyzes of the composite score of healthcare resource allocation in local areas were conducted. Using the local spatial autocorrelation technique, healthcare resource allocation in China was analyzed, and the LISA clustering map of the composite score of healthcare resource allocation was plotted (Figure 4; Table 5).

From the four time-image LISA cluster maps of 2010–2021, HH cluster and LL cluster have obvious pointing characteristics of Hu Huanyong line, the left side of Hu Huanyong line mainly involves 7 western provinces such as Xinjiang, Tibet, Qinghai, Inner Mongolia, Gansu, Ningxia, Sichuan, etc., and the right side of Hu Huanyong line mainly involves 24 regional provinces such as Beijing, Shanghai, Guangdong, Hunan, Hubei, Guangxi, etc. In 2010, there are 13 provinces with significant local spatial autocorrelation analysis, of which 6, 2 and 5 are in the eastern region, central region and western region, respectively. In 2010, the number of provinces with significant local spatial autocorrelation analyzes was 13, of which 6, 2 and 5 were in the eastern, central and western regions, respectively. The provinces in the HH cluster were Xinjiang, Tibet, Inner Mongolia, Ningxia and Hebei, mainly concentrated on the left side of Hu Huanyong line, while the provinces in the LL cluster were Zhejiang, Fujian, Jiangxi, Guangdong, Guangxi and Hainan, all of which were concentrated on the left side of Hu Huanyong line. Guangxi, and Hainan, all of which are concentrated on the right side of the Hu Huanyong line, in addition to Hunan for the HL cluster, and Tianjin for the LH cluster. In 2015, seven provinces passed significant local spatial autocorrelation analyzes, of which four and three were in the eastern and western regions, respectively. The provinces in the HH cluster were Tibet, Sichuan, and Ningxia, all of which were concentrated on the left side of Hu Huanyong line, whereas the provinces in the LL cluster were Zhejiang, Fujian, Guangdong, and Hainan, all of which were concentrated on the right side of Hu Huanyong line. In 2018, the number of provinces whose local spatial autocorrelation analyzes passed as significant was 11, of which the eastern region, the central region, and the western region accounted for 4, 1, and 6, respectively. The provinces in the HH cluster are Tibet, Qinghai, Gansu, Ningxia, and Shaanxi, Sichuan, mainly concentrated on the left side of the Hu Huanyong line, while the provinces in the LL cluster are Zhejiang, Fujian, Guangdong, and Jiangxi, all of which are concentrated on the right side of the Hu Huanyong line, in addition to the province in the HL cluster, Hainan. In 2021, the local spatial autocorrelation analyzes pass the significant provinces, of which the eastern, central, and western regions accounted for 4, 2, and 7, respectively. The provinces in the HH clusters are Xinjiang, Tibet, Qinghai, Sichuan, and Shaanxi, which are mainly concentrated on the left side of the Hu Huanyong line, while the LL clusters are Zhejiang, Fujian, Guangdong, and Hainan, all of which are concentrated on the right side of the Hu Huanyong line, in addition to the HL clusters of Jiangxi, Hunan, and Guangxi, and the LH cluster of provinces is Ningxia.

Overall, the provinces with spatial autocorrelation and passing the significance test undergo changes in spatial patterns over time. The HH cluster provinces that passed the significance test were mainly distributed on the left side of the Hu Huanyong line, indicating that the healthcare resource allocation in the provinces on the left side of the Hu Huanyong line, such as Tibet, Xinjiang, Qinghai, Ningxia, Gansu, Inner Mongolia, Sichuan, geographically had the spatial characteristics of the HH cluster, whereas the LL cluster provinces that passed the significance test were mainly distributed on the right side of the Hu Huanyong line, indicating that the healthcare resource allocation in the southeastern coastal provinces, such as Zhejiang, Fujian, Guangdong, Hainan, geographically had the spatial characteristics of the LL cluster. The local spatial autocorrelation analysis of the healthcare resource allocation composite scores was verified with the above spatial pattern of "high in the west and low in the east" in the healthcare resource allocation composite scores, to reveal the spatial and temporal variations in China's healthcare resource allocation, and to provide empirical evidence for the optimal allocation of China's healthcare resources.

3.4 Quadrant analysis of healthcare resource allocation

Considering the dynamic changes in healthcare resource allocation, we adopt a two-dimensional quadrant analysis method, dividing the healthcare resource allocation of 31 provinces into four quadrants from 2010 to 2021, to reveal the dynamic characteristics of healthcare resource allocation in each province. The origin of the coordinates in the four quadrants is the average of the composite scores of healthcare resource allocation in 2010 and 2021. Quadrant I indicates that healthcare resourcing in a province is above average in both 2010 and 2021 time points; Quadrant II indicates that healthcare resourcing in a province is below average in 2010 but above average in 2021; Quadrant III indicates that healthcare resourcing in a province is below average in both 2010 and 2021 time points; and Quadrant IV indicates that healthcare resourcing in a province is above average in 2010 but below average in 2021.

The spatial differentiation of the composite score of healthcare resource allocation in China's 31 provinces in 2010–2021 is obvious (Figure 5), which is manifested in three aspects: firstly, the number of provincial units that are higher or lower than the mean of the composite score of healthcare resource allocation in the two-time

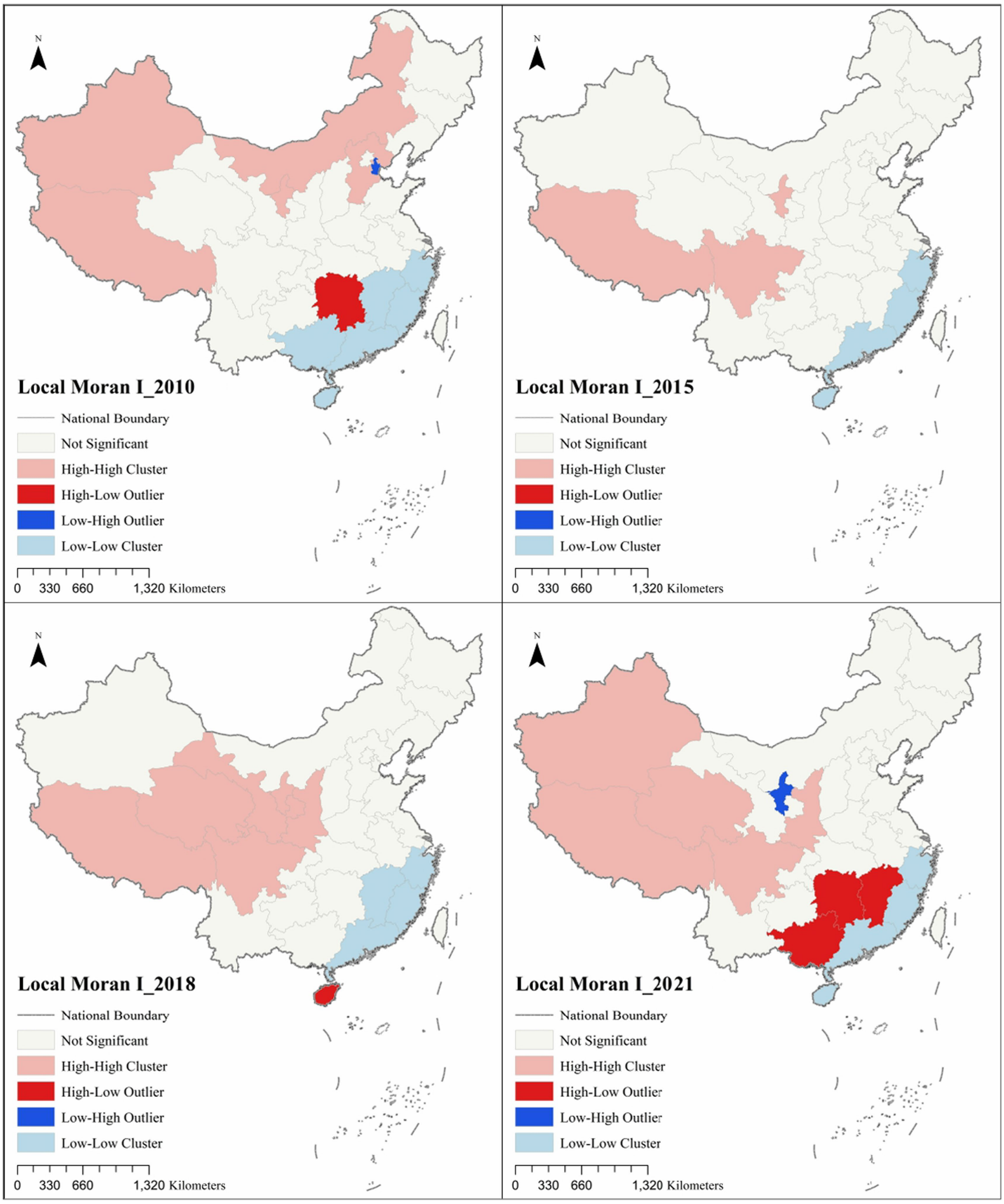

FIGURE 4
Healthcare resource allocation LISA cluster by province, 2000–2021.

nodes of 2010–2021 are 13 (located in the first quadrant) and 11 (located in the third quadrant), respectively, which shows a polarization trend. Secondly, the number of provinces with improved healthcare resourcing composite scores is higher than the number of provinces with declining composite scores, that's provincial cells located in Quadrant II (6) are higher than provincial cells in Quadrant IV (1). Thirdly, the largest number of provinces in the western region (5) are located in the first quadrant, and the largest number of provinces in the eastern region (7) are located in the third quadrant, while the fact that three provincial units in the eastern region, including Beijing, Hebei, and Shandong, are located in the first quadrant, is an important reason for the large variations within the eastern region.

Healthcare resource allocation is located in the first quadrant I for 13 provinces, including 3 provinces in the northeastern region, 3 provinces in the eastern region, including Beijing, Hebei, and Shandong, 5 provinces in the west region, including Xinjiang, Tibet, Inner Mongolia, Shaanxi, and Qinghai, and 2 provinces in the central region, including Shanxi and Hunan. Healthcare resource allocation is located in Quadrant II for 6 provinces, including two provinces in

TABLE 5 Healthcare resource allocation cluster type by province, 2010–2021.

Year	HH cluster	HL cluster	LH cluster	LL cluster
2010	Xinjiang, Tibet, Inner Mongolia, Ningxia, Hebei	Hunan	Tianjin	Zhejiang, Fujian, Jiangxi, Guangdong, Guangxi, Hainan
2015	Tibet, Sichuan, Ningxia			Zhejiang, Fujian, Guangdong, Hainan
2018	Tibet, Qinghai, Gansu, Ningxia, Shaanxi, Sichuan	Hainan		Zhejiang, Fujian, Guangdong, Jiangxi
2021	Xinjiang, Tibet, Qinghai, Sichuan, Shaanxi	Jiangxi, Hunan, Guangxi	Ningxia	Zhejiang, Fujian, Guangdong, Hainan

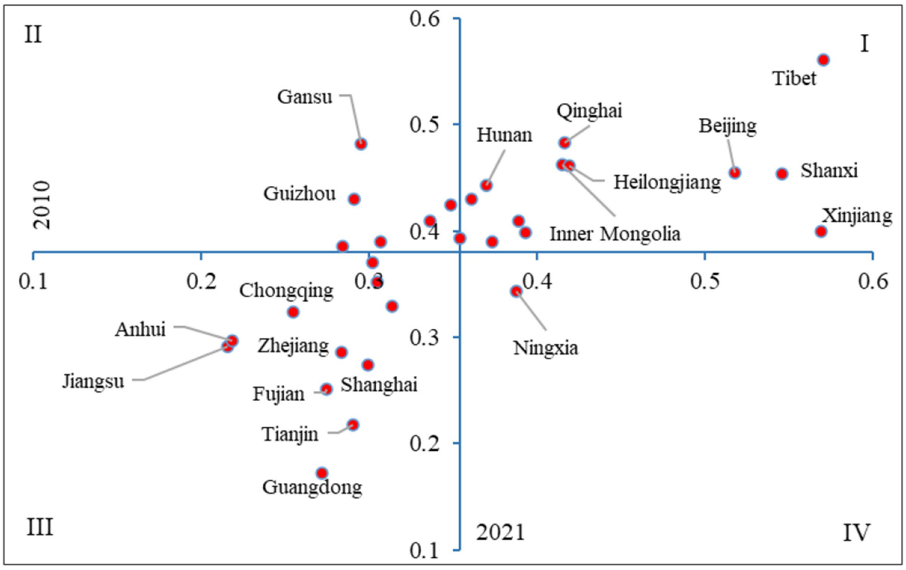

FIGURE 5
Two-dimensional quadrant classification of healthcare allocation composite scores by province in China.

the central region, that's Henan and Hubei, and four provinces in the western region, that's Sichuan, Guizhou, Yunnan, and Gansu. Healthcare resource allocation is located in Quadrant III for 11 provinces, including 7 provinces in the eastern region (Tianjin, Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong, Hainan, etc.), 2 provinces in the western region (Guangxi and Chongqing), and 2 provinces in the central region (Anhui and Jiangxi). Healthcare resource allocation is located in the fourth quadrant (IV), which is located in the western region, but only in the province of Ningxia province.

Further analysis of healthcare resource allocation in the four quadrant provinces:

Quadrant 1 case province Tibet. As a western province with a low population density, Tibet has the highest composite score for healthcare resource allocation in the country. Between 2010 and 2021, Tibet's Healthcare Facilities score increased from 0.3200 to 0.3324, the Healthcare Personnel score increased from 0.1261 to 0.1324, and the Healthcare Beds score decreases from 0.1244 to 0.0965. Although the comprehensive score of Tibet's healthcare resource allocation decreases from 0.5710 in 2010 to 0.5610 in 2021, it still maintains the first place in the country, indicating that Tibet is better developed in terms of the quantity of healthcare resource allocation. Of course, Tibet also has shortcomings, such as a low Healthcare Beds score, indicating that there is still room for further improvement in the quality of its healthcare resource allocation.

Quadrant 2 case province Gansu. As a western province with a low population density, Gansu's healthcare resource allocation composite score rises rapidly from 22nd in 2010 to 3rd in 2021. Between 2010 and 2021, Gansu's Healthcare Facilities score grows from 0.1102 to 0.1770, and Healthcare Personnel score grows from 0.0606 to 0.1075. The highest contribution to Gansu's composite score is made by the Healthcare Beds score, which increases from 0.1247 to 0.1971. From 2010 to 2021, Gansu's Healthcare Facilities score increases from 0.1102 to 0.1770, Healthcare Personnel score from 0.0606 to 0.1075, and Healthcare Beds score from 0.1247 to 0.1971. The highest contribution to Gansu's overall score is made by the Healthcare Beds score, reflecting that Gansu has been comprehensively improved in healthcare resource allocation.

Quadrant 3 case province Guangdong. As an eastern province with a high population density, Guangdong's healthcare resource allocation composite score ranks rather poorly, as it drops from 28th in 2010 to 31st in 2021.Between 2010 and 2021, Guangdong's Healthcare Facilities score decreases from 0.0259 to 0.0224, and its Healthcare Facilities score of Guangdong decreases from 0.1251 to 0.0566, Healthcare Personnel score from 0.1207 to 0.0934. The decrease of Healthcare Facilities score of Guangdong is not large, but the decrease of Healthcare Personnel and Healthcare Beds scores is large, reflecting that the *per capita* healthcare in Guangdong is not as large as it should be. The decrease in Healthcare Facilities score is not large, but the decrease in Healthcare Personnel and Healthcare Beds scores is large, reflecting the low *per capita* healthcare resources in Guangdong, which to a certain extent reveals a large contradiction between people's demand for healthcare resources and the supply of healthcare resources in Guangdong.

Quadrant 4 case province Ningxia. As a province in the western region, Ningxia has a low population density, but its healthcare resource allocation composite score ranking drops from 10th in 2010 to 25th in 2021.Between 2010 and 2021, Ningxia's Healthcare Facilities score decreases from 0.1167 to 0.1063, Healthcare Personnel score decreases from 0.1369 to 0.1226, and Healthcare Beds score decreases from 0.1340 to 0.1140.Ningxia's Healthcare Facilities, Healthcare Personnel, and Healthcare Beds scores all decrease, resulting in a decline in the overall score ranking at a significant rate, reflecting Ningxia's decline in recent years. The speed is obvious, reflecting the fact that Ningxia's healthcare resources in recent years have been developing at a slower pace than the national average, both in terms of quantity and quality.

The first quadrant, in which the allocation of health care resources in a province is above average in both 2010 and 2021, concentrates most western provinces, while the third quadrant, in which the allocation of health care resources in a province is below average in both 2010 and 2021, concentrates most eastern provinces, reflecting spatial and temporal variations in the allocation of health care resources in the four major zones. From the perspective of balanced development, the four major zones tend to be in a relatively balanced state in terms of the quantity of healthcare resource allocation, but there are still gaps in the quality of regional healthcare resource allocation. The eastern region is still the region where high-quality health-care resource allocation is concentrated, while the western region still has room for further improvement in the quality of its health-care resource allocation for historical, economic and other reasons.

4 Discussion

4.1 Quantitative and qualitative balance in the allocation of healthcare resources

The allocation of healthcare resources in China's four major zones has undergone a process of change from "unbalanced quantity to relatively balanced quantity," with a spatial pattern of "high in the west and low in the east" in terms of the composite score of healthcare resources, and a spatial pattern of "high in the east and low in the west" in terms of the high quality of healthcare resources. According to Fudan University's 2021 National Top 100 Hospitals Ranking, China's leading tertiary hospitals are highly concentrated in Beijing (22), Shanghai (19), Guangzhou (10), Hangzhou (5), Wuhan (5), Chengdu (4), Nanjing (4), Xi'an (4), Chongqing (4), Tianjin (3), Changsha (3), Fuzhou (2), Harbin (2), Hefei (2), and Jinan (2), Shenyang (2), Zhengzhou (2), Nanchang (1), Qingdao (1), Shenzhen (1), Suzhou (1), Changchun (1) and other provincial capitals and municipalities, which are 22 cities that concentrate the nation's best healthcare resources. By region, the top 100 hospitals in the country account for 70% in the Central and Eastern regions, 13% in the Central region, 12% in the Western region and 5% in the Northeast. High-quality healthcare resources are highly concentrated in the eastern region, which is consistent with the findings of related scholars. Zhao et al. pointed out that China's provincial and prefectural-level municipal-scale high-quality healthcare resources are mostly concentrated in the area east of the Hu Huanyong line (22), reflecting that China's provincial healthcare resource allocation has basically achieved quantitative parity in the development pattern, but qualitatively, it has not achieved parity. This reflects that China has basically achieved equalization in the allocation of healthcare resources by province in terms of quantity, but the spatial pattern of "high in the east and low in the west" in terms of quality is still difficult to change.

4.2 Internet plus healthcare resource allocation in the age of artificial intelligence

The high concentration of quality healthcare resources in megacities has its own regularity and inevitability. Such cities are able to provide sufficient financial support for the research and development of healthcare technology, have strong key healthcare disciplines and teams of specialists, and facilitate the technological research of difficult and complicated diseases, which, to a certain extent, contributes to the advancement of healthcare technology across the country and even in the world. However, the high concentration of high-quality healthcare resources has also brought confusion to patients. Famous hospitals in mega cities such as Beijing and Shanghai undertake the rescue and treatment of difficult and complicated diseases in the whole country, resulting in overcrowding in tertiary hospitals in general, and the limited high-quality healthcare resources have been squeezed, and the problem of conflicts in access to healthcare care is particularly prominent. The Opinions on Deepening the Reform of the Medical Security System provides institutional guarantee for solving the problem of unbalanced and inadequate development of healthcare security, while the development of "Internet+" intelligent healthcare in the era of artificial intelligence provides technical means for solving the contradiction between limited high-quality healthcare resources and difficulties in accessing healthcare care. The organic combination of artificial intelligence and the Internet can make the allocation of healthcare resources more efficient, accurate and personalized, and through 5G communication technology, artificial intelligence, Internet of Things technology and cloud platforms, it can carry out remote healthcare diagnosis, remote surgery, emergency guidance, share high-quality healthcare resources and promote the optimal allocation of high-quality healthcare resources.

5 Conclusion

The article collects panel data on healthcare resource allocation by province in China from 2010 to 2021, and comprehensively uses the Analytic Hierarchy Process, the composite score method, the regional difference analysis method and the spatial autocorrelation analysis to reveal the regional differences, spatial and temporal patterns and development characteristics of healthcare resource allocation in 31 provincial administrative units in China. The study reveals the regional differences, spatial and temporal patterns and development characteristics of healthcare resource allocation in 31 provincial administrative units in China. The main findings are as follows:

First, in terms of regional differences, the overall scores of healthcare resource allocation in the four major zones show a fluctuating trend of growth, which is manifested in the process of "rising-declining-rising-declining," with the intra-zone differences in healthcare resource allocation tending to narrow and the inter-zone differences tending to widen. The contribution rate of intra-zone differences declined from 90.93 per cent in 2010 to 62.99 per cent in 2021, while the contribution rate of inter-zone differences increased from 9.07 per cent in 2010 to 37.01 per cent in 2021.

Second, from the perspective of spatial pattern, the high or low scores of healthcare resource allocation in each province in China are bounded by the Hu Huanyong line, and the provinces on the left side of the Hu Huanyong line generally have high scores and show the spatial characteristics of centralized and continuous distribution, while the provinces on the right side of the Hu Huanyong line have relatively low scores and show the spatial characteristics of discrete distribution. The spatial pattern of healthcare resource allocation in each province is characterized by a significant growth rate in the number of hospitals and the number of hospital beds, a spatial pattern of "high in the west and low in the east" in terms of the overall score, and a spatial pattern of "high in the east and low in the west" in terms of high-quality healthcare resources.

Third, from the perspective of spatial and temporal analyzes, the sample period of 2010–2021 shows the development trend of "decreasing-rising-increasing." From a global perspective, the spatial agglomeration effect of provinces with close scores in healthcare resource allocation shows a development trend of "weakening and then strengthening." The HH cluster provinces that passed the significance test were mainly distributed on the left side of the Hu Huanyong line, indicating that the healthcare resource allocation in the provinces on the left side of the Hu Huanyong line, such as Tibet, Xinjiang, Qinghai, Ningxia, Gansu, Inner Mongolia, Sichuan, geographically had the spatial characteristics of the HH cluster, whereas the LL cluster provinces that passed the significance test were mainly distributed on the right side of the Hu Huanyong line, indicating that the healthcare resource allocation in the southeastern coastal provinces, such as Zhejiang, Fujian, Guangdong, Hainan, geographically had the spatial characteristics of the LL cluster.

Fourth, from the quadrant analysis, the comprehensive score of healthcare resource allocation in each province is divided into four quadrants, the first quadrant where the healthcare resource allocation in a province is above the average in both 2010–2021-time nodes concentrate most of the western provinces, while the third quadrant, where healthcare resource allocation is below average in both 2010 and 2021, concentrates most of the eastern provinces.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: http://www.stats.gov.cn/sj/ndsj.

Author contributions

HR: Conceptualization, Writing – original draft. CL: Writing – review & editing, data curation. YH: Methodology.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Extended Medicaid coverage will improve access but insufficient to enhance postpartum care utilization: a secondary analysis of the 2016–2019 Arizona Medicaid claims

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Introduction: Postpartum Medicaid eligibility extensions may increase access to healthcare for low-income women. However, its implications for healthcare utilization are unknown.

Methods: We analyzed the linked-infant birth certificate and claims data of women whose childbirths were paid for by Medicaid between 2016 and 2019 in Arizona, United States. We evaluated associations between postpartum care visits and Medicaid insurance type and assessed effect modification by the delivery route and type of residence.

Results: Women with pregnancy-related Medicaid insurance were less likely to attend postpartum visits, with an adjusted odds ratio (aOR) of 0.70 and a 95% confidence interval (CI) of 0.66 to 0.74 than those with continuous Medicaid insurance. Younger age, rural residence [aOR 0.83, CI 0.78, 0.88], vaginal delivery route [aOR 0.11, CI 0.10, 0.12], and the absence of complications during/after childbirth [aOR 0.58, CI 0.49, 0.70] were associated with the absence of postpartum care visit. Low-income women who lost their pregnancy-related Medicaid coverage after 60 days in Arizona experienced lower rates of postpartum care utilization.

Discussion: Interventions to improve postpartum utilization should be considered beyond extending postpartum Medicaid coverage for low-income women.

KEYWORDS

postpartum, low-income insurance, healthcare utilization, Medicaid extension, maternal health

Introduction

Health agencies worldwide are expanding their focus to ensure that birthing women and their babies do not merely survive the process of childbirth but also thrive and reach their potential for health and well-being (1–3). The postpartum is a critical period for women and newborns. It determines long-term women's health and well-being because the availability and quality of care and support provided during postpartum enhance preconception and inter-conception health (4).

The American Congress of Obstetricians and Gynecologists (ACOG) recommends that postpartum care be ongoing and tailored to meet the individual needs of women. ACOG also notes that optimized postpartum care should provide an initial assessment for women and ongoing care as needed. Ongoing care should include comprehensive well-woman visits, counseling and contraception services, and managing preconception comorbidities through coordinated care that should extend up to 1 year after childbirth (5). Postpartum healthcare supports women's health by screening and assessing physical, mental, and social health risks (1). This care also provides opportunities to prevent, diagnose, and treat complications from pregnancy and childbirth, manage preconception health issues such as hypertension and diabetes, provide contraception and family planning services, facilitate community support, and address other social needs. Given the opportunities that postpartum care offers, improving women's access to high-quality postpartum care becomes a priority for policy implementation.

Despite the many benefits of postpartum healthcare and recommendations from various health agendas, many women do not have access to care or fail to utilize available healthcare during postpartum. Over 40% of childbearing women in the United States (U.S.) do not attend postpartum care (6, 7). Several studies have shown that access to postpartum care primarily depends on health insurance (8–10). Furthermore, postpartum care utilization is contingent on affordability and social determinants of health, such as place of residence, availability of transportation, and childcare services that facilitate care utilization (11–13). As such, women who belong to disparity populations, including low-income, rural, and racial minorities, may be disproportionately affected by inequities in access and use of postpartum care, increasing the disparities in the risk for adverse maternal outcomes and deaths (14).

Medicaid, a United States federal and state-funded program, provides health coverage to eligible low-income adults. In 2019, Medicaid was the payment source for 42% of births in the United States (15). Low-income women who do not qualify for continuous adult Medicaid insurance may gain eligibility for pregnancy-related Medicaid insurance that covers medical care during pregnancy and up to 60 days after childbirth. While pregnancy-related Medicaid insurance provides critical support for low-income women who earn above the threshold for continuous adult insurance, access to care is short-lived since this coverage expires after 60 days postpartum. This coverage disruption or loss reduces access to routine and *ad hoc* medical services from Day 61 to Day 365 (1 year) after birth (16). Extending Medicaid postpartum coverage through the first year after childbirth will increase access to care for beneficiaries of pregnancy-related insurance (17, 18). Several federal and state initiatives are implementing policies to improve access to healthcare during postpartum (4, 5, 19, 20). More recently, the 2021 American Rescue Plan Act (ARP) provides a pathway for states to extend postpartum insurance through an 1,115 waiver or a State Plan Amendment under the Medicaid and Child Health Insurance (CHIP) plans (19).

The Arizona Medicaid Agency, known as the Arizona Health Care Cost Containment System (AHCCCS), provides continuous medical assistance to low-income women with a household income at and below 133% federal poverty level (FPL) and pregnancy-related insurance for women with household income between 133 and 156% FPL (21). AHCCCS pays for about 50% of births in Arizona (22). In 2022, AHCCCS approved extending Medicaid pregnancy-related insurance eligibility up to 1 year after childbirth through federal matching funds provided by the 2021 American Rescue Plan Act. The state allocated $2.7 million to offer health insurance coverage to eligible low-income women with household income 133–156% FPL (23). The plan to extend postpartum coverage of pregnancy-related insurance raises several questions: How will this policy impact federal and state budgets? How will it improve postpartum care utilization and women's health outcomes, particularly among populations that experience excess health disparities? Because Medicaid policies vary by state, a granular understanding of baseline postpartum care utilization is crucial to implementing Arizona's new Medicaid (AHCCCS) policy. Thus, this study aims to describe insurance coverage patterns and postpartum care utilization for women whose pregnancy care and childbirths were paid for by AHCCCS and to investigate factors associated with postpartum healthcare utilization among this cohort. This analysis will contribute important baseline information to guide health financing and policy implementation for maternal and child health in the United States.

Materials and methods

Study design and data source

This study is a secondary analysis of deidentified Arizona Medicaid claims data to assess the association between Medicaid insurance type and postpartum healthcare utilization and the effects of other individual and structural factors. The unit of observation was mothers of live births between 2016 and 2019 in Arizona. We obtained claims data files for women whose childbirth was paid for by AHCCCS between January 1, 2016, and December 31, 2019, from the Arizona State University Center for Health Information Research, managed on behalf of Arizona. The data included information on women's demographics, Medicaid insurance eligibility, and health care claims, including outpatient and inpatient claims and diagnoses. Women's demographic, eligibility, and claims information were linked to the Arizona infant birth records and women's hospital discharge data from the Arizona Department of Health and Services. All the data files met the Health Insurance Portability and Accountability Act's definition of a limited dataset. The study was approved by the University of Arizona Institutional Review Board (IRB_STUDY#00000208) and was exempted from further review. This study followed the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guideline for cohort studies.

Study sample

We linked infant birth data and women's hospital discharge data, demographics, Medicaid insurance eligibility, diagnoses, and claims files to identify a cohort of women aged 18–49 years whose delivery was paid for by AHCCCS. Included in the cohort were women who gave birth to singleton newborns in Arizona between January 1, 2016, and December 31, 2019. For women with more than one live birth during this period, we selected the most recent birth to be included in the cohort. We excluded women who needed emergency delivery services but were ineligible for Medicaid pregnancy-related insurance and women who were incarcerated at childbirth whose pregnancy care and childbirth were covered by the correctional healthcare service agency (21).

Exposure variable

The primary exposure variable was the type of AHCCCS insurance: Medicaid pregnancy-related, which expires 60 days after childbirth, or continuous Medicaid insurance, which is continuous medical assistance for low-income adults and does not expire based on pregnancy status. To determine the enrollment period after pregnancy under AHCCCS insurance, we used eligibility beginning and ending dates to define a period of eligibility between 6 months before and 12 months after childbirth. For each woman in the study sample, the follow-up period was defined as 365 days after the infant's date of birth. Subsequently, we categorized women's insurance types into continuous and pregnancy-related insurance using two criteria (Supplementary Table 1.0). First, by subtracting the end date of insurance enrollment from her infant's birth date to evaluate the eligibility period, and second, by confirming insurance type by the enrollment category codes (24).

Outcome variable

The outcome of interest was postpartum care utilization. We defined postpartum care utilization as a woman's use of healthcare for routine medical and gynecological services billed as claims for postpartum encounters to Medicaid within the first year after childbirth according to the CDC vital statistics reporting guidance and existing literature on the postpartum period (25, 26). Postpartum encounters were identified by linking the AHCCCS claims file with the diagnosis files within the one-year postpartum period. To examine the types of postpartum care and evaluate women's use of healthcare services after childbirth, we adapted the 2021 HEDIS Documentation and Coding Guideline definition and codes for postpartum care. We used the International Classification of Disease Codes (ICD-10), the Health Care Common Procedure Coding System (HCPCS), and Current Procedural Terminology (CPT) codes from the 2021 HEDIS guideline to categorize postpartum care into three types: care for birth complications, cervical cytology, and postpartum visits (Supplementary Table 2.0), (27).

The indicator for postpartum care utilization was a binary variable: the presence or absence of at least one postpartum care visit. For sensitivity analysis, we also computed the frequency of postpartum care visits (0, 1, 2, 3, 4, 5, and > 5 visits within the first 365 days after childbirth). First, we estimated the start date of each type of postpartum care from the claims using infants' birth dates to calculate the start date of postpartum for each associated claim. Subsequently, we determined the timing of each postpartum visit in days postpartum by deducting the infant's birth date from the service date on the claims. This action created a longitudinal claims dataset for women in the study cohort. We then determined the frequency of postpartum visits by counting the number of visits for each woman in the cohort and recategorized visits into a binary postpartum visit variable (yes/no).

Covariates

We extracted information on women's demography and birthing outcomes from the infants' birth and women's hospital discharge records. The following covariates were selected based on the literature on covariates of postpartum care utilization (6, 13). Residential zip codes were linked to the USDA Rural–Urban Commuting Area (RUCA) crosswalk (28) to categorize them into rural and urban residences according to the Health Resources and Services Administration's RUCA categorization of 1–4 as rural and 5–10 as urban areas (29). Categories of maternal age at childbirth (< 20, 20–29, 30–39, and 40–49), race/ethnicity (Asian, Black/African American, Hispanic, Native American, Other, Pacific Islander, and White), type of residence (rural or urban), prenatal care attendance (yes or no), type of delivery facility (hospital or other), route of delivery (vaginal or cesarean section), and maternal complications at childbirth based on infant record (yes or no) were also included as covariates in our analyses.

Statistical analysis

We assessed the distribution of maternal characteristics by insurance type, and chi-square tests were used to compare these characteristics between women with AHCCCS pregnancy-related insurance and AHCCCS continuous insurance. We analyzed the association between insurance type and postpartum care visits in two models using logistic regression analysis that yielded odds ratios (OR) and 95% confidence intervals (CI). Model 1 evaluated the independent relationship between postpartum utilization with insurance type and covariates. Model 2 was an adjusted multivariable logistic regression analysis and incorporated interaction terms between insurance type and two covariates, route of delivery, and type of residence, to evaluate potential effect modification. We evaluated model fit using the Hosmer-Lemeshow goodness-of-fit test and c-statistic to assess model discrimination.

For sensitivity analysis, we utilized the frequency of visits variable (0, 1, 2, 3, 4, 5, and >5) and conducted Poisson regression analysis with robust error variance using a generalized linear model to evaluate the association between insurance type and the frequency variable of postpartum visits and covariates. Data files were read, merged, and cleaned using RStudio statistical software, and all statistical analyses were performed with SAS Version 9.4 (SAS Institute: Cary, NC, United States). We set all statistical tests and 95% confidence intervals (CI) with a two-tailed value of p less than 0.05 as statistically significant.

Results

Having received insurance from AHCCCS between 2016 and 2019, 58,500 women who met the inclusion criteria for the cohort analysis were identified. Of the 124,513 claims linked with this cohort, 51% were billing for services for cervical cytology, 21% for labor and delivery complications services, and 28% for routine postpartum services (Figure 1). The types of health care services utilized during postpartum did not differ by type of insurance.

The pregnancy-related AHCCCS group had a higher percentage of women between 18-20 years old (11% vs. 5%) and a lower proportion of women between 30 to 39 years (25% vs. 29%) compared to the continuous AHCCCS group. Both groups of women had similar proportions for race and ethnicity, U.S. citizenship, residence, delivery facility, and complications following childbirth. Women in the pregnancy-related AHCCCS group were less likely to attend prenatal visits (94% vs. 97%), use tobacco (16% vs. 18%), and participate in postpartum visits (60% vs. 69%) as compared to the continuous AHCCCS group.

In the analytic cohort sample of 58,500 women, 38,628 (68%) attended at least one postpartum care visit, when stratified by insurance type, more of the continuous AHCCCS group were likely to participate in at least one postpartum visit (42% vs. 39%), attend two visits (17% vs. 14%), and attend three visits (6% vs. 4%) than the pregnancy-related AHCCCS group. In addition, women in the pregnancy-related group were more likely to have no postpartum visits in the first year after childbirth (40%) compared to the continuous insurance group (31%) (Figure 2).

Table 1 reports the characteristics of women aged 18 - 49 with singleton births whose childbirths and postpartum care were paid for by AHCCCS, grouped by continuous and pregnancy-related insurance categories as provided. Six thousand four hundred and thirty-eight (6,438) women had pregnancy-related insurance (11%), and 52,062 had continuous insurance (89%). Of all women in the cohort, 1,170 were Asian (2%), 6,677 African American (11.4%), 6,346 Hispanic (10.8%), 3,206 American Indian & Alaskan Native (5.5%), 287 Pacific Islander (0.5%) and 38,7768 White (66%) individuals; Other included 2,046 (3.5%) individuals who identified as mixed race or ethnicity. Fifty-five thousand, five hundred and eighty-one (55,581) women were U.S. citizens (89%). The majority, 52,447 (90%), lived in urban areas in Arizona at the time of birth of their infants, and 10,644 (18%) reported using tobacco before pregnancy. Over 99% of women had their deliveries at a hospital, 97% had at least one prenatal visit before childbirth, 46,519 (80%) gave birth through vaginal delivery, and 782 (1%) had complications immediately following childbirth.

Based on logistic regression analysis Model 1, women with pregnancy-related insurance had lower odds of attending postpartum visits, OR 0.69, 95% CI: 0.65, 0.73 than those with continuous insurance (Table 2). Postpartum visits were associated with rural residence [OR: 0.84, 95% CI: 0.80, 0.89], prenatal visit attendance [OR: 1.63, 95% CI: 1.48, 1.81], delivery route [OR: 0.11, 95% CI: 0.10, 0.12], and complications during or after childbirth [OR: 1.93, 95% CI: 1.61, 2.30]. In the multivariable logistic regression Model 2, we observed that women with pregnancy-related insurance had lower odds of attending postpartum visits [Adjusted Odds Ratio (aOR: 0.70, 95% CI: 0.66, 0.74] than those with continuous insurance. Compared to women younger than 20 years, older age was associated with 20% - 31% higher odds of a postpartum visit. At the same time, rural residents had 17% lower odds of a postpartum visit than urban residents [aOR: 0.83, 95% CI: 0.78, 0.88], and prenatal visit attendance was associated with higher odds of a postpartum visit [aOR: 1.73, 95% CI: 1.43, 1.92]. Compared to women who delivered their babies through cesarean section, those who delivered through the vaginal route had 89% lesser odds of a postpartum visit [aOR: 0.11, 95% CI: 0.10, 0.12] meanwhile, women with no complication after childbirth had 52% lower odds of a postpartum visit [aOR: 0.58, 95% CI: 0.49, 0.70] (Table 2). The route of delivery (cesarean or vaginal birth) and type of residence (rural or urban) did not modify the relationship between postpartum visit and insurance type (Supplementary Table 3.0).

A sensitivity analysis that tested the association between postpartum visits and frequency (counts) of postpartum care visits as the outcome variable in a multivariable Poisson regression model was congruent with our primary research. Women with pregnancy-related AHCCCS were less likely to have more postpartum visits, incident risk ratio (IRR) was 0.85 (Supplementary Table 4.0). The logistic regression models for the primary analysis (Models 1 & 2) were assumed to be independent observations. The C-statistic was 0.65, and the *p*-values for the Hosmer and Lemeshow test of goodness of fit for the adjusted model was 0.2719 (Supplementary Tables 5.0.A,B).

Discussion

We observed statistically significant differences in postpartum care utilization by AHCCS insurance type, rurality of residence, history of prenatal visits during pregnancy, the delivery route, and complications during or after childbirth. Overall, Arizona women with pregnancy-related Medicaid insurance were less likely to attend

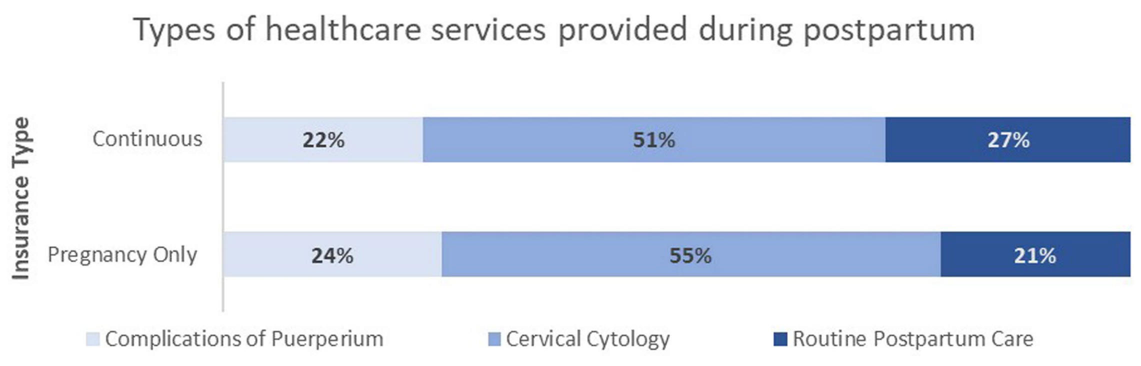

FIGURE 1
Type of services received by women in the cohort during postpartum.

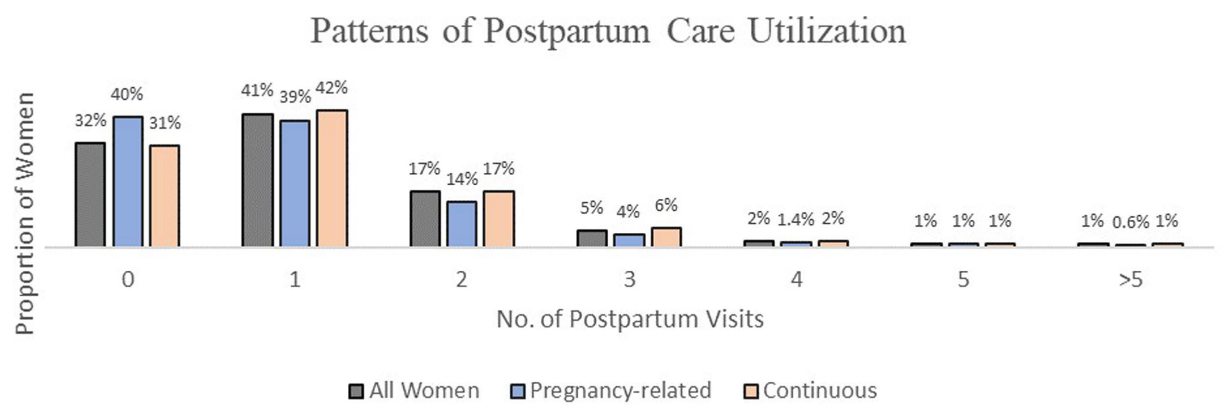

FIGURE 2
Patterns of postpartum care utilization in the cohort.

any postpartum care than their counterparts with continuous eligibility for low-income adult Medicaid insurance. This relationship remained statistically significant after adjusting for differences in individual characteristics and events during pregnancy and childbirth. We observed patterns of postpartum care utilization similar to those in prior studies (18, 30, 31). Women on pregnancy-related Medicaid insurance are generally understood to be prone to insurance transitions or loss between 60 and 90 days after childbirth, resulting in inadequate or no postpartum care (16, 18). While it is assumed these women could afford commercial insurance after delivery because they come from low-income households with higher income levels than those with continuous adult coverage, many still experience disruptions or total loss of coverage that reduce their access to all forms of postpartum care. Comparisons between the two groups of Medicaid-financed insurance in Wisconsin reported that women with pregnancy-related insurance were younger, and prenatal visit attendance was the strongest predictor of postpartum visits (30). Comparing our study to the Wisconsin study, the most robust correlates in our analysis were the delivery route and complications during or after childbirth.

A study on postpartum care utilization in Illinois found that utilization differed by race, ethnicity, and rural residence (31). In our research, rural residents had a lower likelihood of postpartum visits than their urban counterparts. Still, compared to the Illinois study, postpartum care utilization did not vary by race or ethnicity. ACOG's recommendations for postpartum care imply value-based care that centers on the individual needs of the women and the quality of care. Leaving some latitude for flexibility with standards of care, ACOG urges postpartum care to be continuous and coordinated (5). Our study findings did not suggest any form of routine or coordinated postpartum visits. Postpartum visits appeared isolated from routine clinical visits. Like Rankin et al. (31), we found that women utilized healthcare services during postpartum but not primarily for routine postpartum care. In our analysis, over 51% of claims were for cervical cytology and only 25% for routine postpartum care. This loosely implies that providing insurance is necessary for access to care but insufficient for the actual utilization of services. Given the low postpartum utilization rates irrespective of the type or duration of insurance, we can infer that women are not taking advantage of the opportunity that ensures continuity of care during postpartum. Hence, interventions must tackle all the barriers to postpartum care utilization.

Nearly 90% of the population in Arizona is urban, concentrated in two counties flanked by anchoring cities along the United States. Mexico border (32). With a substantial population of racial minority groups (Latinx and Native Americans) and a fiscally conservative state legislature, our study provides compelling findings about postpartum care utilization for populations with excess disparities in maternal outcomes. Our dataset was comprised of nearly all low-income childbearing women in Arizona for 4 years, assuming that Medicaid covered them. With Medicaid paying for about 50% of maternity care in Arizona, our comprehensive and diversified analytical sample was representative of low-income birthing women in Arizona (33). We applied the standardized HEDIS definitions and ICD-10 codes for postpartum care to characterize medical services provided to women after childbirth, making it possible for other researchers to replicate our definitions in different regional and state datasets. Our analysis explored the effect of other categorizations of disparity populations beyond low income, notably rural residence, as well as race and ethnic minority, which have strong relevance to Arizona's population and demography.

Our data analysis also had some limitations. First, the AHCCCS Medicaid claims data did not contain information on women's education, income, contraception care, behavioral health services, or *ad hoc* services requiring postpartum visits. AHCCCS does not pay for postpartum family planning services under pregnancy-related insurance for women, and behavioral health services are funded under another type of state-level policy (34). These issues raised concerns about data quality and prevented sub-analyses that could have highlighted other disparities in care utilization. Second, we could not evaluate the role of social determinants of health (SDOH), such as transportation and childcare services, because the data needed to contain related SDOH variables.

We could not ascertain if women who lost coverage gained commercial or other forms of insurance. Managing duplicate claims from multiple types of providers on the same service date was a challenge and required that we make assumptions, and we would expect some non-differential misclassification (35). The quality of postpartum visits or information on women's satisfaction with care should be evaluated since Medicaid pays for about 50% of childbirths

TABLE 1 Distribution of maternal characteristics and outcomes by AHCCCS insurance type.

Characteristics	Participants, No. (%)			
		Insurance type		
	All women	Pregnancy-related	Continuous	Chi-square
	N = 58,500	N = 6,438	N = 52,062	p value
Age				<0.0001
18–20	3,363 (6)	677 (11)	2,686 (5)	
21–29	37,344 (64)	4,016 (62)	33,328 (64)	
30–39	16,469 (28)	1,608 (25)	14,861 (29)	
40–49	1,324 (2)	137 (2)	1,187 (2)	
Race/Ethnicity				<0.0001
Asian	1,170 (2)	126 (2)	1,044 (2)	
Black/African American	6,677 (11)	654 (10)	6,023 (12)	
Hispanic	6,346 (11)	863 (13)	5,483 (11)	
Native American	3,206 (6)	406 (6)	2,800 (5)	
Other[a]	2046 (3.5)	306 (5)	1,737 (3)	
Pacific Islander	287 (0.5)	39 (1)	251 (0.5)	
White	38,768 (66)	4,044 (63)	34,724 (66.5)	
Citizenship				0.023
US Citizen	55,581 (95)	6,076 (94)	49,505 (95)	
Other[b]	2,919 (5)	358 (6)	2,561 (5)	
Type of residence				0.313
Rural	6,053 (10)	646 (10)	5,407 (10)	
Urban	52,447 (90)	5,792 (90)	46,655 (90)	
Delivery facility				0.8238
Hospital	58,417 (99.9)	6,430 (99.9)	51,987 (99.9)	
Other[c]	83 (0.1)	8 (0.1)	75 (0.1)	
Prenatal visit				0.0001
Yes	56,885 (97)	6,212 (94)	50,673 (97)	
No	1,615 (3)	226 (4)	1,389 (3)	
Route of delivery				<0.0001
Vaginal delivery	46,519 (80)	5,259 (82)	41,260 (79)	
Cesarean section	11,981 (20)	1,179 (18)	10,802 (21)	
Complications during/after childbirth				0.4588
Yes	782 (1)	93 (1)	689 (1)	
No	57,811 (99)	6,438 (99)	51,373 (99)	
Tobacco use				0.0002
Yes	10,644 (18)	1,062 (16)	9,582 (18)	
No	47,856 (82)	5,376 (84)	42,480 (82)	
Any postpartum visit				<0.0001
Yes	39,628 (68)	3,871 (60)	35,757 (69)	
No	18,872 (32)	2,567 (40)	16,305 (31)	
No. of postpartum visits				<0.0001
0	18,872 (32)	2,567 (40)	16,305 (31)	
1	24,337 (41)	2,533 (39)	21,804 (42)	
2	9,954 (17)	910 (14)	9,044 (17)	
3	3,256 (5)	246 (4)	3,010 (6)	
4	1,096 (2)	93 (1.4)	1,003 (2)	
5	442 (1)	51 (1)	391 (1)	
>5	543 (1)	38 (0.6)	505 (1)	

[a]Women who identified as multiple races or ethnicities. [b]Non-US citizens or permanent residents. [c]Facilities different from a hospital, e.g., physicians' clinics, birthing centers, and residential facilities.

TABLE 2 Logistic regression model of factors associated with postpartum care visit.

	Model 1	Model 2*
Characteristic	OR (95% CI)	aOR (95% CI)
Insurance type		
Pregnancy-related	0.69 (0.65, 0.73)	0.70 (0.66, 0.74)
Continuous	1 [Reference]	1 [Reference]
Age		
21–29	1.34 (1.24, 1.44)	1.20 (1.11, 1.29)
30–39	1.68 (1.56, 1.81)	1.31 (1.21, 1.42)
40–49	1.85 (1.60, 2.12)	1.28 (1.10, 1.48)
18–20	1 [Reference]	1 [Reference]
Race/Ethnicity		
Asian	1.15 (1.01, 1.30)	1.11 (0.97, 1.27)
Black/African American	1.06 (1.01, 1.13)	0.98 (0.93, 1.04)
Hispanic	0.94 (0.89, 0.99)	0.95 (0.90, 1.01)
Native American	1.14 (1.03, 1.26)	1.17 (1.06, 1.30)
Other	0.99 (0.77, 1.27)	0.98 (0.76, 1.27)
Pacific Islander	0.84 (0.78, 0.91)	0.87 (0.80, 0.94)
White	1 [Reference]	1 [Reference]
Type of residence		
Rural	0.84 (0.80, 0.89)	0.83 (0.78, 0.88)
Urban	1 [Reference]	1 [Reference]
Prenatal visit		
Yes	1.63 (1.48, 1.81)	1.73 (1.55, 1.92)
No	1 [Reference]	1 [Reference]
Route of delivery		
Vaginal	0.11 (0.10, 0.12)	0.11 (0.10, 0.12)
Cesarean	1 [Reference]	1 [Reference]
Complications during/after childbirth		
No	0.52 (0.44, 0.62)	0.58 (0.49, 0.70)
Yes	1 [Reference]	1 [Reference]

*Model 2 was adjusted for age, race, type of residence, prenatal visit, route of delivery, and complication during or after childbirth.
OR, Odds ratio; Ref, Reference; aOR, Adjusted odds ratio; CI, Confidence interval.

in Arizona (22). Future research must determine postpartum care utilization among women who had miscarriages early in pregnancy, stillbirth, or neonatal deaths because the motivations and reasons for postpartum care may differ from those of women without health insurance.

Policy implications

The findings from this study point to critical policy implications. Our findings of low postpartum utilization among all AHCCCS beneficiaries create the imperative for interventions to promote the demand and use of postpartum care. These interventions must accompany the policy that extends insurance coverage throughout the first year after delivery because the determinants of postpartum utilization are complex and require multifaceted approaches. Second, from the supply perspective, policy interventions must involve all stakeholders, including facility-based and community-based providers. Extending insurance to improve access to care for women relies on care transitions that allow for continuity of care. Care providers, particularly obstetricians, must prioritize referrals for women to their primary care providers for follow-up care after the immediate postpartum period (42 days after birth) (36). Policy solutions facilitating smooth care transitions during postpartum toward care providers are critical to the success of the postpartum coverage extension policy.

Low-income childbearing women who live in rural communities or underprivileged urban areas are often socially isolated and may have limited geographical access to postpartum care despite insurance coverage. Community-based models of care may improve access to essential medical and support services for these women. Therefore, community-based systems of care must be integrated into solutions for access and continuity of care (37). Additionally, social determinants of health, such as transportation and childcare services, play critical roles in postpartum care utilization, and rural residents may need assistance with services that facilitate care utilization (37). Rural residents may need assistance with services that facilitate utilization. Reimbursements for community-based services such as doula services can improve access and use of postpartum services and reduce disparities in adverse maternal outcomes.

Conclusion

We found that low-income women who lost their pregnancy-related Medicaid coverage after 60 days in Arizona experienced lower rates of postpartum care utilization. Among women who lost coverage after 60 days postpartum, rural residence, absence of prenatal visits during pregnancy, childbirth through vaginal delivery, and having no complications during or after childbirth reduced the likelihood of postpartum care utilization. This supports the evidence that several supply and demand factors beyond access to health insurance influence healthcare utilization. These findings have important implications for implementing Medicaid postpartum policy; an effective policy rollout for low-income women must target nuanced determinants of postpartum utilization among rural residents in Arizona.

Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: the dataset can only be obtained from the Arizona Department of Health Services. Requests to access these datasets should be directed to https://www.azdhs.gov/licensing/vital-records/index.php.

Author contributions

AO: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. IA: Supervision, Writing – review & editing. CO: Data curation, Formal analysis, Methodology, Software, Validation, Writing – review & editing. PM: Writing – review & editing. DM: Writing – review & editing. LF: Writing – review & editing. HA: Project administration, Resources, Supervision, Writing – review & editing, Validation.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The author(s) declared that they were an editorial board member of Frontiers, at the time of submission. This had no impact on the peer review process and the final decision.

Publisher's note

Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2023.1281574/full#supplementary-material

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Digital economy and high-quality development of the healthcare industry

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The high-quality development of the healthcare industry is of great significance for improving people's health and promoting the construction of a harmonious society. This paper focuses on the relationship between the development of China's digital economy and the high-quality development of the healthcare industry. Based on the panel data of 30 provinces in China from 2011 to 2020, this paper empirically studies whether the development of the digital economy promotes the high-quality development of the healthcare industry. This study finds that the development of digital economy has significantly promoted the high-quality development of the medical and health industry. The results of this study are still valid after a series of robustness tests including variable substitution, sample adjustment, and endogenous problem mitigation. Heterogeneity analysis shows that the effect of this policy is more significant in the eastern region and southern areas. The results of spatial econometric analysis show that the development of digital economy has obvious spatial spillover effect. The research in this paper can provide reference for developing countries to enhance the development level of digital health industry and improve people's lives.

KEYWORDS

digital economy, high-quality development, healthcare industry, provinces, China

1 Introduction

The outbreak of COVID-19 in 2020 has greatly affected the safety of people's lives and property around the world (1–3). In the face of numerous public health emergencies and global population aging trend, the establishment and improvement of medical care system is of great significance and key role for economic growth. On the other hand, the digital wave is sweeping the world (4, 5). With information technology as the core and mobile payment, 5G, cloud computing, and other representatives of the new generation of digital economy (DE), it is reshaping the industrial structure and production mode (6–8), profoundly changing the comparative advantage between countries, and then affecting the global economic and geographical pattern (9).

China is the most populous country in the world, and the aging of the population is obvious. According to the seventh census released by the government of China, the older adult population in China accounts for 13.5 percent of the total, and the older adult dependency ratio is close to 20 percent (10). In the context of high demand for healthcare, the rapidly expanding market demand for healthcare calls for the development of a higher level of healthcare industry, and new opportunities have been ushered in for the development of healthcare industry (11–14). Especially at the dawn of the DE, how the healthcare industry can better apply information technology to the industrial growth, and then promote the high-quality development of the healthcare industry (HDHI). How the development of the DE promotes the transformation and upgrading of the healthcare industry and summarizes the characteristic facts and general laws are the important premise and basis for achieving HDHI.

Previous studies have posited that the integration of technology and healthcare has the potential to enhance the healthcare sector and offer improved and superior services (15). Digital technology has the potential to enhance customer service by leveraging extensive data to better comprehend individual needs and provide tailored experiences (16). Additionally, digital technology's capacity to disseminate information across temporal and spatial boundaries can serve as a means to reduce social isolation among service recipients, thereby enhancing social integration for marginalized populations (17). The progress in information technology has significant prospects for the healthcare sector, although it also entails certain possible challenges that warrant careful consideration. The field of information technology exhibits a significant level of novelty, necessitating a particular level of group learning ability in order to efficiently acquire mastery. Nevertheless, it is important to acknowledge that the implementation of such measures may result in a "digital divide" phenomenon, particularly impacting certain demographics such as the older adult (18). The progress of the digital health sector is contingent upon the utilization of extensive data for informed decision-making. However, this reliance on data presents a significant obstacle to safeguarding personal privacy and ensuring the security of data assets, particularly within the healthcare domain (19, 20).

Compared to the high quality development-related research that has been published (21–23), this paper argues that high-quality development of healthcare industry (HDHI) has multi-dimensional characteristics. The HDHI is driven by the government and the market, taking innovation, coordination, green, open, and share as the development goals, and aiming at the resources allocation of the healthcare industry. Different from previous studies, this study mainly focuses on the relationship between DE and the HDHI, that is, whether the DE promotes or inhibits HDHI. We further explored the heterogeneous effects that different levels of DE development and geographical locations may have on the HDHI. Due to the possible spatial spillover effect of the development of DE, we further explore this spatial linkage relationship from the perspective of spatial econometrics.

The present study primarily investigates the following three facets. First, the HDHI in China was thoroughly assessed, and the index system was built using four dimensions: medical service, drug service, technical service, and upgrade service. Subsequently, an econometric model is built to determine the correlation between the DE and HDHI. Thirdly, the spatial econometric model is utilized to discover and validate the spatial spillover effect of the development of DE on the HDHI.

2 Methods

2.1 Benchmark regression model

On the basis of previous research (9), we construct the following econometric model (1) to identify the relationship between DE and HDHI:

$$HDHI_{i,t} = \alpha_1 DE_{i,t} + \sum_{k=2}^{6} \alpha_k X_{i,t} + province_i + year_t + \varepsilon_{i,t} \quad (1)$$

HDHI represents high-quality development of the healthcare industry. DE represents the level of DE development. X is a set of control variables. α is the estimated coefficient, and the coefficient we are most concerned about in this paper is α_1. $province_i$ represents the fixed effect of the province, $year_t$ represents the fixed effect of the year, and ε is the random disturbance term.

2.2 Quantile regression model

In order to explore the possible differential impact of different levels of DE development on HDHI, we built a quantile regression model in the following form:

$$Q_\tau\left(HDHI_{i,t}\right) = \zeta_{1\tau} + \zeta_{2\tau} DE_{i,t} + \sum_{k=3}^{7} \zeta_{k\tau} X_{i,t} + \varepsilon_{i,t} \quad (2)$$

In model (2), $Q_\tau(HDHI_{i,t})$ is the dependent variable, representing the HDHI at different quantile levels. $\zeta_{2\tau} \cdots \zeta_{7\tau}$ represent the explanatory variables at different quantile levels. Where, ζ_2 is the quantile regression coefficient which we are concerned about.

2.3 Spatial Durbin model

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} \omega_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} \omega_{ij}} \quad (3)$$

There is a spatial correlation and clustering relationship between the DE and the HDHI. According to existing research (24–27), this paper uses the global Moran index to measure this degree of focus and correlation, so as to reflect its overall characteristics.

In formula (3), S^2 is the variance of the sample, which is used to represent the degree of dispersion of the sample. ω_{ij} represents a two-dimensional element of a space vector matrix (*i, j*). When the index is greater than 0, it indicates that there is a positive spatial correlation between provinces. When the index is less than 0, it indicates that there is a negative spatial correlation between provinces. When the index is 0, there is no spatial correlation.

On this basis, the paper further constructs a spatial Durbin model to identify the spatial correlation between the *DE* and the *HDHI* formula (4).

$$HDHI_{it} = \alpha_0 + \rho W_{ij} DE_{it} + \sum_{k=2}^{6} \alpha_1 X_{kit} + \sum_{k=2}^{6} \alpha_2 W_{ij} X_{kit} + \varepsilon_{it} \quad (4)$$

W_{ij} is the space vector weight matrix. ρ is the spatial autocorrelation coefficient of the explained variable. $\alpha_2 = 0$, spatial

TABLE 1 Evaluation index system of high-quality development of the healthcare industry.

First grade index	Second grade index	Third grade index	Attribute
High-quality development of the healthcare industry	Medical service	Number of tertiary level hospitals	+
		Number of health care institutions	+
		Number of beds in medical institutions	+
	Drug service	Production of chemical drugs	+
		Number of post offices	+
		Number of express	+
	Technical service	Number of patents granted by region	+
		R&D investment	+
		Number of health education training personnel of health education professional institutions	+
	Upgrade service	Number of travel agencies	+
		Number of beds for older people in nursing homes	+
		Number of tourism employees	+

Author collation.

Durbin model degenerates into spatial lag model (SAR). $\alpha_2 + \rho\alpha_1 = 0$, spatial Durbin model degenerates into spatial error model (SEM).

3 Data sources

3.1 Dependent variable: high-quality development of the healthcare industry

In the measurement of the HDHI, we have carried out measurement from four aspects, including medical service, drug service, technical service, and upgrade service. In this index system, a total of 12 indicators are selected for measurement, in order to reflect the HDHI in China. Since this paper chooses a multi-index measurement method, it is necessary to measure the comprehensive level. Therefore, this paper adopts entropy weight method to synthesize the indicators in the index system (Table 1).

$$\text{Positive } u_{ij} = \left(X_{ij} - \min X_{ij}\right) / \left(\max X_{ij} - \min X_{ij}\right). \tag{5}$$

$$\text{Negative } u_{ij} = \left(\max X_{ij} - X_{ij}\right) / \left(\max X_{ij} - \min X_{ij}\right) \tag{6}$$

$$U_j = \sum_{i=1}^{n} w_i u_{ij} \tag{7}$$

The use of entropy weight method first needs to judge the attribute of the index, that is, whether the index is positive or negative. Secondly, standardize the index. Thirdly, the weight of the whole index system is obtained. Finally, the comprehensive score of the index is obtained by multiplying the standardized index value and the calculated index weight. For the specific calculation steps of entropy weight method, see formula (5)–(7).

3.2 Independent variable: digital economy

The independent variable is each province's DE in China. The development of DE has always been centered on the internet, an essential carrier (28), and has a profound impact on economic growth in China. In the indicators of DE constructed in this paper, we focus on the two dimensions of internet development and digital transactions. According to existing studies (29), we select four indicators: the number of internet access users, the proportion of computer service and software employees in urban units, telecommunications traffic *per capita*, and the number of mobile phones among 100 people. Moreover, considering that digital transactions are booming in the era of DE, digital financial inclusion has become an important driving force for the development of DE (30). Therefore, the index of digital financial inclusion is added to the research. The above data are all from the statistical yearbook of China's provinces. The digital financial inclusion comes from the Digital inclusive Finance Development index compiled by the Digital Finance Research Center of Peking University and Ant Financial Services Group[1] (31). Through principal component analysis (PCA), the indexes were standardized and dimensionality reduced to obtain each province's DE development level.

3.3 Control variables

Gross Domestic Product (GDP): GDP is one of the most representative indicators of economic growth. China's huge economic scale is the basis for HDHI (32). Openness (OPEN): we use foreign direct investment to measure regional openness. Number of patents granted (PAT): technological innovation is an essential driving force to optimize industrial structure and promote economic development. HDHI cannot be separated from the

1 See https://idf.pku.edu.cn/yjcg/zsbg/513800.htm

technical support. Population size (POP): the number of permanent residents in each province; we also control the quadratic term of population size (POP^2) to capture the nonlinear relationship. Urbanization (URB): the ratio of urban population to total population is measured in this paper. Table 2 shows descriptive statistics of variables.

The research data in this paper come from China's national statistical data, including China Statistical Yearbook, statistical yearbook, and statistical bulletin issued by Chinese provinces, China Health and Family Planning Statistical Yearbook, China Culture and Tourism Statistical Yearbook, etc. When there are missing values in the panel data we construct, we supplement the missing data with interpolation method to ensure that the panel data we construct is a balanced one. Due to the limitation of research data, the research period of this paper is selected from 2011 to 2020. The research region covers 30 provinces (autonomous regions and municipalities directly under the Central Government) in China, among which Tibet, Hong Kong Special Administrative Region, Macao Special Administrative Region, and Taiwan Province were not included in the study sample due to lack of data (Figure 1).

4 Empirical results

4.1 Baseline regression analysis

This part is based on the econometric model (1) set above (Section 2.1), and Stata 17.0 software is used to calculate and analyze the data. In the baseline regression of Table 3, column (1) is listed as the regression result only included two-way fixed effect (province fixed effect and year fixed effect). Based on the regression results, we find a significant positive relationship between DE and HDHI. We include all the control variables and no longer control the fixed effect in column (2). We find that the regression result still has a significant positive relationship. Based on column (2), we add the fixed effect of the year in column (3) and the fixed effect of the province in column (4), and the result remains robust. We include all control variables and fixed effects and adopt more rigorous robust standard error statistics in column (5). The results are still positive and significant, indicating that DE significantly positively affects HDHI.

TABLE 2 Descriptive statistics of variables.

Variable	*N*	*Mean*	*SD*	*Min*	*Max*
HE	300	0.651	0.539	0.165	0.856
DE	300	0.938	1.278	−1.023	6.958
GDP	300	2.484	2.054	0.137	11.115
OPEN	300	0.200	0.342	0.003	2.745
PAT	300	5.860	8.937	0.050	70.973
POP	300	45.998	28.378	5.680	126.240
URB	300	0.590	0.122	0.350	0.896

4.2 Robustness test

4.2.1 Robustness test I: replace independent variables

The principal component analysis is used to construct the index system for independent variables in baseline regression. In order to avoid the interference of weight on the results, we weighted the indicators in the benchmark regression by a new weight calculation method to obtain the development level of DE calculated based on different methods in this section. We combine the analytic Hierarchy Process (AHP), entropy weight method (EVM), and least squares decision (LSD) model to control further the randomness and inaccuracy of index weight calculation (33). The weight calculation method can control the deviation of weight calculation in a minimum range (34). The specific calculation method is as follows formula (8).

$$\min H(w) = \sum_{i=1}^{m}\sum_{j=1}^{n}\left\{\left[\left(u_j - w_j\right)X_{ij}\right]^2 + \left[\left(v_j - w_j\right)X_{ij}\right]^2\right\} \tag{8}$$

where subjective weight vector $v=(v_1, v_2,\dots, v_n)$T, objective weight vector $u=(u_1, u_2,\dots, u_n)^{\mathrm{T}}$, integrated weight vector $w=(w_1, w_2,\dots, w_n)$ T, $\sum_{i=1}^{n} w_i = 1$, $w_i \geq 0$ $(i=1,2,\dots,n)$.

In Table 4, column (1) lists the development level of *DE* obtained by changing the weight calculation method. The relationship between DE and HDHI is still positively significant. This indicates that the weight calculation method does not affect the conclusion of baseline regression.

4.2.2 Robustness test II: change different estimation methods

In the previous article, ordinary least square (OLS) method tests the relationship between DE and HDHI. Although the OLS method has advantages (e.g., simple calculation principle, convenient calculation, and fast computing speed), it is also subject to the interference of many problems (e.g., endogeneity, heteroskedasticity). Therefore, we replace the estimation method used in the baseline regression analysis and use the First-order Differential Generalized Method of Moments (GMM) and System Differential GMM for the robustness test. We use the least square dummy variable method (LSDV) to control the fixed effects in baseline regression. We choose the intra-group transformation method to control the fixed effects of province and year. The estimated results are reported in column (2) of Table 4. Moreover, First-order Differential GMM and System Differential GMM are adopted for estimation (35). The regression results are reported, respectively, in columns (3) and (4) of Table 4, which show that the difference in estimation methods does not lead to the change in baseline results.

4.2.3 Robustness test III: subsample regression test

In order to avoid the effects that special samples have on the regression results, we remove special provinces (municipalities directly administered by the Central government and ethnic minority regions) from the database. This is because municipalities directly administered by the central government of China have

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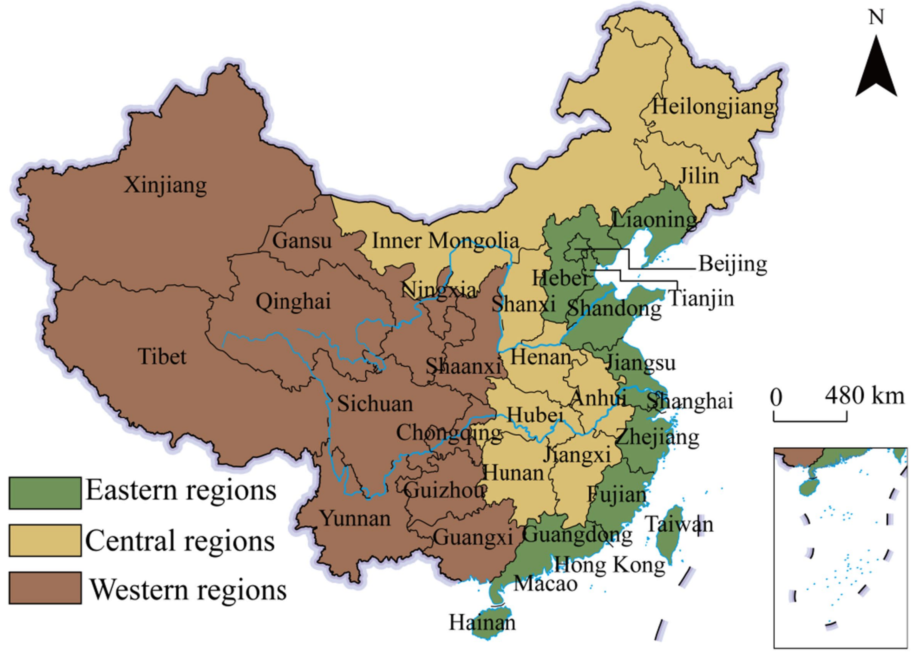

FIGURE 1
Study areas.

TABLE 3 Baseline regression results.

	(1)	(2)	(3)	(4)	(5)
	HC	*HC*	*HC*	*HC*	*HC*
DE	0.632*** (0.116)	0.511*** (0.112)	0.566*** (0.166)	0.684*** (0.126)	0.671*** (0.140)
GDP		0.566*** (0.192)	0.725*** (0.204)	−0.114* (0.064)	−0.109 0.083
OPEN		−0.401 (0.465)	−0.310 (0.469)	0.011 (0.116)	0.013 (0.126)
PAT		−0.081*** (0.021)	−0.079*** (0.016)	0.004 (0.010)	0.004 (0.011)
POP		0.029* (0.015)	0.025 (0.015)	0.183*** (0.026)	0.175*** (0.031)
POP^2		−0.000 (0.000)	0.000 (0.000)	−0.000** (0.000)	−0.000** (0.000)
URB		4.098*** (1.236)	4.671*** (1.410)	−1.798 (1.513)	−1.798 (1.568)
Constant	3.174*** (0.419)	−0.776 (0.793)	−1.619* (0.945)	2.283 (1.440)	2.283 (1.675)
Year F. E.	Yes	No	Yes	Yes	Yes
Province F. E.	Yes	No	No	Yes	Yes
Observations	300	300	300	300	300
R^2	0.914	0.469	0.563	0.917	0.925

(Robust) Standard errors are shown in parentheses, *, **, and *** stand for statistical significance at the 0.1, 0.05, and 0.01 significance levels, respectively.

TABLE 4 Robustness test.

	(1)	(2)	(3)	(4)	(5)	(6)
	CE	*CE*	*CE*	*CE*		
L.CE			1.058*** (0.009)	0.934*** (0.037)		
DE	0.574*** (1.231)	0.654*** (0.126)	0.043*** (0.014)	0.029*** (0.002)	0.771*** (0.149)	0.369*** (0.093)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year F. E.	Yes	Yes			Yes	Yes
Province F. E.	Yes	Yes			Yes	Yes
AR(1)			0.035	0.035		
AR(2)			0.233	0.244		
Sargan test			0.453	0.255		
Observations	300	300	270	240	260	260
R^2	0.983	0.313			0.984	0.992

Standard errors are shown in small parentheses, *, **, and *** stand for statistical significance at the 0.1, 0.05, and 0.01 significance levels, respectively.

more policy support, while Chinese ethnic minorities inhabit autonomous regions. In order to support the development of ethnic minority regions, the central government of China adopts specific supportive policies. Although municipalities and autonomous regions are at the same administrative level as provinces, they differ regarding development mode and policy support. This could interfere with the research results of this paper. Therefore, we refer to existing studies (36), excluded the samples of Beijing, Shanghai, Tianjin, and Chongqing, and excluded the samples of Xinjiang, Ningxia, Inner Mongolia, and Guangxi autonomous regions, respectively. The regression results are reported in columns (5) and (6) of Table 4.

4.2.4 Robustness test VI: instrumental variable estimation

In baseline regression, the results may be biased due to the omitted variable, which is challenging to observe or measure. Moreover, the regression model may have the problem of reverse causation. This is because the HDHI needs to rely on information, digitalization, and intelligence. Therefore, the HDHI will force the region to enhance the development of the DE. Therefore, we adopt instrumental variable to alleviate the endogenous problems.

There are two conditions (relevance and exclusion) for using instrumental variable. We choose the geographical distance from the capital city to Hangzhou as the instrumental variable. On the one hand, Hangzhou is the origin of China's DE with a high level of development of DE (30), which gather many internet enterprises represented by Alibaba, NetEase, and Byte dance. The region near Hangzhou is more likely to be affected by the development of DE in Hangzhou, which satisfies the relevance of instrumental variable. On the other hand, geographical distance is an exogenous variable (37), which has no direct impact on HDHI. Geographical distance is the cross-section datasets, so fixed effects in the model absorb it. Therefore, we multiply it with the number of internet employees to get the interaction term as the instrumental variable. Moreover, we also report the estimated results of constructing interaction terms using spherical distance.

We find that the Anderson canon. Corr. LM statistics significantly reject the null hypothesis, showing that there is not insufficient identification, based on instrumental variable estimation findings shown in Table 5. An endogenous variable and an instrumental variable are correlated. The existence of weak instrumental variables is strongly rejected, and the Crag-Donald Wald F statistic is much greater than the Stock-Yogo weak ID test critical values. It is shown that the estimation contains no weak instrumental variables. The robustness of the baseline regression is demonstrated by the estimated results, which indicate a considerable beneficial influence of DE on HDHI.

4.3 Heterogeneity test

4.3.1 Heterogeneity of the development level of the digital economy

Geographical location can vary the identification results of causal effects (38–40). This part focuses on the differences in HDHI brought by different degrees of development of DE. We explore this heterogeneity based on the quantile regression model. The panel quantiles divide the data into five quantiles (5, 25, 50, 70, and 95th) to investigate the relationship between DE and HDHI. Based on the development level of DE heterogeneity's estimation results in Table 6, we find that the positive effect of DE on HDHI is significantly below the 50-quantile level. The relationship between DE and HDHI above the 50-quantile level is positive but insignificant. The HDHI of the DE presents an inverted U-shaped trend of first increasing or decreasing below the 50-quartile level. The results provide exciting and unique policy implications.

4.3.2 Regional heterogeneity of provinces

China has a vast territory. Different regions have considerable differences in factor endowment, industrial institutions, and economic base (41–43). The impact of DE on HDHI may vary systematically depending on the development level and region of DE (44–46). First of all, we divide China's geographical areas into two dimensions:

TABLE 5 Estimation results of instrumental variables.

	(1)	(2)	(3)	(4)
	HC	*HC*	*HC*	*HC*
DE	0.318* (0.154)	0.925*** (0.314)	0.327* (0.177)	0.968*** (0.332)
Controls	Yes	Yes	Yes	Yes
Year F. E.	No	Yes	No	Yes
Province F. E.	No	Yes	No	Yes
Observations	300	300	300	300
Anderson canon. corr. LM statistic	118.459 [0.000]	72.435 [0.000]	118.355 [0.000]	72.345 [0.000]
Cragg-Donald Wald F statistic	189.32	79.325	192.39	78.326
Stock-Yogo weak ID test critical values: 10% maximal IV size	16.38	16.38	16.38	16.38
The first-stage regression results				
	(5)	(6)	(7)	(8)
	DE	*DE*	*DE*	*DE*
IV	2.756*** (0.295)	1.985*** (0.321)	2.925*** (0.205)	1.963*** (0.217)
Controls	Yes	Yes	Yes	Yes
Year F. E.	No	Yes	No	Yes
Province F. E.	No	Yes	No	Yes
Observations	300	300	300	300
R^2	0.769	0.985	0.719	0.983

Standard errors are shown in small parentheses, *p* value are shown in middle parentheses *, **, and *** stand for statistical significance at the 0.1, 0.05, and 0.01 significance levels, respectively.

TABLE 6 Estimation results of heterogeneity of developmental level of digital economy.

	Q5	Q25	Q50	Q75	Q95
	HC	*HC*	*HC*	*HC*	*HC*
DE	0.211*** (0.047)	0.267*** (0.042)	0.233** (0.100)	0.371 (0.233)	0.219 (0.424)
Controls	Yes	Yes	Yes	Yes	Yes
Constant	−1.962*** (0.349)	−1.053*** (0.297)	−0.765 (0.733)	−1.787 (1.499)	−3.867 (3.507)
Observations	300	300	300	300	300
Pseudo R^2	0.463	0.365	0.333	0.325	0.310

Standard errors are shown in small parentheses, *, **, and *** stand for statistical significance at the 0.1, 0.05, and 0.01 significance levels, respectively.

east–west horizontal and north–south vertical. For relevant standards, see (29). Based on the estimation results of the regional heterogeneity in Table 7, we find that the DE significantly promote HDHI in the eastern and central-western regions. However, the effect of the DE on the HDHI will be stronger in the eastern regions than in the central-western regions. Compared with the northern region, the DE has a significant impact on HDHI in the southern region. However, the DE has not had a significant impact on the HDHI in the northern region.

4.4 Spatial econometric model analysis

4.4.1 Spatial autocorrelation test

Ignoring the spatial effects of each variable in the research may cause bias in the estimation results, so it is necessary to analyze the spatial correlation of each variable before setting the model. The global Moran's I for the high-quality development of the DE and the health industry is significantly positive at the level of 1%, rejecting the null hypothesis that there is no spatial autocorrelation. The relevant estimates are presented in Table 8.

4.4.2 Spatial Durbin model

LM test was used to judge the model, and the LM statistic coefficients of SEM and Robust LM statistic coefficients were 6.215 and 11.065, respectively. The LM statistic coefficients of SAR and Robust LM statistic coefficients are 10.235 and 14.269, respectively, and the four variables are all significant at 1% confidence level. Therefore, the Spatial Durbin Model is required for spatial effect estimation.

The SAR, SEM, and SDM regression results are reported in Table 9. The regression results of SDM model show that the spatial spillover effect coefficient of DE on the HDHI is 0.612, which is

TABLE 7 Estimation results of regional heterogeneity of provinces.

	Eastern region	Central-western regions	Northern region	Southern region
	HC	HC	HC	HC
DE	0.614*** (0.136)	0.587** (0.211)	0.069 (0.235)	0.843*** (0.168)
Constant	3.657* (1.884)	−3.596** (1.616)	−5.449*** (1.787)	−0.339 (1.628)
Controls	Yes	Yes	Yes	Yes
Year F. E.	Yes	Yes	Yes	Yes
Province F. E.	Yes	Yes	Yes	Yes
Observations	110	190	150	150
R^2	0.584	0.468	0.498	0.392

Standard errors are shown in small parentheses, *, **, and *** stand for statistical significance at the 0.1, 0.05, and 0.01 significance levels, respectively.

TABLE 8 Global Moran's I of digital economy and high-quality development of the healthcare industry.

Year	Moran' s I	Variance	Z-score	p value
2011	0.325/0.456	0.008/0.012	4.125/4.698	0.000/0.000
2012	0.416/0.469	0.009/0.011	4.269/4.879	0.000/0.000
2013	0.459/0.519	0.007/0.019	4.375/5.102	0.000/0.002
2014	0.496/0.568	0.008/0.014	4.444/5.329	0.000/0.000
2015	0.516/0.614	0.008/0.018	4.958/5.598	0.000/0.001
2016	0.558/0.625	0.006/0.021	5.021/5.981	0.000/0.000
2017	0.579/0.646	0.008/0.017	5.264/6.108	0.000/0.000
2018	0.654/0.692	0.007/0.012	5.569/6.541	0.000/0.002
2019	0.713/0.749	0.009/0.014	5.987/6.894	0.000/0.000
2020	0.815/0.796	0.007/0.019	6.1977.102	0.000/0.004

statistically significant at 1% level. In the economic sense, it means that the healthcare industry has obvious agglomeration spillover effect in space, and the high-quality development of the local healthcare industry will drive the HDHI in the neighboring region. The estimated coefficient of W*DE is 0.597, which is statistically significant at 1% level. In an economic sense, for every 1% increase in the level of high-quality development of the local healthcare industry, the healthcare industry in the neighboring region will increase by 0.597%.

4.4.3 Spatial spillover effect decomposition

Since the SDM model includes the spatial vector weight matrix, the feedback effect of the spatial lag term may be brought in the recognition, and the estimation results of the model cannot be accurately recognized. Therefore, in order to explain the estimation results of SDM model more scientifically and reasonably, partial differential method is used to calculate the total utility, direct effect, and indirect effect of each variable (47–49). According to the decomposition results, the estimated coefficients of total utility, direct effect, and indirect effect are 0927, 0.623, and 0.601, respectively, and are statistically significant at 1% level. This means that the development of the DE will significantly drive the HDHI in the overall region, the local region and the neighboring region.

TABLE 9 Spatial spillover effect regression results.

	SAR	SEM	SDM
	HC	HC	HC
*W*DE*			0.597*** (0.211)
DE	0.526*** (0.005)	0.594*** (0.091)	0.614*** (0.165)
rho	0.564*** (0.015)		0.612*** (0.085)
lambda		0.621*** (0.169)	
LR test	13.564***	12.678***	
Wald test	14.635***	15.658***	
R^2	0.841	0.859	0.965

Standard errors are shown in small parentheses, *, **, and *** stand for statistical significance at the 0.1, 0.05, and 0.01 significance levels, respectively.

5 Conclusion and policy implications

5.1 Conclusion

In the rapid development of DE, this paper focuses on the DE enabling HDHI. We empirically studied the relationship between DE and HDHI based on panel data from 30 Chinese provinces from 2011 to 2020. The main conclusions are as follows:

We find that DE significantly positively affects HDHI. This result is robust after a series of robustness tests (e.g., replace independent variables, change different estimation methods, and sub-sample regression test). The results also remain robust to overcome the endogenous problem.

Heterogeneity analysis shows that the impact of DE on the HDHI is only significant below the median. Regional heterogeneity analysis shows that the impact of DE on the HDHI is more significant in the eastern and southern regions.

The results of spatial econometric analysis show that the development of DE has a significant spatial spillover effect on the

HDHI. The development of DE in this region will significantly promote the high-quality development level of healthcare industry in neighboring regions.

5.2 Policy implications

China should prioritize the advancement of coordinated and balanced development of DE across various regions, while also striving to reduce the digital divide that exists across these regions. China should strategically align the growth of DE between the eastern and central-western regions, as well as between the southern and northern regions. The Chinese government ought to actively encourage the development of digital infrastructure in underdeveloped regions and facilitate the widespread adoption of digitalization efforts across all regions.

China should prioritize the implementation of well-designed high-quality development plans and guidelines for the healthcare business, as well as for the growth of DE, in order to steer development in a scientifically planned manner. The implementation of classified policies, addressing the health care gap resulting from the development of the digital economy, providing targeted attention to various industrial actors, and establishing the operational mechanism and development model of the health care industry ecosystem in the context of digitalization are imperative.

5.3 Future research

This study uses the data at the provincial level of China, but we do not study at the global, national, prefecture, county, and household scales. We believe that we can find some interesting conclusions.

In this paper, reduced form estimation method is adopted. In the future, structural form estimation method can be considered to estimate the relationship between DE and HDHI, in order to get more scientific and reasonable conclusions.

This paper uses the index system method to measure DE. Some exogenous impacts can be considered. For example, China's digital city construction and big data pilot zones will provide us with quasi-natural experiments.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://idf.pku.edu.cn/yjcg/zsbg/513800.htm.

Author contributions

ZD: Writing – original draft. XQ: Writing – review & editing. CL: Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The impact of basic health insurance participation characteristics on the health of mobile populations: the mediating role of health service utilization behavior

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Objectives: It is a pivotal element of China's health system reform to improve the health security of health insurance for the mobile population. Achieving this objective is integral to the success of the reform. The aim of this study was to analyze the impact of different enrollment characteristics of basic health insurance on the health of the mobile population and to investigate the mediating role of health service utilization behavior.

Methods: This cross-sectional study included 135,372 migrants who participated in the 2018 China Migrants Dynamic Survey (CMDS). Two indicators were employed in this study to assess the characteristics of the mobile population's involvement in basic health insurance–namely, whether or not they participated in local health insurance and the type of health insurance in which they participated. The health status of the mobile population was measured using self-assessed health. Health service utilization behavior was divided into public health service utilization and medical service utilization. Multivariate ordered logistic regression was employed to examine the effect of health insurance on the health of the mobile population. Subsequently, the Bootstrap method was applied to analyze the mediating effect of health service utilization behavior in the relationship between health insurance and the health of the mobile population.

Results: Health insurance had a positive impact on health, public health services, and health service utilization among the mobile population. However, enrollment in local health insurance (OR = 1.088, 95% CI = 1.043–1.134) and enrollment in Basic Medical Insurance for Urban Employees (OR = 1.178, 95% CI = 1.090–1.273) were more likely to be associated with higher levels of health and a greater likelihood of receiving health service utilization. The results of the mediating mechanism analysis indicated that health education, health records, family doctor contracting, receiving inpatient services, and being hospitalized locally all played a partially mediating role in the impact of the place of enrollment on health. Regarding the effect of the type of enrollment on health, three types of services–namely, health education, health records, and contracting with a family doctor–played a partially mediating role, while receiving inpatient services and being hospitalized locally did not exhibit a mediating effect. The effect of the type of participation on health is partially mediated.

Conclusion: Based on the impact of the different enrolment characteristics of basic health insurance on the health of the mobile population and the mediating role of health service utilization in this impact, furthermore, improvement of health insurance coverage for the mobile population should focus on improving the accessibility of health services, increasing the level of health insurance coverage, mitigating differences in treatment between the different insurance systems, and simplifying the process of transferring the health insurance relationships.

KEYWORDS

health insurance, mobile population, public health services, medical services, China

Introduction

The concept of the mobile population has developed under China's household registration system (1), referring to individuals who move and reside outside the designated family registration as stipulated by the household registration system (2, 3). Rapid economic development and accelerated urbanization have led to a redistribution of the population in China (4). An increasing number of people are becoming part of the mobile population due to reasons such as family relocation, reunification, and employment (5, 6). According to the results of the seventh national population census conducted by the Chinese government in 2020, the number of mobile population in China in 2020 will be close to 380 million, an increase of 150 million compared to 2010, representing a growth of nearly 70% (7). With the increase in the scale and frequency of mobility, the health protection of the mobile population has received more and more attention. Previous findings on mobile populations from different countries indicate lower education levels, subpar working and living conditions (8, 9), heightened disease risks (10–12), and a greater likelihood of foregoing necessary health services compared to residents (13–15). Moreover, the majority of public policies and social welfare initiatives in China are formulated and implemented based on household registration (hukou) rather than the actual population residing in a specific region (16). Consequently, many social welfare benefits, including medical insurance, are restricted to urban residents with registered household status, leaving the mobile population unable to fully access or with limited access (17). This results in the mobile population facing heightened health losses and a deteriorated health condition.

Medical insurance is a crucial health protection system that can positively impact the health of the mobile population by reducing the economic barriers to medical services and increasing the accessibility of medical services (18). However, China's unique medical insurance system leads to differentiated effects on the health of the mobile population based on different enrollment characteristics. Firstly, this is because China's medical insurance is determined by the location of household registration (18). Under the urban–rural dual system in China, the place where the mobile population participates in medical insurance may not align with their actual residence. Moreover, due to the lower coordination level of China's medical insurance, the fragmented issues caused by localized management make it challenging for the mobile population to transfer their health insurance relationships. The reimbursement procedures for medical expenses are complex, and the costs are high. Mobile populations often need to spend more time reimbursing medical expenses incurred in locations other than their household registration, and they are required to prepay medical expenses for treatment in other places. Secondly, the differences between various types of medical insurance systems in China also impact the equitable access of healthcare services for the mobile population. China's healthcare insurance system revolves around basic medical insurance, supplemented by medical assistance and commercial medical insurance, forming a multi-tiered healthcare protection system (19, 20). Among these, basic medical insurance includes rural and urban residents' basic medical insurance as well as urban employees' basic medical insurance. These two distinct types of healthcare insurance systems target different insured populations, who not only differ in their occupations but also in the level of healthcare protection they receive. Some studies indicate that compared to rural and urban residents' basic medical insurance, participating in urban employees' medical insurance allows the mobile population to access a higher percentage of medical expense reimbursement and a more comprehensive range of healthcare services (21–23). The disparities between these insurance types also affect the healthcare protection level for the health of the mobile population. Moreover, there are differences in the quality of medical services and accessibility between various regions in China. In China, the government plays a dominant role in healthcare services and carries significant fiscal responsibilities in the allocation of medical resources (24). However, due to the implementation of a "graded management and separate funding" fiscal investment system, local governments bear the primary fiscal powers and expenditure responsibilities in the field of healthcare (25). As a result of substantial variations in the fiscal capacities of different regional governments, there are differences in the government's fiscal contributions to healthcare resources. This leads to variances in the quality of medical services and accessibility between different regions, and these disparities may also impact the health of the mobile population.

The relationship between health insurance and the health of the mobile population can be summarized into three aspects based on relevant research. Firstly, the impact of participating in health insurance on the health of the mobile population has been studied. Research focusing on China's mobile population suggests that, compared to those without health insurance, participation in health insurance can increase the utilization of medical services and preventive health services among the mobile population (26), leading

Abbreviations: CMDS, China Migrants Dynamic Survey; BMISURR, Basic Medical Insurance System for Urban and Rural Residents; BMIUE, Basic Medical Insurance for Urban Employees.

to an improvement in their overall health (27). Wassink conducted a study on the health insurance coverage and access to medical services for Mexican cross-border returning immigrants, finding a generally low health insurance enrollment rate and poor accessibility to medical services among this group. The study recommends expanding insurance coverage (28). Secondly, the influence of the location of health insurance enrollment on the health of the mobile population remains inconclusive. Some studies analyzing the impact of enrolling in health insurance in the registered residence or current residence on the health of older adult mobile population found no significant differences in health between the two scenarios (1). However, other studies suggest that compared to enrolling in health insurance at the registered residence, enrolling in health insurance at the current residence helps improve the health status of the mobile older adult (29). Meanwhile, research results indicate that mobile populations enrolling in health insurance outside their current residence, due to difficulties in accessing insurance funds, are more likely to forego regular medical service needs (30, 31). Similar conclusions were drawn by Birch and others, who systematically analyzed the achievements and challenges of the Canadian health insurance system. They pointed out that the mobile population faces difficulties in health insurance enrollment and reimbursement processes, reducing their accessibility to medical resources (32). Thirdly, the impact of participating in different types of health insurance on the health of the mobile population shows consistent results in related studies. The research indicates that different types of health insurance systems have varying effects on the health security of the mobile population (33). For example, studies by Zhao and Cai both demonstrate that, compared to participating in rural and urban residents' health insurance, participating in urban employee health insurance provides higher reimbursement rates and more medical services for the mobile population (20, 21).

On the other hand, some studies have analyzed the mechanisms through which health insurance influences health, summarizing three main pathways. Firstly, health insurance enhances the accessibility of medical services, including regular check-ups, preventive treatment, and high-quality health services, which positively contribute to improving health (34, 35). For instance, Aggarwal's study on a community-based health insurance project implemented in the Yeshavini region of India found that community health insurance positively promoted the health of insured individuals by increasing the utilization of health services (36). Secondly, health insurance may improve health by influencing individual behavior because participating in health insurance provides access to more preventive healthcare services. Insured individuals may reduce or cease unhealthy behaviors such as drinking or smoking (37, 38). Lastly, health insurance affects health by reducing the cost of obtaining medical services. The reduction in medical expenses implies a decrease in the uncertainty of future medical services and savings in healthcare costs (39). For example, Kim Thuy Nguyen and colleagues, through a survey of 706 households in Dai Dong, Vietnam, analyzed the impact of the Vietnamese health insurance plan on the healthcare expenses and health outcomes of hospitalized and outpatient patients. They found that health insurance, by directly reducing medical expenses and indirectly reducing income losses due to illness, reduced the vulnerability of households facing high healthcare costs (40).

From the aforementioned studies, it is evident that scholars have extensively examined the relationship between medical insurance and the health of the mobile population. Nevertheless, there is still room for further expansion in this area. Firstly, the impact of whether to participate in health insurance at the place of residence on the health of the mobile population is controversial, and relevant studies have not reached a consistent conclusion. Secondly, in terms of research content analysis, existing studies primarily focus on the impact of health insurance on the self-perceived health of the mobile population, with insufficient research on the utilization of health services by the mobile population. Finally, in terms of the influence pathway, current studies mainly analyze the impact pathway of whether or not to participate in health insurance. However, the mechanism through which the characteristics of mobile population participation and the type of insurance affect their health remains unclear. Therefore, further exploration is needed to understand the pathway through which health insurance influences the health of the mobile population. Based on the above analysis and considering that China has already achieved the goal of universal coverage of basic health insurance (29), this paper focuses on studying the characteristics of the mobile population's participation in health insurance, including whether to enroll locally and the type of enrollment's impact on the health of the mobile population. Additionally, the study further analyzes the mediating effect of health service utilization behavior in this context. The goal is to improve health insurance policies for the mobile population and enhance their overall health, providing valuable insights for policymaking and raising the health standards of the mobile population.

Materials and methods

Study design and data sources

The China Migrants Dynamic Survey (CMDS) is a nationwide large-scale cross-sectional questionnaire survey conducted by the National Health Commission of the People's Republic of China to monitor the dynamics of the domestic mobile population (2). This nationally representative survey commenced in 2009 and has been conducted annually since. The data utilized in this study is derived from the 2018 nationwide survey on the dynamic monitoring of the mobile population.

The CMDS is acknowledged for its representativeness and minimal sampling error (41). This survey employs a multi-stage stratified probability proportionate to size (PPS) cluster sampling strategy for sample selection (42). In the first stage, townships (towns, streets) are selected using the PPS method. In the second stage, villages (residential committees) within the chosen townships (towns, streets) are sampled using the PPS method. In the third stage, individuals are selected for the survey within the chosen villages (residential committees). Rigorous measures have been implemented to ensure data quality, including scientifically designed questionnaires, training for surveyors, survey supervisor verification of questionnaires, and quality checks through telephone follow-ups.

The CMDS encompasses a rich set of variables (43) and spans across 32 provincial-level administrative regions in China (31 provinces, autonomous regions, municipalities, and the Xinjiang Production and Construction Corp). The survey collected a total of 152,000 samples from the mobile population. The target population for this survey includes individuals aged 15 or above who have resided outside their registered residence (urban or rural) for more than 1 month. Consequently, this study defines the mobile population as those residing in their current location for 1 month or more without local residence registration. The content of the CMDS includes not only demographic and socio-economic characteristics of respondents and their family members but also their health status and utilization of public health services and medical services. For this study, samples with missing values in important variables, extreme values, and those participating in two or more health insurance programs were excluded. The final analytical sample size is 135,372, accounting for 89.06% of the total survey samples.

Variables

Dependent variable

In this study, self-rated health is used to assess the health status of the mobile population, a commonly used indicator in previous research (20). Respondents were asked about their health status, with four possible responses: unable to take care of oneself, unhealthy but able to take care of oneself, basically healthy, and healthy. Therefore, this study categorizes these four results into three situations: combining unable to take care of oneself and unhealthy but able to take care of oneself as unhealthy, and considering basically healthy and healthy as separate categories. These three situations are assigned values of 1, 2, and 3, representing the respective outcomes. Self-rated health is thus an ordered variable, with higher values indicating better health conditions.

Independent variable

The independent variables in this study focus on the insurance characteristics of the mobile population, which, as mentioned earlier, can be divided into three categories: whether to participate in health insurance, the location of health insurance participation (i.e., whether to participate in health insurance at the place of residence), and the type of health insurance participation. Considering China's extensive medical insurance coverage and the achievement of universal coverage of basic health insurance, the study defines insurance characteristics as two scenarios. Firstly, a binary variable is established to indicate whether the mobile population participates in health insurance at the place of residence, where respondents are asked if they have enrolled in health insurance at their place of residence (yes = 1, no = 2). Secondly, the type of health insurance participation is categorized into two groups: Basic Medical Insurance for Urban Employees (BMISUE) and Basic Medical Insurance for Urban and Rural Residents (BMISURR), with values of 1 and 2, respectively.

Mediating variable

Mediating variables analyze the pathway through which health insurance affects the health of the mobile population. In selecting mediating variables, this study, based on existing literature (37, 38) and data availability, chooses the healthcare service utilization behavior of the mobile population as the mediating variable. The study divides the healthcare service utilization behavior into public health service utilization behavior and medical service utilization behavior. Public health service utilization behavior includes whether individuals received health education, measured by the question "In the past year, have you received health education on any of the following aspects in your current place of residence or workplace?" The education includes occupational disease prevention and control, prevention and control of chronic diseases, among seven others. If an individual received education on one or more of these aspects, it is assigned a value of 1; otherwise, it is assigned a value of 2. Other variables include whether individuals have established health records locally (yes = 1, no = 2) and whether they have signed contracts with local family doctors (yes = 1, no = 2). Medical service utilization behavior mainly refers to the hospitalization service utilization behavior of the mobile population, including whether they were hospitalized (yes = 1, no = 2) and whether they were hospitalized at their place of residence (yes = 1, no = 2). Due to the 2018 CMDS survey not including interviews on the outpatient service utilization behavior of the mobile population, this study only analyzes the mediating effect of the hospitalization service utilization behavior between health insurance and health.

Control variables

Based on the Andersen Healthcare Service Utilization Model (39, 42) and relevant existing research, combined with data availability, the study selects control variables to adjust for confounding effects. These variables fall into three categories: predisposing characteristics, enabling resources, and contextual characteristics. Predisposing characteristics include gender, age, marital status, and education level (44). As economic, social environments, and health insurance policies vary across provinces (45), the study also controls for the province of residence according to related literature (46). Enabling resources comprise family income level, employment status, and hukou type (43). Contextual characteristics include the reasons for migration and the scope of migration (47). Specific settings based on the selected data conditions are as follows: gender is a dummy variable with males coded as 1 and females coded as 2; age is calculated as the difference between the interview year-month and birth year-month; marital status is a dummy variable where individuals who are initially married, remarried, or cohabiting are coded as 1, and those unmarried, divorced, or widowed are coded as 2; education level is a five-level variable based on individual education: never attended school = 1, primary school = 2, middle school = 3, high school = 4, and college or above = 5; family income level is transformed into rankings within each province (<percentile 20, percentile 20–39, percentile 40–59, percentile 60–79, and ≥ percentile 80) for data analysis; employment status is a dummy variable, with employed coded as 1 and unemployed coded as 2; hukou type is a dummy variable, with urban coded as 1 and rural coded as 2; reasons for migration are coded as follows: work-related migration = 1, other reasons = 2, family-related migration = 3; the scope of migration is coded as follows: Intercity = 1, Interprovince = 2, Intercounty = 3.

Integrating these analyses, our study develops a theoretical framework that examines the interplay among individual characteristics, health outcomes, and health service utilization behaviors within mobile populations. Additionally, it explores how the location and type of health insurance enrollment impact the health of mobile populations through their health service utilization behaviors (Figure 1).

Statistical method

Ordered multicategorical logistic regression model

In this study, the dependent variable, the health of the mobile population, is an ordered variable with values ranging from 1 to 4.

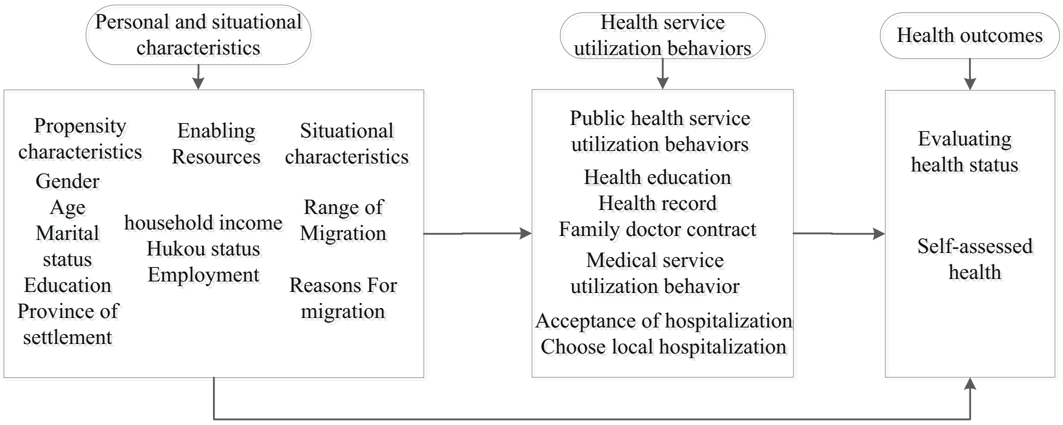

FIGURE 1
Theoretical framework of mobile population health service utilization behavior based on Anderson model.

Therefore, we employed an ordered logistic regression model to analyze the impact of medical insurance on the health of the mobile population. In the test for the applicability of the model, variables were included in a multivariate ordered logistic regression analysis. The resulting Logit connection function scale models for the location of insurance enrollment and the type of insurance enrollment showed corresponding Sig values of 0.000, which were significant at the 1% significance level, indicating the significant fitting of the regression models. The goodness-of-fit tests for the location of insurance enrollment and type of insurance enrollment regression models using the Pearson and Deviance methods yielded p-values of 1.000, indicating that the model adequately fits the data. Simultaneously, in the parallelism test, both p-values were greater than 0.05, suggesting that the location parameters are the same across corresponding categories, meeting the conditions for using the multivariate ordered logistic regression model. The basic form of this model is as follows:

$$\ln\left(\frac{P(Y \le j)}{1 - P(Y \le j)}\right) = \beta_0 + \beta_1 X + \beta_{2m} C_m + \varepsilon$$

Where Y denotes the health self-assessment status of the mobile population, β_0 is the intercept term, X denotes the location or type of health insurance for the mobile population, β_1 denotes the coefficient of the effect of the location or type of health insurance on health self-assessment, C_m denotes other control variables, β_{2m} denotes the coefficient of the control variables, ε is the error term.

Binary logistic regression model

In this study, given that both the utilization of public health services and hospitalization services among the mobile population is represented as dummy binary variables, we employed a binary logistic regression model to examine the influence of health insurance on health service utilization within this population. After conducting the Hosmer-Lemeshow (HL) goodness-of-fit test, the regression models for the utilization of health services among the mobile population all passed the HL test ($p > 0.05$), indicating that the model fit is good. The basic form of the model is as follows:

$$\log it \frac{P_i}{1 - P_i} = \beta_0 + \beta_1 Insurance_i + \beta_2 Control_i + \varepsilon_i$$

Here, P_i denotes the probability of receiving health care or medical services among the mobile population, β_0 is the intercept term, denotes the participation of the mobile population in health insurance, $Insurance_i$ including the location of participation or type of health insurance, β_1 denotes the coefficient of the effect of the location or type of participation on health behavior, $Control_i$ denotes other control variables, β_2 denotes the coefficient of the control variables, ε_i is the error term.

Bootstrap mediated effects model

According to existing research literature (37, 38), the utilization of health services by insured individuals may play a mediating role between health insurance and well-being. Therefore, to analyze the underlying mechanisms and pathways through which health insurance influences the health of mobile populations, this study employs the Bootstrap method to examine the mediating effects of health service utilization behavior in the impact of health insurance on the health of mobile populations. This choice is based on the significant advantages of the Bootstrap method compared to other mediation analysis techniques, such as Sobel tests and the product of coefficients method (48). First, this method allows for a direct significance test of the coefficients of the mediating effect, without assuming the existence of a significant direct effect. Second, it enables mediation analysis with different levels of moderating variables based on the same model, thereby enhancing testing effectiveness and avoiding data omission issues. In this study, the dependent variable is the self-perceived health status of mobile populations, which is an ordinal categorical variable. The mediating variable is the health service utilization behavior of mobile populations, which is a categorical variable. Therefore, this paper adopts the mediation testing method proposed by Iacobucci in 2012 (49) and utilizes the Bootstrap program in SPSS 23.0, with a sample size set at 5000 and a confidence level of 95% for conducting the mediation effects test. The specific testing model is as follows:

Firstly, establish the following three regression equations. Since the dependent variable in this study is an ordinal variable, the Logit regression model was chosen

$$Y = b_{01} + cX + e_1$$

$$M = b_{02} + aX + e_2$$

$$Y = b_{03} + c'X + bM + e_3$$

Where X is the independent variable, Y is the dependent variable, M denotes the mediating variable, c, a, c', b are the coefficients to be estimated, where regression coefficient c is the effect of the independent variable X on the dependent variable Y, regression coefficient a is the effect of the independent variable X on the mediating variable M, regression coefficient b is the effect of M on Y after controlling for the effect of X, coefficient c' is the effect of X on Y after controlling for the effect of M. e_1, e_2, e_3 and is the random error term.

Next, utilizing the coefficients obtained from the above regression models, calculate the following values: $z_a = \hat{a} / \hat{s}_a$, $z_b = \hat{a} / \hat{s}_b$, $z_{a \cdot b} = z_a \cdot z_b$, $\hat{\sigma}_{z_{ab}} = \sqrt{z^2{}_a + z^2{}_b + 1}$. Finally, $z_{Mediatiaon}$ is calculated and then the significance of the mediating effect is tested based on its belonging to the normal distribution at the significance level of 0.05, if $z_{Mediatiaon} > 1.96$, then the mediating effect is significant. $z_{Mediatiaon}$ is calculated as follows.

$$z_{Mediatiaon} = \frac{z_{a \cdot b}}{\hat{\sigma}_{z_{ab}}} = \frac{z_a \cdot z_b}{\sqrt{z^2{}_a + z^2{}_b + 1}}$$

Results

Characteristics of respondents

Table 1 presents the basic characteristics of the mobile population. The results indicate that 28.56% of the mobile population participates in local health insurance, while 71.44% do not. Regarding the type of health insurance, the majority of the mobile population (76.9%) opts for rural and urban resident medical insurance, with only 23.1% choosing urban employee medical insurance. In terms of public health service utilization, the highest proportion of the mobile population receives health education services (81.78%). Simultaneously, among those participating in local health insurance, the proportion receiving this service (85.92%) is significantly higher than that of those not participating locally (80.13%). For the other two preventive healthcare behaviors, only 33.19% of the mobile population establishes health records locally, and 14.55% sign contracts with local family doctors. Among the mobile population participating in local health insurance, this proportion is only 16.85%. In terms of healthcare service utilization behaviors, only 28.9% of the mobile population chooses hospitalization. Concerning the choice of hospitalization location, 72.98% of the mobile population opts for local hospitals. In other characteristics, the education level of the mobile population is relatively low, with 80.71% having a high school education or below. Over 68% of the mobile population belongs to agricultural households, and 48.75% are inter-province migrants.

The impact of medical insurance enrollment characteristics on the health of the mobile population

The results of the impact of basic health insurance enrollment characteristics on the health of the mobile population are shown in Tables 2, 3. Table 2 presents the results of ordered logistic regression on the impact of the location of health insurance enrollment on the health of the mobile population, while Table 3 displays the results of the impact of the type of health insurance on the health of the mobile population. From the regression results in Table 2, it can be observed that, compared to those not locally enrolled in health insurance, those locally enrolled are more likely to have a better health status (OR = 1.088, 95% CI = 1.043–1.134). The regression results in Table 3 reveal that different types of health insurance enrollment have differentiated impacts on the health of the mobile population. Compared to rural and urban resident medical insurance, participants in urban employee medical insurance have a greater likelihood of having a higher health status (OR = 1.178, 95% CI = 1.090–1.273).

The impact of health insurance enrollment characteristics on health service utilization behavior of mobile population

The influence of health insurance enrollment location and type on the health service utilization behaviors of mobile populations is depicted in Tables 4, 5. The regression results in Table 4 reveal that enrolling in health insurance locally increases the likelihood of accessing public health services and medical care. Specifically, individuals with local health insurance are more likely to avail themselves of services such as health education (OR = 1.336, 95% CI = 1.290–1.384), health records (OR = 1.505, 95% CI = 1.460–1.550), and family doctor sign-up services (OR = 1.445, 95% CI = 1.390–1.502) in public health service utilization behaviors. Similar conclusions are supported in the healthcare service utilization behaviors of mobile populations, indicating that individuals with local health insurance are more likely to obtain inpatient services (OR = 1.286, 95% CI = 1.179–1.401) and receive inpatient services locally (OR = 3.118, 95% CI = 2.602–3.735).

Table 5 presents the regression results of the impact of health insurance types on the health service utilization behaviors of mobile populations. The results suggest that participating in urban employee medical insurance increases the likelihood of accessing public health services and medical care. Specifically, in health education (OR = 1.210, 95% CI = 1.125–1.302), health records (OR = 1.484, 95% CI = 1.405–1.568), and family doctor sign-up (OR = 1.781, 95% CI = 1.663–1.907) - three categories of public health service utilization behaviors, as well as whether hospitalization is involved (OR = 1.220, 95% CI = 1.026–1.451) and whether local hospitalization is received (OR = 2.137, 95% CI = 1.359–3.359) - two categories of medical service utilization behaviors, mobile populations with urban employee medical insurance are more likely to utilize these services compared to those participating in rural resident medical insurance. Furthermore, this difference is more pronounced in health care

TABLE 1 Characteristics of respondents with and without local health insurance.

Variable	Definition	Sample size		Number of respondents				*p* Value
		n	%	With local insurance		Without local insurance		
				n	%	*n*	%	
Health status	Unhealthy = 1	2,918	2.16	660	1.71	2,258	2.53	<0.001
	Basically Healthy = 2	15,123	11.17	3,685	9.53	11,438	11.83	
	Healthy = 3	117,331	86.67	34,311	88.76	83,020	85.84	
Type of health insurance	BMIUE = 1	30,966	23.10	11,982	31.11	18,984	19.85	<0.001
	BMISURR = 2	103,166	76.90	26,527	68.89	76,629	80.15	
Health education	Yes = 1	110,708	81.78	33,213	85.92	77,495	80.13	<0.001
	No = 2	24,664	18.22	5,443	14.08	19,221	19.87	
Establishing a health record	Yes = 1	36,069	33.19	12,651	38.89	23,418	30.76	<0.001
	No = 2	72,600	66.81	19,878	61.11	52,722	69.24	
Family doctor contract	Yes = 1	15,930	14.55	5,626	16.85	10,304	13.40	<0.001
	No = 2	94,345	85.55	27,754	83.15	66,591	86.60	
Acceptance of hospitalization	Yes = 1	4,423	28.90	1934	31.11	3,029	27.99	0.021
	No = 2	10,879	71.10	3,087	68.89	7,792	72.01	
Choose local hospitalization	Yes = 1	3,228	72.98	1,201	86.15	2027	66.92	<0.001
	No = 2	1,195	27.02	193	13.85	1,002	33.08	
Gender	Male = 1	69,526	51.36	19,762	51.12	49,764	51.55	0.070
	Female = 2	65,846	48.68	18,894	48.88	46,952	48.45	
Age	15–30 = 1	41,467	30.63	13,156	34.03	28,311	29.27	<0.001
	31–45 = 2	61,161	45.18	19,233	49.75	41,928	43.35	
	46–60 = 3	27,298	20.17	5,466	14.14	21,832	22.57	
	61 + =4	5,446	4.02	802	2.07	4,644	4.80	
Education	Illiterate = 1	3,400	2.51	463	1.20	2,937	3.03	<0.001
	Primary school = 2	18,551	13.70	2,806	7.26	15,745	16.28	
	Junior middle school = 3	57,428	42.42	10,785	27.90	46,443	48.23	
	Senior middle school = 4	29,877	22.07	8,788	22.73	21,089	21.81	
	University/college = 5	26,116	19.29	15,814	40.91	1.302	10.65	
Marriage Status	Married = 1	110,845	81.88	30,621	79.21	80,224	82.95	<0.001
	Unmarried = 2	24,527	18.12	8,306	20.79	16,491	17.05	
Employment	Employed = 1	113,112	83.56	34,654	89.64	78,458	81.12	<0.001
	Unemployed = 2	22,260	16.44	4,002	10.36	18,258	18.88	
Hukou status	Urban Account = 1	42,651	31.51	17,754	45.93	24,897	25.74	<0.001
	Rural household registration = 2	92,721	68.49	20,903	54.07	71,818	74.26	
Range of migration	Intercity = 1	45,501	33.61	14,184	36.69	31,317	32.38	<0.001
	Interprovince = 2	65,982	48.75	19,356	50.07	46,626	48.21	
	Intercounty = 3	23,899	17.65	5,117	13.24	18,772	19.41	
Reasons for migration	Work = 1	114,497	84.58	33,625	86.98	80,872	83.62	<0.001
	Others = 2	2,330	1.72	492	1.27	1838	1.90	
	Family = 3	18,545	13.70	4,540	11.74	14,005	14.48	
Household income ranking	Lowest (<percentile 20) = 1	29,799	22.01	5,869	15.18	23,930	24.74	<0.001
	Lower (percentile 20–39) = 2	27,384	20.23	6,662	17.23	20,722	21.43	
	Middle (percentile 40–59) = 3	27,276	20.15	7,489	19.37	19,787	20.46	
	Higher (percentile 60–79) = 4	26,436	19.53	8,865	22.93	17,571	18.17	
	Highest (≥percentile 80) = 5	24,477	18.08	9,772	25.28	14,705	15.20	
Total		135,572	100	38,719	28.56	96,858	71.44	

P value in the table were obtained by χ^2 test; BMISURR, Basic Medical Insurance System for Urban and Rural Residents; BMIUE, Basic Medical Insurance for Urban Employees.

TABLE 2 Ordered logistic regression results of the location of health insurance participation affecting the health of the mobile population.

Variable		OR	95%CI	*p* Value
Health = 1		0.154	0.137–0.173	<0.001
Health = 2		1.521	1.359–1.702	<0.001
Enrolment with a local health insurance	No (reference)			
	Yes	1.088	1.043–1.134	<0.001
Gender	Female (reference)			
	Male	1.010	0.974–1.048	0.578
Age	61-(reference)			
	15–30	10.084	9.317–10.915	<0.001
	31–45	5.013	4.666–5.386	<0.001
	46–60	2.203	2.053–2.364	<0.001
Education	University/college (reference)			
	Illiterate	0.442	0.401–0.487	<0.001
	Primary school	0.644	0.601–0.691	<0.001
	Junior middle school	0.902	0.849–0.958	0.001
	Senior middle school	0.960	0.901–1.024	0.215
Marriage status	Unmarried (reference)			
	Married	1.211	1.147–1.277	<0.001
Employment	Unemployed (reference)			
	Employed	2.301	2.192–2.415	<0.001
Hukou status	Rural household registration(reference)			
	Urban Account	1.036	0.996–1.078	0.078
Range of migration	Countering (reference)			
	Intercity	1.103	1.052–1.157	<0.001
	Inter province	1.251	1.196–1.310	<0.001
Reasons for migration	Family (reference)			
	Work	1.077	1.020–1.137	0.007
	Others	0.742	0.671–0.822	<0.001
Household income ranking	Highest(≥percentile 80) (reference)			
	Lowest (<percentile 20)	0.697	0.657–0.741	<0.001
	Lower (percentile 20–39)	0.844	0.793–0.898	<0.001
	Middle (percentile 40–59)	0.924	0.868–0.983	0.013
	Higher (percentile 60–79)	0.993	0.932–1.058	0.831
Pseudo R^2		0.114		
N		135,372		
Province of settlement		Control		

Due to the covariance between the variables of location of participation and type of participation, we did not include the type of participation in our analysis of the effect of location of participation, the same below.

behaviors, as the OR values for the three health care behaviors are all greater than those for medical service behaviors.

Analysis of the mediating mechanism of health insurance participation characteristics affecting health

Mediating mechanisms of participant location influencing health

Table 6 and Figure 2 illustrate the impact pathways of the location of participating in health insurance on the health of the mobile population. From the results, it can be observed that both health care behaviors and medical service behaviors play a partial mediating role in this impact pathway, indicating that whether to participate in local health insurance can influence the health of the mobile population through these channels. In terms of the main effect analysis, the main effect of whether to participate in local health insurance on the health of the mobile population is significant at the 1% statistical level. From the analysis of direct and indirect effects, whether in the intermediary variables of health education, health records, and family doctor signing in health care behaviors, or in the intermediary variables of whether hospitalization and local hospitalization in medical service

TABLE 3 Ordered logistic regression results of the type of medical insurance affecting the health of the mobile population.

Variable		OR	95%CI	p Value
Health = 1		0.207	0.163—0.264	<0.001
Health = 2		1.910	1.506—2.423	<0.001
Type of Health Insurance	BMISURR (reference)			
	BMIUE	1.178	1.090—1.273	<0.001
Gender	Female (reference)			
	Male	0.976	0.909—1.048	0.503
Age	61-(reference)			
	15–30	11.851	9.870—14.230	<0.001
	31–45	6.645	5.604—7.880	<0.001
	46–60	2.776	2.345—3.287	<0.001
Education	University/college (reference)			
	Illiterate	0.307	0.247—0.381	<0.001
	Primary school	0.573	0.502—0.654	<0.001
	Junior middle school	0.919	0.830—1.017	0.101
	Senior middle school	0.979	0.884—1.084	0.684
Marriage status	Unmarried (reference)			
	Married	1.137	1.026—1.260	0.014
Employment	Unemployed (reference)			
	Employed	2.363	2.137—2.612	<0.001
Hukou status	Rural household registration (reference)			
	Urban Account	1.133	1.053—1.218	0.001
Range of migration	Intercounty (reference)			
	Intercity	1.109	1.001—1.228	0.047
	Interprovince	1.242	1.225—1.371	<0.001
Reasons for migration	Family = 1 (reference)			
	Work = 2	0.941	0.845—1.048	0.269
	Others = 3	0.800	0.627—1.019	0.070
Household income ranking	Highest(≥percentile 80) (reference)			
	Lowest (<percentile 20)	0.687	0.611—0.771	<0.001
	Lower (percentile 20–39)	0.875	0.779—0.982	0.023
	Middle (percentile 40–59)	0.993	0.886—1.114	0.910
	Higher (percentile 60–79)	1.041	0.931—1.164	0.478
Pseudo R^2		0.158		
N		38,509		
Province of settlement		Control		

Due to the covariance between the variables of place of enrollment and type of enrollment, we did not include place of enrollment in our analysis of the effect of type of enrollment, the same below. BMISURR, Basic Medical Insurance System for Urban and Rural Residents; BMIUE, Basic Medical Insurance for Urban Employees.

utilization behaviors, their direct effects are all significant, and the confidence intervals of the indirect effects do not include 0, indicating that the indirect effects of these intermediary variables are also significant, thus indicating the existence of partial mediating effects. However, there are significant differences in the magnitude of the effects of different intermediary variables. Among them, the mediating effect of whether local hospitalization is the largest, with an effect size of 0.0214, followed by whether to establish health records locally, whether to receive health education, whether to be hospitalized, and whether to sign with a local family doctor, with mediating effect sizes of 0.0015, 0.0012, 0.0011, and 0.0006, respectively.

Mediating mechanisms of health insurance types affecting the health of mobile populations

Due to significant differences in payment ratios, coverage scope, and benefit levels between urban and rural residents' medical insurance and urban employee medical insurance, there may

TABLE 4 Binary logistic regression results of enrollment location affecting health service utilization behavior of mobile population.

Variable			Public health service utilization behavior			Medical service utilization behavior	
			Health education	Establishing a health record	Family doctor contract	Acceptance of hospitalization	Choose local hospitalization
Enrolment with a local health insurance	No (reference)						
	Yes	OR	1.336	1.505	1.445	1.286	3.118
		95%CI	1.290–1.384	1.460–1.550	1.390–1.502	1.179–1.401	2.602–3.735
		p Value	<0.001	<0.001	<0.001	<0.001	<0.001
Gender	Female (reference)						
	Male	OR	0.912	0.872	0.914	0.729	0.987
		95%CI	0.885–0.940	0.849–0.897	0.882–0.948	0.672–0.791	0.839–1.162
		p Value	<0.001	<0.001	<0.001	<0.001	0.877
Age	61- (reference)						
	15–30	OR	1.413	0.795	0.741	1.700	1.118
		95%CI	1.307–1.529	0.737–0.858	0.674–0.814	1.449–1.995	0.835–1.496
		p Value	<0.001	<0.001	<0.001	<0.001	0.454
	31–45	OR	1.343	0.791	0.740	0.963	1.003
		95%CI	1.244–1.449	0.735–0.852	0.675–0.810	0.827–1.121	0.757–1.329
		p Value	<0.001	<0.001	<0.001	0.626	0.983
	46–60	OR	1.063	0.759	0.769	0.857	0.914
		95%CI	0.985–1.147	0.704–0.819	0.701–0.844	0.738–0.994	0.696–1.201
		p Value	0.117	<0.001	<0.001	0.042	0.521
Education	University/college (reference)						
	Illiterate	OR	0.572	0.766	0.878	0.755	0.604
		95%CI	0.623–0.625	0.695–0.844	0.777–0.993	0.615–0.927	0.416–0.977
		p Value	<0.001	<0.001	0.038	0.007	0.008
	Primary school	OR	0.698	0.913	0.914	0.815	0.783
		95%CI	0.659–0.739	0.865–0.963	0.852–0.981	0.705–0.944	0.598–1.025
		p Value	<0.001	0.001	0.012	0.006	0.075
	Junior middle school	OR	0.897	1.031	0.964	0.870	0.894
		95%CI	0.856–0.940	0.990–1.073	0.914–1.016	0.773–0.980	0.716–1.117
		p Value	<0.001	0.136	0.173	0.022	0.326
	Senior middle school	OR	1.118	1.113	1.008	0.892	1.114
		95%CI	1.064–1.175	1.068–1.160	0.955–1.065	0.788–1.010	0.875–1.418
		p Value	<0.001	<0.001	0.764	0.072	0.382
Marriage Status	Unmarried (reference)						
	Married	OR	0.971	1.288	1.327	2.560	1.098
		95%CI	0.931–1.013	1.238–1.340	1.257–1.401	2.268–2.891	0.869–1.387
		p Value	0.168	<0.001	<0.001	<0.001	0.432
Employment	Unemployed (reference)						
	Employed	OR	1.237	1.047	0.963	0.388	0.814
		95%CI	1.183–1.294	1.004–1.092	0.913–1.016	0.352–0.427	0.687–0.965
		p Value	<0.001	0.030	0.164	<0.001	0.018
Hukou status	Rural household registration (reference)						
	Urban account	OR	1.052	1.003	0.916	1.068	1.053
		95%CI	1.017–1.087	0.974–1.033	0.881–0.952	0.982–1.160	0.900–1.232
		p Value	0.003	0.837	<0.001	0.124	0.521

(Continued)

TABLE 4 (Continued)

Variable			Public health service utilization behavior			Medical service utilization behavior	
			Health education	Establishing a health record	Family doctor contract	Acceptance of hospitalization	Choose local hospitalization
Range of migration	Intercounty (reference)						
	Intercity	OR	0.954	0.859	0.824	0.872	0.749
		95%CI	0.913–0.997	0.829–0.891	0.788–0.862	0.788–0.965	0.619–0.907
		p Value	0.036	<0.001	<0.001	0.008	0.003
	Interprovince	OR	0.653	0.549	0.487	0.655	0.610
		95%CI	0.627–0.680	0.530–0.569	0.465–0.509	0.593–0.723	0.506–0.735
		p Value	<0.001	<0.001	<0.001	<0.001	<0.001
Reasons for migration	Family (reference)						
	Work	OR	1.081	0.852	0.712	1.116	1.024
		95%CI	1.030–1.134	0.816–0.889	0.675–0.750	1.007–1.237	0.851–1.231
		p Value	0.002	<0.001	<0.001	0.036	0.804
	Others	OR	1.132	1.030	0.991	1.105	1.14
		95%CI	1.013–1.264	0.932–1.139	0.878–1.117	0.898–1.361	0.764–1.623
		p Value	0.028	0.858	0.877	0.347	0.575
Household income ranking	Highest (≥percentile 80)						
	Lowest (<percentile 20) (reference)	OR	0.957	1.108	1.219	1.064	1.014
		95%CI	0.912–1.005	1.060–1.159	1.148–1.295	0.933–1.213	0.794–1.294
		p Value	0.078	<0.001	<0.001	0.354	0.913
	Lower (percentile 20–39)	OR	1.050	1.072	1.108	1.050	0.931
		95%CI	1.000–1.103	1.025–1.120	1.044–1.177	0.919–1.199	0.728–1.192
		p Value	0.052	0.002	0.001	0.476	0.513
	Middle (percentile 40–59)	OR	1.080	1.066	1.108	1.023	0.961
		95%CI	1.029–1.134	1.020–1.114	1.045–1.175	0.896–1.169	0.747–1.236
		p Value	0.002	0.004	0.001	0.736	0.757
	Higher (percentile 60–79)	OR	1.135	1.062	1.104	1.036	1.032
		95%CI	1.082–1.192	1.017–1.108	1.041–1.170	0.907–1.182	0.797–1.336
		p Value	<0.001	0.006	0.001	0.605	0.811
Pseudo R^2			0.024	0.043	0.055	0.151	0.026
N			135,372	108,668	110,274	15,302	4,423
Province of settlement			Control				

be variations in the pathways through which these two insurances impact the health of migrant populations. Considering the advantages of urban employee medical insurance in terms of funding levels and reimbursement standards, and based on the above analysis results, it is evident that urban employee medical insurance has a more significant positive impact on the health of migrant populations. Therefore, this study takes urban residents' medical insurance as a reference and focuses on analyzing the mediating mechanisms through which urban employee medical insurance influences the health of migrant populations, as shown in Table 7. From the results, it can be observed that in the analysis of the mediating role of urban employee medical insurance on the health of migrant populations, the main effects of urban employee medical insurance on the health of migrant populations are all significant. The direct effects and indirect effects of variables such as whether to receive health education, whether to establish a local health record, and whether to sign a contract with a local family doctor are all significant. This indicates that these three variables play a partial mediating role, with respective mediating effect sizes of 0.0004, 0.0012, and 0.0010. However, whether hospitalization and local hospitalization play a mediating role in the utilization of medical services behavior is not evident (Figure 3).

Discussion

In this study, we conducted an in-depth exploration of the impact and pathways of basic health insurance enrollment characteristics on the health of migrant populations, aiming to enhance the support of

TABLE 5 Binary logistic regression results of the type of insurance coverage affecting the health service utilization behavior of the mobile population.

Variable			Public health service utilization behavior			Medical service utilization behavior	
			Health Education	Establishing a health record	Family doctor contract	Acceptance of hospitalization	Choose local hospitalization
Type of health insurance	BMISURR (reference)						
	BMIUE	OR	1.210	1.484	1.781	1.220	2.137
		95%CI	1.125–1.302	1.405–1.568	1.663–1.907	1.026–1.451	1.359–3.359
		p Value	<0.001	<0.001	<0.001	0.024	<0.001
Gender	Female (reference)						
	Male	OR	0.989	0.909	0.924	0.529	1.005
		95%CI	0.928–1.053	0.867–0.954	0.868–0.983	0.456–0.613	0.647–1.721
		p Value	0.721	<0.001	0.012	<0.001	0.831
Age	60 + (reference)						
	15–30	OR	1.377	0.679	0.598	1.347	1.060
		95%CI	1.111–1.707	0.566–0.815	0.489–0.732	0.934–1.942	0.118–9.557
		p Value	0.003	<0.001	<0.001	0.111	0.958
	31–45	OR	1.184	0.702	0.608	0.881	1.310
		95%CI	0.961–1.460	0.587–0.839	0.499–0.741	0.621–1.249	0.147–11.641
		p Value	0.113	<0.001	<0.001	0.477	0.809
	46–60	OR	0.977	0.734	0.690	0.799	1.006
		95%CI	0.791–1.206	0.612–0.879	0.3565–0.842	0.566–1.128	0.110–9.193
		p Value	0.826	<0.001	<0.001	0.202	0.996
Education	University/college (reference)						
	Illiterate	OR	0.612	0.730	0.830	0.536	1.039
		95%CI	0.481–0.780	0.587–0.908	0.642–1.073	0.340–0.846	0.247–4.375
		p Value	<0.001	0.005	0.155	0.007	0.958
	Primary school	OR	0.829	0.939	0.915	0.883	0.825
		95%CI	0.727–0.945	0.844–1.044	0.802–1.045	0.668–1.169	0.388–1.754
		p Value	0.005	0.243	0.190	0.386	0.617
	Junior middle school	OR	1.044	1.007	0.941	0.886	0.937
		95%CI	0.957–1.139	0.942–1.075	0.892–1.057	0.722–1.088	0.540–1.626
		p Value	0.337	0.846	0.497	0.248	0.817
	Senior middle school	OR	1.198	1.076	0.973	0.865	0.936
		95%CI	1.099–1.307	1.011–1.146	0.887–1.046	0.707–1.058	0.538–1.628
		p Value	<0.001	0.022	0.374	0.159	0.814
Marriage status	Unmarried (reference)						
	Married	OR	0.881	1.272	1.012	3.814	1.116
		95%CI	0.808–0.960	1.190–1.358	1.191–1.421	3.024–4.809	0.518–2.406
		p Value	0.004	<0.001	<0.001	<0.001	0.779
Employment	Unemployed (reference)						
	Employed	OR	1.402	0.983	1.025	0.426	0.799
		95%CI	1.265–1.555	0.904–1.069	0.915–1.119	0.351–0.517	0.512–1.246
		p Value	<0.001	0.688	0.818	<0.001	0.332
Hukou status	Rural household registration (reference)						
	Urban Account	OR	1.086	1.029	0.958	1.078	0.975
		95%CI	1.018–1.160	0.980–1.080	0.963–1.091	0.932–1.247	0.649–1.463
		p Value	0.013	0.254	0.433	0.310	0.902

(Continued)

TABLE 5 (Continued)

Variable			Public health service utilization behavior			Medical service utilization behavior	
			Health Education	Establishing a health record	Family doctor contract	Acceptance of hospitalization	Choose local hospitalization
Range of migration	Intercounty (reference)						
	Intercity	OR	0.967	0.865	0.855	0.853	0.400
		95%CI	0.870–1.074	0.806–0.928	0.786–0.931	0.692–1.051	0.166–0.964
		p Value	0.527	<0.001	<0.001	0.136	0.041
	Interprovince	OR	0.637	0.547	0.501	0.606	0.380
		95%CI	0.577–0.704	0.511–0.586	0.460–0.546	0.492–0.747	0.156–0.931
		p Value	<0.001	<0.001	<0.001	<0.001	0.034
Reasons for migration	Family (reference)						
	Work	OR	1.111	0.857	0.715	1.065	1.043
		95%CI	1.007–1.226	0.795–0.942	0.654–0.782	0.877–1.292	0.598–1.817
		p Value	0.035	<0.001	<0.001	0.527	0.882
	Others	OR	1.071	1.024	0.768	1.447	1.556
		95%CI	0.822–1.395	0.832–1.261	0.598–0.986	0.857–2.443	0.319–7.594
		p Value	0.610	0.820	0.038	0.167	0.585
Household income ranking	Highest (≥percentile 80) (reference)						
	Lowest (<percentile 20)	OR	1.139	1.085	1.180	0.973	0.885
		95%CI	1.025–1.266	0.999–1.178	1.062–1.312	0.762–1.241	0.446–1.757
		p Value	0.016	0.054	0.002	0.823	0.727
	Lower (percentile 20–39)	OR	1.289	1.091	1.124	1.049	0.704
		95%CI	1.164–1.426	1.010–1.177	1.017–1.242	0.830–1.326	0.373–1.330
		p Value	<0.001	0.026	0.022	0.688	0.279
	Middle (percentile 40–59)	OR	1.236	1.084	1.109	1.171	0.546
		95%CI	1.123–1.359	1.008–1.165	1.007–1.220	0.936–1.466	0.296–1.007
		p Value	<0.001	0.030	0.035	0.167	0.170
	Higher (percentile 60–79)	OR	1.272	1.087	1.183	1.056	0.053
		95%CI	1.163–1.391	1.016–1.164	1.081–1.294	0.851–1.310	0.437–1.551
		p Value	<0.001	0.016	<0.001	0.622	0.546
Pseudo R^2			0.030	0.036	0.035	0.116	0.064
N			37,133	32,397	33,251	4,463	1,225
Province of settlement			Control				

BMISURR, Basic Medical Insurance System for Urban and Rural Residents; BMIUE, Basic Medical Insurance for Urban Employees.

health insurance for the well-being of mobile populations. As the world's most populous developing country with a significant migrant population, the empirical evidence from China holds substantial practical significance. The research findings indicate that health insurance exerts a positive influence on the utilization of healthcare services and the overall health of mobile populations. This conclusion aligns with previous studies on the relationship between health insurance and the health of migrant populations, such as research utilizing health survey data from Canada and the United States in 2002 and 2003. Through cross-national comparisons, researchers investigated the impact of health insurance on the disparities in access to primary healthcare services between immigrants and non-immigrants. They identified health insurance as a key factor contributing to these disparities and suggested the need to expand insurance coverage (50). However, compared to other countries, China's mobile population faces more intricate challenges in health security. Firstly, the sheer number of China's mobile population is larger and continues to grow rapidly. Secondly, China's health insurance policies are more complex, with variations in policies between different regions (51). Additionally, regional disparities in healthcare resources further contribute to the unique nature of healthcare security for China's mobile population. In order to strengthen health insurance coverage for the health security of mobile populations, the Chinese government has implemented various measures within the framework of healthcare system reform. These initiatives include providing free public health services for mobile

TABLE 6 Mediating mechanisms affecting the health of the mobile population at the location of health insurance participation.

Variable	Main effect	Intermediate variables	Direct effect	Indirect effects	upper limit	lower limit	Intermediary Effect	Intermediary Type
Enrollment location	−0.0207***	Health Education	−0.0219***	0.0013***	−0.0153	−0.0260	0.0012 ***	Partial intermediary role
		Establishing a health record	−0.0222***	0.0015***			0.0015***	Partial intermediary role
		Family doctor contract	−0.0213***	0.0006***			0.0006***	Partial intermediary role
	−0.0525***	Acceptance of hospitalization	−0.0514***	−0.0011***	−0.0301	−0.0749	−0.0011**	Partial intermediary role
	−0.0300***	Choose local hospitalization	−0.0514**	0.0214***	0.0111	−0.0712	0.0214***	Partial intermediary role

*indicates significant at the 10% level. **indicates significant at the 5% level. ***indicates significant at the 1% level.

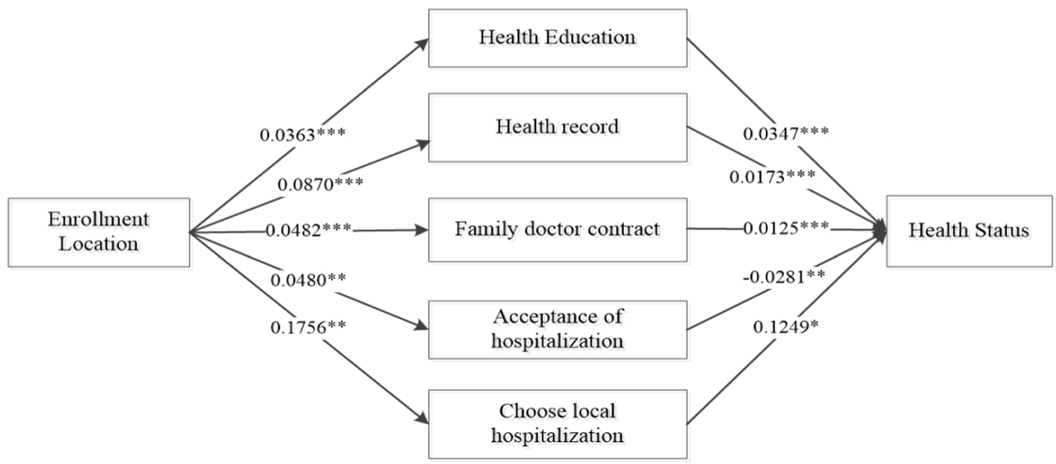

FIGURE 2
Pathway of the impact of the location of participation on the health status of the mobile Population. *indicates significant at the 10% level, **indicates significant at the 5% level, ***indicates significant at the 1% level.

populations through health insurance and establishing a nationwide unified reimbursement system (52). These efforts play a pivotal role in promoting the utilization of healthcare services and improving the health outcomes of China's mobile population.

On the other hand, we need to pay attention to the differentiated impact of different health insurance enrollment characteristics on the utilization of healthcare services and health outcomes among the mobile population. This differentiation manifests in two main aspects. Firstly, individuals participating in local health insurance at their place of residence are more likely to access healthcare services and are also more likely to have better health statuses. Secondly, individuals enrolled in urban employee medical insurance are more likely to access healthcare services and tend to have better health conditions. Despite the integration of fragmented health insurance systems in China, significant policy disparities persist among different regions. These differences encompass levels of insurance coverage, coverage directories, and reimbursement procedures for medical expenses. Additionally, the lower-level coordination within the health insurance system restricts the transferability of health insurance relationships for the mobile population. Opting for local health insurance at the place of residence contributes to obtaining a more comprehensive level of coverage and helps avoid the complexities of reimbursement procedures and associated costs when seeking medical care in different locations. The reasons for the divergent impact of various types of health insurance systems may stem from their distinct targets within the Chinese population, resulting in differences across multiple facets of benefit levels (22). For instance, the mobile population, when covered by urban employee medical insurance compared to rural and urban resident medical insurance, enjoys higher reimbursement benefits, leading to more significant effects on health protection (53). According to the 2018 statistical report on the development of medical insurance released by the National Healthcare Security Administration of the People's Republic of China, the reimbursement ratio for inpatient expenses within the scope of urban employee medical insurance policies is 81.6%, whereas it is 65.6% for rural and urban resident medical insurance policies (54). This implies a 16% difference in the reimbursement ratios between the two insurance systems. This form of unfairness in the utilization of health insurance is a prevalent issue globally. For example, a study utilizing nationwide reimbursement data from South Korea's National Health Insurance between 2002 and 2010 evaluated the policy effects of expanding national health insurance coverage for cancer patients in 2005. The

TABLE 7 Mediating mechanisms by which type of health insurance affects the health of mobile populations.

Variable	Main effect	Intermediate variables	Direct effect	Indirect effects	Upper limit	Lower limit	Intermediary effect	Intermediary type
Type of health insurance	0.0298***	Health Education	0.0302***	−0.0004**	0.0392	0.0203	−0.0004**	Partial intermediary role
		Establishing a health record	0.0311***	−0.0013***			−0.0012***	Partial intermediary role
		Family doctor contract	0.0308***	−0.0010**			−0.0010**	Partial intermediary role
	0.1303***	Acceptance of hospitalization	0.1305***	−0.0002	0.1725	0.0880	0.0003	Intermediary is not established
	0.1524***	Choose local hospitalization	0.1511***	0.0013	0.2270	0.0778	0.0013	Intermediary is not established

*indicates significant at the 10% level. **indicates significant at the 5% level. ***indicates significant at the 1% level.

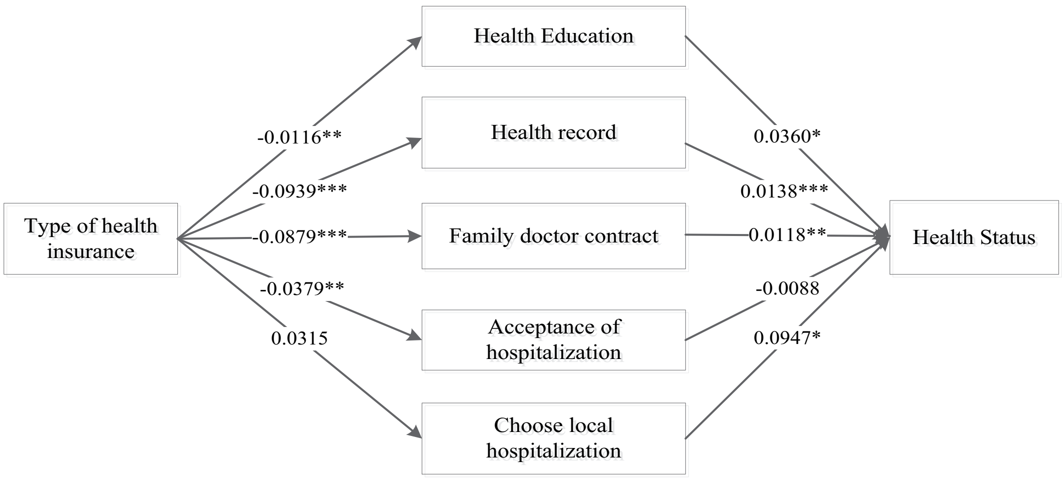

FIGURE 3
The pathway of the influence of the type of medical insurance on the health status of the mobile population. *indicates significant at the 10% level, **indicates significant at the 5% level, ***indicates significant at the 1% level.

findings revealed that the policy partially alleviated income-related inequalities among inpatients in tertiary hospitals but did not improve income-related inequalities among outpatient cancer patients (55). Analyses of healthcare utilization inequalities in the United States also suggest that individuals with and without health insurance experience disparities in healthcare accessibility and overall health. Expanding health insurance coverage is more likely to enhance the quality of life and extend life expectancy (56).

Finally, the results of the intermediary mechanism analysis in this study indicate that health insurance not only has a direct positive impact on the health of the mobile population but also influences their health through the mediation of healthcare service utilization behaviors. In terms of the impact of the location of health insurance participation on the health of the mobile population, behaviors such as receiving health education, establishing health records, and signing contracts with local family doctors, as well as utilizing inpatient services and obtaining inpatient services locally, play a partial intermediary role. The most significant intermediary effect is observed in receiving inpatient services locally, possibly because the reimbursement focus in China's health insurance reform is predominantly on inpatient services, providing comprehensive coverage for the mobile population's hospitalization needs (57). In the pathway of the impact of health insurance types on the health of the mobile population, health education, health records, and family doctor signing behaviors play a partial intermediary role, while behaviors such as receiving inpatient services and obtaining inpatient services locally do not act as intermediaries in the mechanism. Therefore, to further enhance health coverage for the mobile population through health insurance, attention should be given to the indirect effects of healthcare service utilization behaviors in this influence.

Summing up the above analysis, this study has three main advantages compared to existing relevant research. Firstly, using large sample data, the study not only empirically verifies the impact of health insurance on the health of the mobile population but also delves deeper into the multidimensional analysis of the influence of health insurance on the utilization of healthcare services by the mobile population. This provides a crucial supplement to the current literature on improving the health and healthcare service utilization of the mobile population. Secondly, we examine the impact of different enrollment characteristics of health insurance on the health and service utilization of the mobile population. This holds practical significance for the government in enhancing the performance of healthcare security and reinforcing health protection for the mobile population. Thirdly, the study analyzes the intermediary role of healthcare service utilization, contributing to better health improvement for the mobile population and suggesting more effective health insurance policies to alleviate inequalities in healthcare security for the mobile population. However, the study has some limitations. Firstly, due to data constraints, we mainly focus on the intermediary role of two types of healthcare service behaviors, namely, public health service utilization and inpatient service utilization, in the relationship between health insurance and the health of the insured. Future research, with richer data, can further include other pathways such as individual health behaviors, outpatient service utilization, and medical expenses in intermediary mechanism analysis for a more comprehensive exploration of how health insurance affects the health of the mobile population. Secondly, the study utilizes cross-sectional data from the 2018 CMDS database, limiting our ability to determine trends or long-term associations between health insurance and the health of the mobile population. It also hinders the verification of specific causal relationships between mechanisms. In future research, adopting longitudinal or experimental designs could better determine the direction of causality between health insurance and health, ensuring more robust and reliable causal inferences. Thirdly, as the 2018 CMDS only uses self-assessed health status as the sole measurement criterion for the health condition of the mobile population, it becomes challenging to measure health status through other objective indicators. With richer data in the future, incorporating additional objective indicators to assess health could enhance the analysis.

Policy implications

Based on our research findings, we offer some recommendations for reference. First, there is a need to further improve the accessibility of health services for the mobile population. In the future, more healthcare services could be included in the coverage of medical insurance to enhance the equality of public health services. The government can enhance disease and medical knowledge among the mobile population through health education and medical examinations, enabling them to scientifically assess their own health conditions and promote awareness of health management. The government should optimize the allocation of medical service resources, innovate service models, and improve the accessibility of medical services based on the characteristics of the mobile population's work, residence, major health issues, and health conditions, ensuring that they can easily access medical services (21, 43). Second, there is a need to reduce the disparities in treatment between different regions and insurance systems. The government could further elevate the coordination level of basic medical insurance to promote the uniformity of medical insurance policies between different regions, facilitating the mobility and reimbursement of medical expenses for the mobile population. Regarding the differences in coverage between different medical insurance systems, efforts can be made to reduce disparities in aspects such as the deductible standard, payment ratio, maximum payment limit, and types of reimbursable diseases from the medical insurance fund to achieve equality in welfare benefits between different insurance systems (58). Third, simplifying the procedures for transferring medical insurance relationships is crucial. For mobile populations with longer durations of mobility, they could be encouraged to transfer their medical insurance relationships to their places of residence, actively encouraging participation in local medical insurance. Simultaneously, for mobile populations with formal employment, active encouragement to participate in urban employee medical insurance should be provided to enhance health security performance.

Conclusion

The mobile population has made significant contributions to China's economic and social development. With the continuous growth of the mobile population, addressing the health issues they face has become an integral part of building a Healthy China. This article, based on cross-sectional data from the 2018 CMDS database, analyzes the relationship between the characteristics of medical insurance enrollment and the health of the mobile population, as well as the mediating role of healthcare service utilization. The research results indicate that participating in local medical insurance and urban employee medical insurance significantly enhances the healthcare service utilization and overall health levels of the mobile population. At the same time, public health service utilization and hospital service utilization play important mediating roles in the relationship between medical insurance and the health of the mobile population. However, differences exist in the types of services regarding the nature of mediation and the size of mediating effects. Future efforts should focus on improving the accessibility of healthcare services for the mobile population, narrowing the disparities in treatment between different regions and insurance systems. This will further enhance the health security provided by medical insurance for the mobile population. These findings serve as a basis for refining policies related to the medical security of the mobile population and contribute to the realization of the goals of a Healthy China.

Data availability statement

This study was based on a publicly available database, the China Migrants Dynamic Survey (CMDS), which was conducted annually by the National Health and Wellness Commission of China since 2009. The datasets generated and/or analyzed during the current study are available in the official website (https://www.chinaldrk.org.cn/).

Ethics statement

Ethical approval was not required, as this study was a secondary analysis conducted using public data sets from the CMDS that did not include identifiable personal information. Each volunteer participant obtained a written informed consent based on inclusion criteria. All procedures performed in this study were in accordance with the 1964

Helsinki declaration and its later amendments or comparable ethical standards.

Author contributions

BD collected, cleaned and prepared the data, analyzed and interpreted the data, drafted the manuscript and made subsequent revisions, read and approved the final manuscript.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Medical insurance, vulnerability to poverty, and wealth inequality

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Background: China has made remarkable achievements in alleviating poverty under its current poverty standards. Despite these immense successes, the challenge of consolidating these achievements remains. In reality, health risks are among the significant factors causing rural households to fall into poverty, and medical insurance is the significant factor mitigating household vulnerability to poverty. Therefore, alleviating or guarding against households falling into poverty is essential.

Methods: This paper establishes a multi-equilibrium model that incorporates heterogeneous health risks and medical insurance. Through parameter calibration and value function iteration, numerical solutions are derived.

Results: Heterogeneous health risks significantly increase poverty vulnerability and wealth inequality in rural households. Medical insurance, through its investment incentives and loss compensation effects, efficiently mitigates these issues, especially benefiting those in poorer health. Furthermore, the dual-slanted compensation policy efficiently mitigates the adverse effects of "reverse redistribution."

Conclusion: Medical insurance effectively mitigates household vulnerability to poverty and wealth inequality. Government departments must establish health records for residents. By recognizing variations in health conditions, these departments can provide households with poorer health conditions with a higher medical expense compensation ratio. In addition, the government should further focus medical expense reimbursements toward households on the cusp of escaping poverty to ensure that they are not plunged back (or further) into poverty due to medical expenses.

KEYWORDS

heterogeneous health risks, multi-equilibrium model, reverse redistribution, medical insurance, vulnerability to poverty, wealth inequality

1 Introduction

Poverty is one of the most pressing issues worldwide and remains a primary concern for development economists and policymakers. China has made remarkable achievements in alleviating poverty under its current poverty standards.[1] By 2020, all 832 recognized

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1 According to the current standards set by the World Bank, China has eradicated absolute poverty. For more details, please refer to: https://www.worldbank.org/content/dam/Worldbank/document/WB-goals2013.pdf and https://www.un.org/en/global-issues/ending-poverty.

poverty-stricken counties nationwide had been lifted out of poverty, cleared and nearly 100 million rural residents overcoming poverty. Remarkably, China achieved the United Nations' 2030 Agenda for Sustainable Development's poverty reduction goal a decade early, historically eradicating absolute poverty and creating an unprecedented feat in human poverty reduction history (Table 1).[2]

The positive correlation between health risks and household poverty has been discussed in several studies (1–3). Using household survey data from China, Song et al. (3) and Ma et al. (4) found that health risks are a direct factor leading to poverty vulnerability in households. Liao et al. (1) discovered that under the impact of health risks, increased household medical expenses lead to reductions in total household capital, total labor, and *per capita* capital, ultimately plunging households into poverty. Moreover, health risk shocks also generate health inequality and health poverty issues (2, 5) and can lead to the intergenerational transmission of household poverty (6, 7). This further exacerbates wealth inequality among households and ultimately heightens relative poverty within households (8). However, these studies rarely delve into the impact mechanisms of heterogeneous health risks on vulnerability to poverty and wealth inequality.

Several studies have deeply explored the impact of medical insurance on poverty alleviation. Participation in medical insurance can enhance a household's nonmedical consumption (9), reduce excessive labor supply and out-of-pocket medical expenses (10, 11), improve residents' health conditions (1, 12) and reduce mortality rates (13). Further studies show that participation in medical insurance can stabilize household income (10) and enhance social welfare (14). More importantly, such participation can reduce the likelihood of households falling into poverty due to health risk shocks (1, 15–17) and the income gap between urban and rural residents (18). Korenman et al. (19) developed a health-inclusive poverty measure and found that participation in medical insurance reduced the poverty rate by 2.9 percentage points among people under 65 in Massachusetts and by 3.2 percentage points among children. However, if the coverage of medical insurance is too low, it is less effective (20).

Van Doorslaer et al. (21) found that approximately half of OECD countries experience unbalanced utilization of medical services, with higher-income groups benefiting more. Similar conclusions were also drawn from studies using medical insurance data from Europe, the United States, and Asian countries by van Doorslaer et al. (22) and Lu et al. (23). These studies indicate that despite medical insurance effectively reducing poverty vulnerability and income disparities, it also causes the "reverse redistribution" of wealth. Using health insurance data from Massachusetts, Finkelstein et al. (24) found that a slanted compensation policy could increase participation rates among low-income groups, providing some fuel for addressing the "reverse redistribution" issue.

Therefore, building on these studies, this paper incorporates heterogeneous health risks and medical insurance into a multiple equilibrium model[3] and discusses the impact of heterogeneous health risk shocks, medical insurance, and dual-slanted compensation policies on rural household poverty vulnerability and wealth inequality.

TABLE 1 Poverty-stricken counties, incidence of poverty and number of impoverished populations.

Year	Poverty-stricken counties	Incidence of poverty (%)	Impoverished populations (ten thousands)
2012	832	10.2	9,899
2013	832	8.5	8,249
2014	832	7.2	7,017
2015	832	5.7	5,575
2016	804	4.5	4,335
2017	679	3.1	3,046
2018	396	1.7	1,660
2019	52	0.6	551
2020	0	0	0

The potential marginal contributions of this paper are as follows: First, this paper introduces heterogeneous health risks into the multiple equilibrium model, discussing the impact of heterogeneous health risks on rural household poverty vulnerability and wealth inequality. Second, based on the investment incentive effect of medical insurance and the "reverse redistribution" effect of wealth, this paper discusses the impact of basic medical insurance on household vulnerability to poverty and wealth inequality. Third, to address the "reverse redistribution" issue in medical insurance, we designed a dual-slanted compensation policy based on wealth and health status to further optimize the effect of medical insurance on reducing poverty vulnerability and wealth inequality.

The rest of this research is structured as follows. The next section presents the methodology. The third section provides the results and discussion. The conclusions and policy recommendations are offered in the last section.

2 Methods

2.1 Multi-equilibrium model

2.1.1 Production function

Assume that each household possesses two types of agricultural production technologies, high and low. If the productive asset $k_t \le \bar{k}$, the farmer opts for the technology with lower production efficiency. If $k_t > \bar{k}$, the farmer chooses the technology with higher

2 The data is sourced from: https://www.gov.cn/xinwen/2021-11/16/content_5651269.htm.

3 Previous models on multiple equilibria have primarily discussed the impact of asset risks and agricultural risks on the vulnerability to poverty of rural households (25–27). This paper builds upon these foundations with certain expansions. Furthermore, the existence of poverty traps has been thoroughly discussed in studies by Carter and Barrett (28), Thomas and Gaspart (29), Toth (30), and Radosavljevic et al. (31). This topic is not reiterated in our paper.

production efficiency. $\bar{k}$ denotes the asset threshold for the technology switch. Hence, the non-convex agricultural production function is as follows:

$$f(k_t) = \begin{cases} f_H(k_t) = A_t k_t^{\alpha_H} - \bar{f}_H, k_t > \bar{k} \\ f_L(k_t) = A_t k_t^{\alpha_L} - \bar{f}_L, k_t \le \bar{k} \end{cases} \quad (1)$$

where A_t denotes the total factor productivity in agriculture. $\bar{f}_H$ and $\bar{f}_L$ are the fixed costs associated with the high and low production technologies, respectively. They are also the reasons behind poverty traps (30, 32).[4] α_H and α_L represent the capital output elasticity for high and low production technologies, respectively. The capital technology switch threshold is the intersection of the outputs for both agricultural production technologies, that is:

$$\bar{k} = \{k | f_H(k_t) = f_L(k_t)\}$$

2.1.2 Intertemporal household decision model

We assume an infinite number of homogeneous small-scale farming households, with a fixed family size standardized to 1. Household are immortal and aim to maximize their utility. Each household produces only one homogenous agricultural product. The capital for agricultural production comes internally from the household. The household decides on consumption before making agricultural production decisions, and the initial capital for the household is k_0. The discount factor for household utility is β, and the depreciation rate of the household's assets is δ. Therefore, the objective of maximizing household utility is:

$$\max_{c_t} E_\theta \sum_{t=0}^{\infty} \beta^t u(c_t) \quad (2)$$

where $u(c_t) = \frac{c_t^{1-\gamma}}{1-\gamma}$ represents the constant relative risk aversion (CRRA) power utility function, c_t denotes the household's consumption in period t, and γ is the coefficient of risk aversion. This is subject to the following constraints:

$$c_t \le k_t + f(k_t)$$

$$k_{t+1} = \left(f(k_t) + (1-\delta)k_t - c_t - (1-s_t)m_t\right)\left(1 - \theta_{i,t+1} + I_{t+1}B_{t+1}\right)$$

$$0 \le m_t \le A_t$$

$$c_t, k_t > 0.$$

4 Notably, such a nonconvex production function does not necessarily lead to poverty traps (32, 33). This paper investigates only scenarios that include poverty traps.

The first constraint represents the liquidity constraint on wealth (34), implying that households cannot borrow for consumption or investment. The second constraint is the motion equation for productive assets. $\theta_{i,t+1}$ represents the ratio of total medical expenses paid by the household to its assets, $i \in [b, g]$. b and g denote individuals with poor and good health, respectively. Those with good health have to pay less in medical expenses when confronted with health risk, and $0 \le \theta_{g,t} \le \theta_{b,t} \le 1$. The probability of health risk is $p_{i,t}$, and $0 \le p_{g,t} \le p_{b,t} \le 1$, with health risk being independently and identically distributed. I_t indicates the indicator function for the occurrence of a health risk, $B_t = (1-\theta_{i,t})\eta_t$ represents the ratio of compensation received to assets, and η_t denotes the reimbursement rate, which can also be interpreted as the level of medical insurance coverage. s_t stands for the government subsidy rate for medical insurance premiums, and $(1-s_t)m_t$ represents the medical insurance fees that rural households have to pay themselves. The third constraint suggests that the price of the insurance premium should be greater than or equal to 0 but cannot exceed the total assets of the household. The fourth constraint indicates that both consumption and assets must be positive values.

Based on Eq. 2, and given the state variable k_t, the Bellman equation for utility maximization can be derived:

$$V(k_t) = \max_{c_t} \left\{u(c_t) + \beta E_{\theta_{i,t}}\left[V(k_{t+1}) | c_t, k_t\right]\right\} \quad (3)$$

where $V(k_t)$ represents the value function.

Based on Eqs 2, 3, we derive the first-order condition for the household, illustrating the intertemporal trade-off between consumption and investment as follows:

$$u'(c_t) \ge \beta E_\theta\left[V'(k_{t+1})(1-\theta_{i,t+1})\right] = \lambda(k_{t+1}) \quad (4)$$

where $V'(k_{t+1})$ represents the future value of a unit of capital, and $\lambda(k_{t+1})$ denotes the expected shadow price of the asset.

2.1.3 Medical insurance

The current Urban and Rural Residents' Basic Medical Insurance in China follows a model combining individual payments with government subsidies.[5] Individuals contribute the same amount toward medical insurance premiums, and when confronted with health risk, they receive compensation for medical expenses at the same rate. It is posited that the medical insurance premium is priced based on the principle of expected value, which is:

$$m_t = \eta_t(1-d)\left(\varepsilon_{b,i}\theta_{b,t}p_{b,t} + \varepsilon_{g,i}\theta_{g,t}p_{g,t}\right)\frac{1}{N}\sum_{n=1}^{N} W_{n,t} \quad (5)$$

where $W_{n,t} = f(k_{n,t}) + (1-\delta)k_{n,t} - c_{n,t} - (1-s_t)m_t$ represents the family's wealth after making consumption decisions, $\varepsilon_{i,i}$ denotes

5 In 2016, the New Cooperative Medical Scheme was integrated with the Urban Resident Medical Insurance to form the Urban and Rural Residents' Basic Medical Insurance. Given that the current insurance coverage rate is close to 100%, this paper does not discuss the impact of insurance demand.

the proportion of individuals in healthy and unhealthy states, and N stands for the number of insured individuals.

2.2 Parameter calibration

For total factor productivity A_t, we set $A_t = 1$. According to Liao et al. (26), the capital output elasticity for high and low agricultural production techniques are set at $\alpha_H = 0.5$ and $\alpha_L = 0.1$, respectively. The utility discount rate is set at $\beta = 0.975$. The capital depreciation rate δ is 0.096. According to Liao et al. (26), the risk aversion coefficient is set to $\gamma = 0.53$. For individuals in good health and those in poorer health, the asset loss ratios are set at $\theta_{g,t} = 0.2$ and $\theta_{g,t} = 0.4$, respectively. The proportion of the population in good health compared to that in poorer health is $\varepsilon_{g,t} = 0.72$ and $\varepsilon_{b,t} = 0.28$, respectively. Furthermore, the probability of encountering a health risk for individuals in good health versus those in poor health are set at $p_{g,t} = 0.025$ and $p_{b,t} = 0.05$, respectively. We set the deductible rate as $d = 0$.

According to the actual reimbursement rate data for urban and rural resident medical insurance, released by China's National Medical Security Administration over the past 3 years,[6] this paper estimates an average actual reimbursement rate $\eta_t = 0.6$. The government subsidy rate for the medical insurance of urban and rural residents is approximately $s_t = 0.7$, as referenced by Liu (14). In this study, the fixed costs for high and standard production technologies are set at $\bar{f}_H = 0.95$ and $\bar{f}_L = 0$, respectively.

2.3 Value function iteration method

Building upon the aforementioned parameter calibration, this study further employs the value function iteration method to compute the policy functions for consumption and capital. That is, we calculate the present consumption and the subsequent capital value for each initial capital level. Given that in the theoretical model, the health risk occurs after the household's current consumption decision but before the next period's consumption decision, we designate the consumption c_t of the t period as the control variable. The detailed computational steps are as follows:

First, in period t, based on state variable k_t, we determine the initial range of control variable $c_t \in \left[0, f\left(k_t\right) + k_t - \left(1 - s_t\right) m_t\right]$. For simplicity, we set the initial value series of the value function $V\left(k_t\right)$ to 0. We then define the range for the state variable k_t in period t, ensuring $k_t \in \left[k_{\min}, k_{\max}\right]$. We set $k_{\min} = 0.1$ and $k_{\max} = 20$.

Second, by utilizing the motion equation of capital and the loss distribution from health risk shocks, we identify the initial capital level for the next period. By applying linear interpolation techniques, we establish a one-to-one mapping relationship between the capital in period $t+1$ and the values of the value function sequence $V\left(k_{t+1}\right)$. Together with the loss distribution from health risk, we obtain the value of the value function $V\left(k_t\right)$ corresponding to the state variable k_t.

Third, the state variable k_t is divided into 100 intervals. We obtain the consumption sequence c_t that maximizes utility, as well as the sequence for the value function. The iteration halts when the percentage change between two consecutive value functions $V\left(k_t\right)$ is less than 10^{-10}.

Fourth, based on the distribution of losses due to health risk and the motion equation for capital, we determine the policy function value for capital k_{t+1}.

Finally, by making 100,000 random simulations and modeling 100,000 rural households, we compute a range of results, including the Micawber threshold, vulnerability to poverty among rural households, and wealth inequality.

Notably, this study utilizes the fminbnd function from the Optimization Toolbox in MATLAB to compute the utility-maximizing value function $V\left(k_t\right)$ and its corresponding policy function. Furthermore, regarding the calculation of medical insurance premiums, we rely on Eq. 5. Considering the distribution of household wealth status in Table 2, we simulate 100,000 households, from which we ultimately calculate the average medical insurance premium.

3 Results and discussion

3.1 Vulnerability to poverty and wealth inequality under heterogeneous health risks

Based on the model construction and value function iteration from the second section, we discuss the changes in rural household vulnerability to poverty and wealth inequality under heterogeneous health risk in this section. We measure poverty vulnerability by the probability that a rural household's assets fall below the Micawber threshold.

As illustrated in Figures 1–4, we simulated household out-of-pocket medical expenses and asset levels using Eqs 1–3. We then calculated the shadow prices of assets through Eq. 4 and simulated the vulnerability to poverty for rural households over the next 50 periods. Additionally, we presented scenarios without health risk. The solid black line represents households with good health, the dashed black line indicates households with poor health, and the dashed red line denotes households without health risk. For any given household, the higher the asset level is, the lower the vulnerability to poverty. This is not only because households with higher asset levels possess greater

TABLE 2 Proportion of households at different asset levels.

Asset	0–1	1–2	2–3	3–4	4–5
Proportion (%)	5.6	7.5	9	9.8	9.3
Asset	5–6	6–7	7–8	8–9	9–10
Proportion (%)	8.7	7.6	6.6	5.6	4.8
Asset	10–11	11–12	12–13	13–14	14–15
Proportion (%)	3.9	3.2	2.8	2.4	1.9
Asset	15–16	16–17	17–18	18–19	19–20
Proportion (%)	1.7	1.4	1.2	1	6

6 Please refer to the "National Medical Security Development Statistical Bulletin" published by China's National Medical Security Administration, http://www.nhsa.gov.cn/.

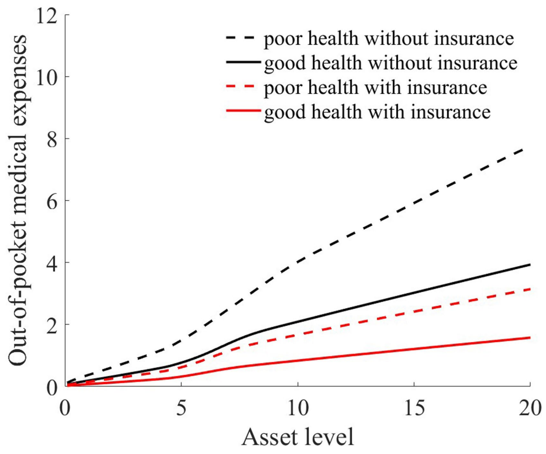

FIGURE 1
Out-of-pocket medical expenses after health risk.

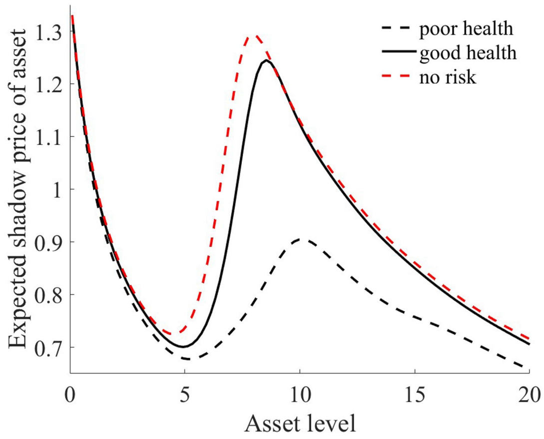

FIGURE 3
Shadow prices of assets.

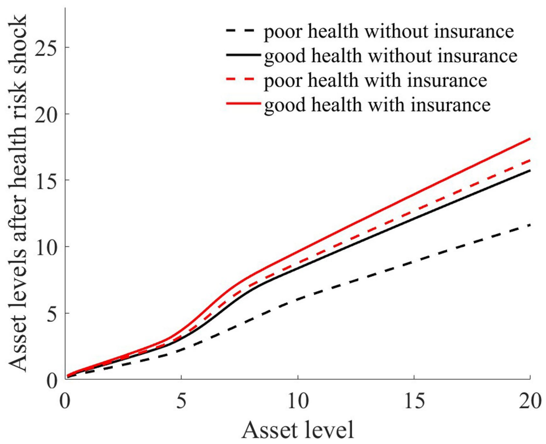

FIGURE 2
Asset levels after health risk.

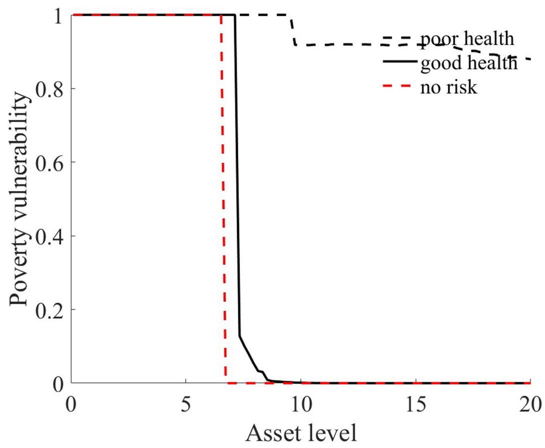

FIGURE 4
Poverty vulnerability.

resilience against risks but also because these households' assets are farther from the Micawber threshold. Moreover, after encountering health risks, there is a decline in the shadow prices of assets (as shown in Figure 3), which reduces household investments in agricultural production, thereby increasing these households' vulnerability to poverty.

Households with better health face fewer health risks in the future than households with poor health. As a result, they incur lower medical expenses (as depicted in Figure 1) and, upon each health risk, experience a smaller proportion of asset loss (Figure 2). Furthermore, even though the shadow price of assets declines after health risk, it remains higher than that of households with poor health (Figure 3). This suggests that they continue to maintain a higher level of investment in agricultural production, anticipating higher future consumption. Due to the stronger investment incentive effect, they are more likely to reach a high steady-state equilibrium. This leads to a considerably lower Micawber threshold (7.0109) for these households than for households with poor health (9.1459). Consequently, households with good health have less vulnerability to poverty than households with poorer health (Figure 4).

In contrast, for households with poorer health, each time they suffer from a health risk, their remaining assets tend to be lower, positioning them closer to the Micawber threshold. Moreover, the shadow price of their assets drops significantly (as illustrated in Figure 3), which inhibits their investment in agricultural production. These households also face a higher Micawber threshold. As a result, these households are more inclined to allocate their wealth toward immediate consumption rather than future consumption, increasing their probability to falling into the poverty trap (as depicted in Figure 4).

Having previously discussed the differentiated vulnerability to poverty under heterogeneous health risks, it is also evident that households with high asset levels and those with low asset levels display distinct vulnerabilities. We further delve into the shifts in wealth inequality. Assuming that wealth inequality initially exists among households, after encountering health risks, households with poorer health invariably face higher medical expenses (as demonstrated in Figure 1). This could lead to an even greater divergence in the asset levels of different households, potentially exacerbating the wealth disparity between them.

Adopting the approach of Cagetti and De Nardi (35), we employ the Gini coefficient to measure wealth inequality. Additionally, to further test the robustness of these results, we use the Theil index as a measure of wealth disparity.

Liao et al. (26), according to the rural household income distribution data published by the National Bureau of Statistics of China for 2012, segmented households into 20 groups from lowest to highest income, detailing the proportion of rural households in each segment. Following this approach, we set the household asset range from 0 to 20, with asset intervals equally distributed. The overall proportions of households with different assets are presented in Table 2.

In our assumption, rural households at varying wealth levels comprise both households in good health and households in poor health. Furthermore, both households with good health and households with poor health are evenly distributed across the different asset groups. We simulate a total of 100,000 households over a span of 50 years. Based on Table 2, we calculate the composition of households in each asset range. For every simulated household, their health status was determined via random sampling. Through this random simulation, we present the Gini coefficient and Theil index under health risk shocks in Figure 5.

Compared to scenarios without risk, when exposed to health risk, households experience a decline in the shadow price of assets (as illustrated in Figure 3). Households tend to use their assets more for consumption than for production investment. This leads to a greater number of households falling into poverty traps, exacerbating the degree of wealth disparity. Households with good health conditions face lower health risks. Although the shadow price of their assets diminishes, it remains considerably higher than that of households with poor health conditions (as shown in Figure 3). They continue to maintain substantial agricultural asset investments that allow rapid capital accumulation, thereby approaching or achieving a high steady-state equilibrium.

Conversely, for households with poor health conditions, consistent exposure to health risk results in a lower expected shadow price for assets. These households are more inclined toward immediate consumption, making them more susceptible to falling into poverty traps. Over time, this disparity in wealth intensifies, leading to a continual expansion in both the Gini coefficient and Theil index (as shown in Figure 5). This indicates that the degree of wealth inequality progressively increases as health risk increases.

3.2 Impact of medical insurance on the vulnerability to poverty among rural households

By employing value function iteration, we derived the policy function for household assets and computed the out-of-pocket medical expenses for households, as well as their assets.

As illustrated in Figures 1, 2, the solid black line represents households with good health conditions that are not enrolled in medical insurance, while the dashed black line signifies households with poor health conditions without medical insurance. Conversely, the solid red line denotes households with good health conditions that have medical insurance, and the dashed red line corresponds to households with poorer health conditions that have medical insurance. Broadly speaking, regardless of insurance enrollment, households with worse health conditions incur higher medical expenses. Moreover, households with more robust economic standing are better equipped to shoulder these increased medical expenses.

As evidenced by Figure 1, medical insurance, through substantial medical expense reimbursements, has alleviated the healthcare burden on rural households. Given that the reimbursement rate is consistent, higher medical expenditures lead to greater reimbursements. This is particularly significant for individuals with poorer health, where medical insurance has considerably reduced the medical financial strain on rural households.

As illustrated in Figure 2, regardless of whether households have good or poor health conditions, after basic medical insurance compensation is received, the out-of-pocket medical expenses

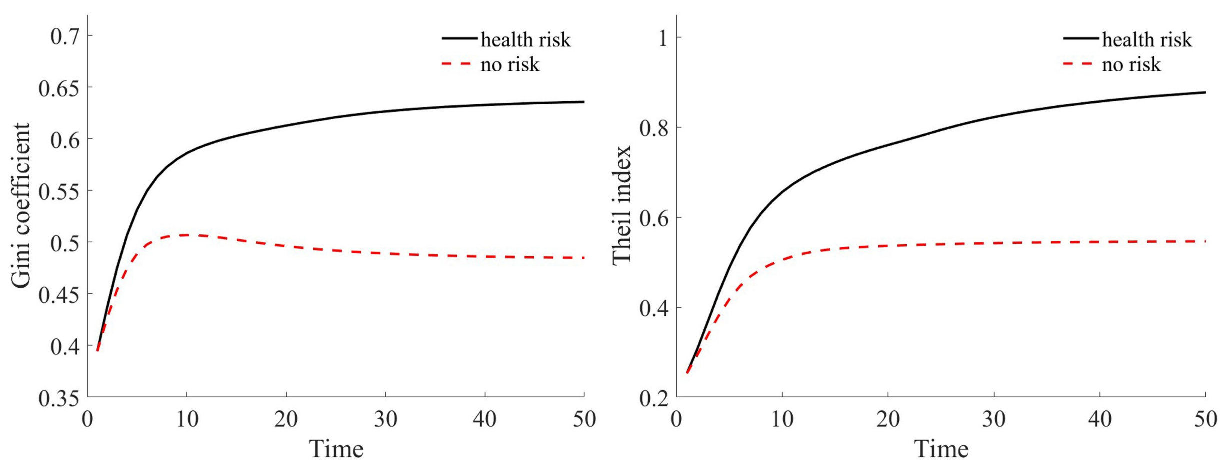

FIGURE 5
Changes in wealth inequality indices.

significantly decline. Consequently, the proportion of asset losses for rural households that receive medical compensation is substantially reduced. This, in turn, elevates the asset levels for the subsequent period, playing a crucial role in wealth accumulation for rural households. Comparatively, medical insurance provides higher compensation for households in poorer health.

The aforementioned results highlight that medical insurance has played an effective role in risk compensation, offering significant support for stabilizing consumption and fostering wealth accumulation for rural households. Furthermore, we compared the changes in vulnerability to poverty across four types of rural households: those in good health without medical insurance, those in poor health without medical insurance, those in good health with medical insurance, and those in poor health with medical insurance.

As illustrated in Figure 6, rural households, regardless of whether they have good or poor health conditions, have significantly reduced their vulnerability to poverty upon enrollment in medical insurance. This finding underscores the role of medical insurance in mitigating the risk of rural households falling into poverty due to health risk.

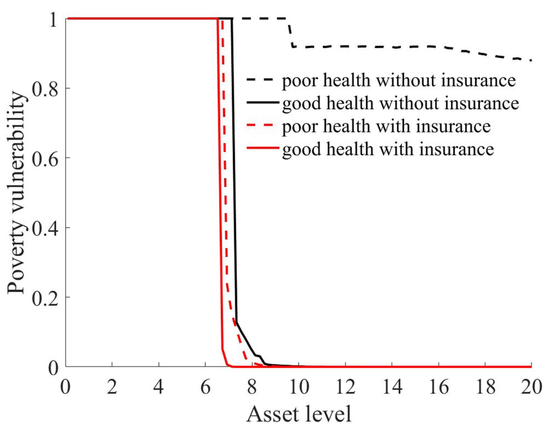

FIGURE 6
Poverty vulnerability.

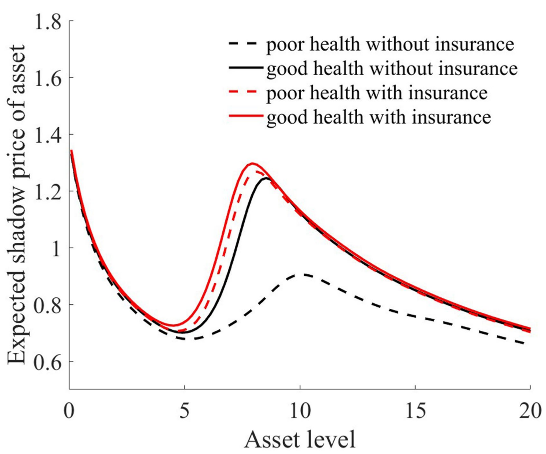

FIGURE 7
Shadow prices of assets.

The reason is that rural households with medical insurance, when facing health risk, can reduce their out-of-pocket medical expenses through insurance compensation, thereby enhancing their post-shock asset levels (as shown in Figure 2). Moreover, due to the risk-protection feature of medical insurance, the shadow price of household assets increases (as shown in Figure 7). Compared to those without medical insurance, this encourages households to engage in more productive investments, aiming for greater future consumption. This notably diminishes the vulnerability of rural households to poverty.

From the perspective of households with varying health conditions, medical insurance appears to be more beneficial for those in poorer health. This is reflected not only in the reduction in out-of-pocket medical costs for these households following health risk (as shown in Figure 1) but also in the increase in the shadow price of assets for households with poorer health conditions (as indicated in Figure 7). This markedly reduces the vulnerability to poverty for households with poorer health conditions (Figure 6). Of course, since all households are required to pay a certain medical insurance premium, these premiums have an erosive effect on assets, which can mitigate the overall impact of the insurance. Overall, medical insurance significantly diminishes the vulnerability to poverty among rural households.

3.3 The impact of medical insurance on wealth inequality

In our previous discussions, we delved into the impact of medical insurance on vulnerability to poverty. However, under an egalitarian compensation system, it becomes imperative to further discuss the fairness of individual benefits from medical insurance.

Public medical service benefits are often measured through the Benefit Incidence Analysis framework, and individuals with different wealth statuses tend to use public medical services differently (36). Therefore, referencing the measurement method of O'Donnell et al. (36), the expression for individual benefits from public medical services is as follows:

$$b_t^n = \frac{e_t}{\sum_{n=1}^{N} u_t^n} u_t^n, e_t = N m_t s_t \tag{6}$$

$$u_t^n = \left(f\left(k_t\right) + \left(1-\delta\right) k_t - c_t - \left(1-s_t\right) m_t \right) I_{t+1} B_{t+1} \tag{7}$$

where e_t represents the government's investment in public medical services, and u_t^n denotes the quantity of public medical services used by the n-th household in period t (that is, the medical reimbursement expenses).

Consistent with the previous section, we simulated the scenarios of 100,000 households. We also presented the benefit statuses of rural households in two health conditions: good health and poor health. Based on Eqs 6, 7, we calculated the benefit values of rural households with different asset levels and health statuses. Additionally, we computed the reimbursement expenses for medical insurance, which are depicted in Figures 8, 9.

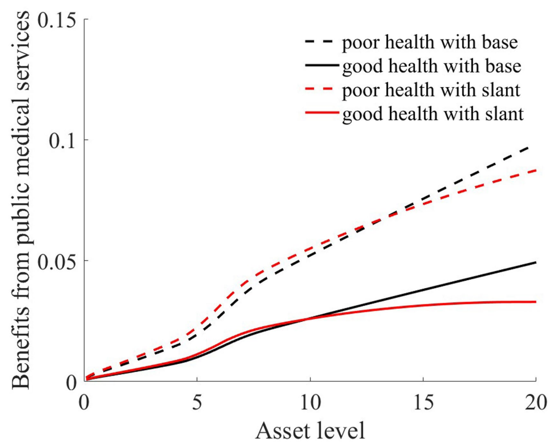

FIGURE 8
Benefits from public medical services.

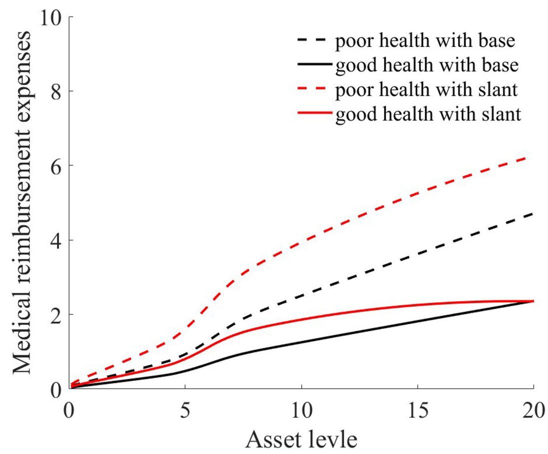

FIGURE 9
Medical reimbursement expenses.

As Figures 8, 9 illustrate, the solid black line represents rural households with good health conditions, while the dashed black line signifies those with poorer health conditions. Both curves demonstrate a consistent trend: the higher the asset level of the household is, the more it benefits from medical services (Figure 8). This is because, despite every household having the same medical insurance premium obligations, those with higher asset levels tend to have higher medical expenditures. Under a proportional compensation policy, they receive higher reimbursements from their medical insurance (Figure 9), thereby accruing greater benefits from medical services. This essentially results in a "reverse redistribution" from households with lower assets to those with higher assets. Simultaneously, a larger proportion of government fiscal subsidies flow to households with higher asset levels. This phenomenon of reverse wealth distribution intensifies wealth inequality among rural households.

Medical insurance provides insured households with a proportionate reimbursement, elevating their asset levels after a health shock. This, in turn, raises their shadow price of assets (as shown in Figure 7), especially for households with poorer health conditions. This incentivizes these households to make greater agricultural production investments, facilitating rapid capital accumulation toward a higher stable equilibrium and preventing these households from falling into poverty traps (as depicted in Figure 6). Thus, both the investment incentive and compensation effects of medical insurance serve to reduce wealth inequality (as measured by the Gini coefficient and Theil index).

In summary, due to uniform medical insurance premiums and proportionate medical expense reimbursements, medical insurance tends to favor households with higher wealth over those with lower wealth, thereby exacerbating the wealth disparities between households. However, the investment incentive effect of medical insurance boosts agricultural production investments among rural households, enabling them to accumulate capital more swiftly and thereby mitigating wealth inequality. Overall, medical insurance contributes to a reduction in wealth inequality (as illustrated in Figure 10).

3.4 Analysis of the effects of dual-slanted reimbursement policies

3.4.1 Impact of the slanted compensation policy on poverty vulnerability

If the medical insurance compensation ratio were to be universally increased for all households (potentially even to 100%), this might render the fiscal policy untenable. Moreover, since households with higher wealth exhibit more substantial spending power, a uniform increase in the reimbursement rate for all could intensify the "reverse redistribution" effect.

Therefore, with a nuanced approach, we tailored a sliding compensation policy targeting both the wealth and health dimensions to alleviate this reverse redistribution challenge stemming from medical insurance. As illustrated in Figure 11, for rural households situated below the Micawber threshold, we peg the compensation ratio at 100%. However, for those surpassing the Micawber threshold, the medical cost compensation ratio diminishes linearly as wealth levels increase. This structured approach particularly aids rural households in poorer health by preferentially increasing their compensation ratios, thereby mitigating their medical expense burdens.

Upon the introduction of the sliding medical insurance compensation policy, there is a noticeable uptick in the reimbursement amounts for households within the middle to lower wealth. Specifically, for individuals in poorer health, the elevated medical insurance compensation ratios (as depicted in Figure 11) lead to increased medical expense reimbursements. This further alleviates the medical financial burdens borne by such rural households.

In the wake of health risk, the wealth disparity between these households and households with better health conditions is reduced. This results in a marked diminution of wealth inequalities exacerbated by health issues. Ultimately, the poverty vulnerability of residents with

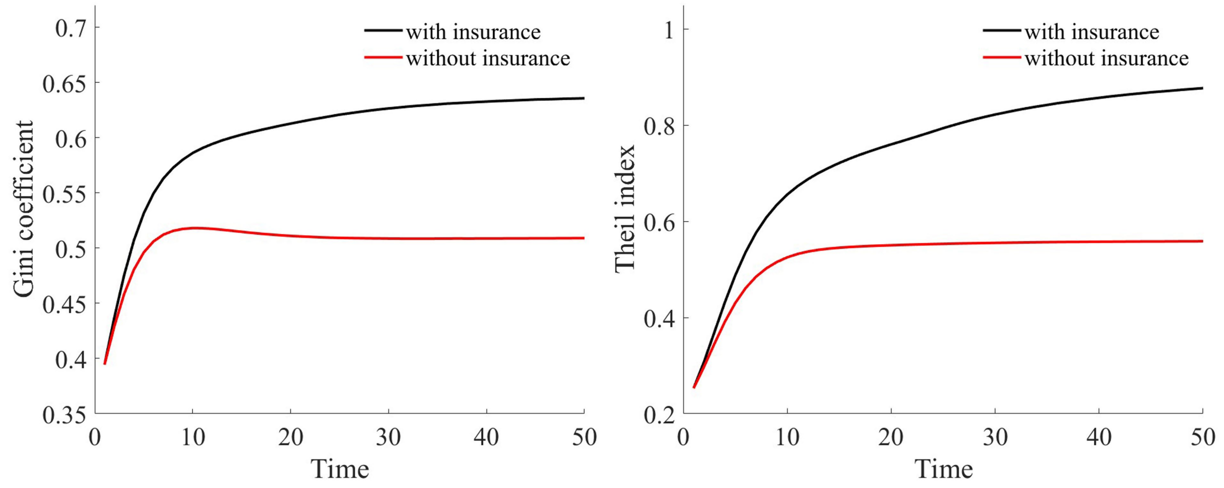

FIGURE 10
Changes in wealth inequality indices.

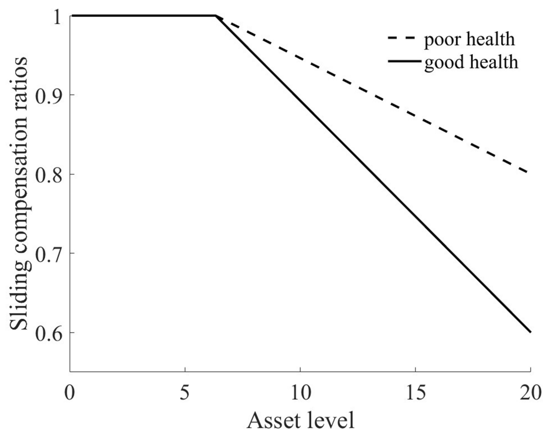

FIGURE 11
Changes in sliding compensation ratios.

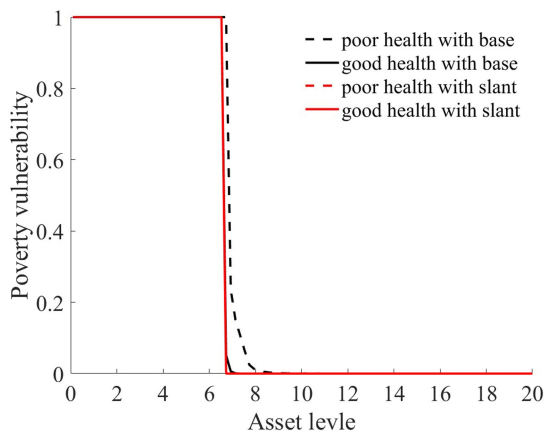

FIGURE 12
Poverty vulnerability.

poor health is mitigated. As shown in Figure 12,[7] the poverty vulnerability of both types of households converges, becoming more aligned.

3.4.2 The impact of the slanted compensation policy on wealth inequality

As shown in Figures 8, 9, the red line represents the situation under the slanted compensation policy, while the black line denotes the baseline scenario (proportional compensation policy). The solid and dashed lines distinguish between individuals in good health and those in poor health, respectively. In comparison to the proportional medical insurance compensation policy, the slanted compensation approach enhances the benefit levels for middle-and low-wealth households. This is because these households, under a more generous medical insurance compensation scheme, receive increased compensation. However, for these middle-to low-wealth households, even with an increased medical insurance compensation rate, their limited capacity for medical expenditure places them at a disadvantage in receiving medical services when compared to high-wealth households (as indicated in Figures 8, 9).

Relative to those in good health, households with poorer health and with middle to low wealth benefit the most from the slanted compensation policy. This slanted compensation strategy adjusts the benefit distribution for households with better financial standing, redirecting more public resources toward middle-and low-wealth households. Especially for households with poor health, the double-tilted compensation approach ensures that rural households with low wealth utilize more public medical service resources. This strategy further reduces the "reverse redistribution" phenomenon

7 In this paper, the red dashed line in Figure 12 represents the poverty vulnerability of households with poor health status under the dual-slanted compensation policy. Notably, under this policy, households with both good and poor health have the same level of poverty vulnerability. Therefore, the red dashed line and the red solid line overlap.

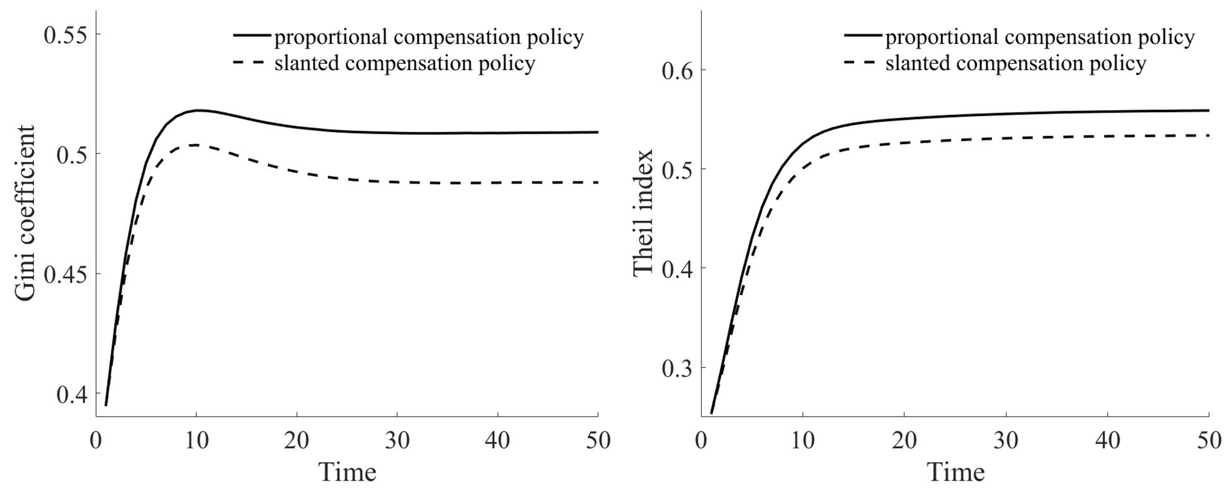

FIGURE 13
Wealth inequality indices under different compensation structures.

where middle-to low-wealth households subsidize their wealthier counterparts.

Owing to the increased reimbursement rates for both middle-to-low wealth households and those with poorer health conditions, there is a clear reduction in vulnerability to poverty for these groups. This reduces their likelihood of falling into poverty traps, as depicted in Figure 12. Such a scenario implies that these households can invest more substantially in agricultural production, consistently accumulate assets, and eventually gravitate toward a high-stable equilibrium. As a consequence, there is also a subsequent reduction in both the Theil index and the Gini coefficient, diminishing the level of wealth inequality among rural households, as illustrated in Figure 13.

4 Conclusions and policy recommendations

This study integrates heterogeneous health risks and medical insurance into a multi-equilibrium framework. By employing the value function iteration algorithm, we computed the policy functions for consumption and assets. Through stochastic simulations, we examined the impact of heterogeneous health risks, medical insurance, and a dual-slanted compensation policy on vulnerability to poverty and wealth inequality among rural households.

Our findings reveal that under the influence of heterogeneous health risks, vulnerability to poverty and wealth inequality among rural households are significantly heightened. Notably, households with poorer health conditions exhibit considerably greater vulnerability to poverty than do their counterparts with better health conditions. With the introduction of medical insurance, due to the investment incentive effect and the compensation mechanism of medical insurance, there is a marked reduction in the vulnerability of households to poverty (with a more pronounced effect for those with poorer health conditions) as well as in the wealth inequality between households. Owing to uniform premium payments and proportional medical expense reimbursements, a “reverse redistribution” phenomenon occurs from low-wealth households to high-wealth households, exacerbating wealth inequality. Overall, medical insurance mitigates both the vulnerability to poverty and wealth inequality among rural households.

In light of the “reverse redistribution” effect caused by medical insurance, this study introduces a dual-slanted medical insurance compensation policy designed around both wealth and health. We discuss the impact of this policy on vulnerability to poverty and wealth inequality. For rural households with poorer health conditions, the slanted compensation approach significantly alleviates their medical financial burdens, reducing their vulnerability to poverty. Concurrently, this approach addresses the wealth “reverse redistribution” issue arising from medical insurance, enhancing the efficiency of public medical service utilization. Ultimately, this results in a decrease in wealth inequality.

This study provides several insights for public health insurance practitioners. (1) The government should invest in establishing a comprehensive and efficient health record system to collect and analyze the health data of rural household members. This approach will provide crucial support for the formulation and implementation of health insurance policies, ensuring that the policies are more precise and effective than those currently in use. (2) Differential medical insurance policies should be designed based on the wealth and health status of households. Households with poor health and lower wealth should be provided with higher medical expense compensation and lower insurance costs. (3) Dual-slanted compensation policies should be implemented within the existing medical insurance system, offering varying levels of compensation based on household wealth and health status. This approach will help alleviate the financial burden of low-income households while reducing the wealth inequality caused by insurance mechanisms. (4) Investment in public medical services in rural areas should be increased, and basic medical infrastructure should be improved. This can enhance access to medical services for low-income households in rural areas, reducing poverty risks due to health hazards. (5) The government should regularly monitor and evaluate the effectiveness of medical insurance policies, especially their impact on low-income and health-challenged households, and adjust and optimize based on evaluation results.

Furthermore, the government should continuously explore and innovate with the implementation methods for dual-slanted compensation policies to adapt to socioeconomic changes and advancements in medical technology in the future. This includes but is not limited to optimizing compensation mechanisms, expanding insurance coverage, enhancing public health investment, and improving policy transparency and public participation.

The implementation of these suggestions is expected to reduce the poverty risks associated with health hazards, decrease wealth inequality, and enhance the overall welfare of rural families. These measures will also lay the groundwork for the long-term development and innovation of dual-slanted compensation policies. The research in this paper helps alleviate the issue of high medical costs for rural families and provides effective suggestions for consolidating achievements in poverty alleviation, thus achieving rural revitalization and shared prosperity.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

XZ: Conceptualization, Funding acquisition, Investigation, Writing – original draft. XY: Conceptualization, Formal analysis, Methodology, Software, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Dual circulation strategy, regional healthcare development, and medical collaborative innovation efficiency: evidence from Chinese cities

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This study analyzes panel data of Chinese cities from 2003 to 2018 as a sample in the context of the dual circulation strategy in China to ascertain the impact of urban healthcare development on medical collaborative innovation efficiency by using the GS2SLS method. Furthermore, it empirically examines the influence mechanism of regional healthcare development on medical collaborative innovation efficiency by using a threshold regression model. Additionally, we identified the heterogeneity of this impact in different cities. The results show the following: (1) There is a significant positive spatial correlation between regional healthcare development and medical collaborative innovation efficiency; (2) Under the dual circulation strategy, the regional investment level in international circulation has the most significant role in the overall strategy, and domestic circulation has been significantly improved after the launch of the innovation-driven strategy; (3) The results of the threshold test show that while domestic and international circulation promote the efficiency of collaborative innovation by 0.83, the promotion effect is more obvious under a higher regional healthcare development level. The research in this paper can provide specific guidance for the development of China's healthcare industry under the background of dual-cycle strategy, and can also provide valuable reference for developing countries in the world.

KEYWORDS
dual circulation strategy, medical collaborative innovation efficiency, threshold test, regional healthcare development, China

1 Introduction

China proposed in 2020 to develop a new development pattern with the domestic cycle as the main body, where the domestic and international dual circulation strategies promote each other. A country cannot achieve high-quality development without developing its own domestic economic development cycle or an external international economic development cycle. The cycle of domestic economic development in the country, especially the process of globalization over the past century, has increased the impact of the cycle of international economic development. Driven by the industrial revolution, and scientific and technological progress, a large number of commodities took advantage of their comparative advantages to flock to the international market; thereby promoting globalization and the development of the world economy. Economic globalization accelerated again in the early years of the State, following the weakening of the two world wars, restrictions on immigration, and the Great Depression, especially after many developing countries joined the international economic cycle in the 1980s. Since the reform and opening up of its economy, China has actively integrated into the world market to participate in the international cycle. The upgradation of the industrial structure and the development of technological innovation has systematically improved China's position and voice in the global value chain.

However, in the face of the outbreak of COVID-19, some shortcomings in the construction and development of China's medical system have gradually emerged, such as insufficient reserves of special drugs, high drug prices, and relatively backward medical science and technology. The high-quality development of the medical and health industry is an important guarantee for the safety of people's lives. It is an important goal of health economics to improve the level of medical science and technology innovation and realize the optimal allocation of medical resources under the condition of resource constraints. Therefore, in the context of the new dual-cycle development pattern, how to achieve high-quality development of medical care and improve the level of regional medical collaborative innovation is of great significance to achieve high-level development.

At present, although a large number of research literatures have carried out in-depth analysis of the double-cycle strategy, there are few literatures that specifically examine the development of healthcare and the collaborative innovation of inter-regional medical industry under the background of the double-cycle strategy. At the same time, most of the existing research literature is based on linear regression model, ignoring the inter-regional collaborative innovation and spatial spillover effect, and to some extent ignoring the inter-regional linkage effect. This not only has a bias in the estimation results of empirical research, but also cannot provide very accurate policy recommendations.

This paper thus constructs an analytical framework, and explores domestic and international dual circulation based on the impact of domestic and international dual circulation strategies on the medical collaborative innovation efficiency by combining it with the level of regional healthcare development. It achieves this by taking 283 cities at the prefecture level and above in China from 2003 to 2018 as a sample, and the efficiency of urban industry-university-research medical collaborative innovation as the explanatory variable. The different impact effects and degrees of the development level of each specific link of the strategy under the threshold of the healthcare development level of different regions are analyzed to enrich and deepen the current research on healthcare innovation and development under the new development pattern, and provide useful enlightenment and policy suggestions for cities in different regions at different stages of development to better achieve medical innovative development.

2 Literature review and theoretical analysis

2.1 Literature review

The literature on the dual circulation strategy mainly focuses on the elaboration of the theoretical level, which is an objective need that has not changed in the last 100 years (1) and has many decisive factors (2). China already has a strong production and supply capacity, and the data released by the National Bureau of Statistics in January 2020 show that the average gross domestic product (GDP) of China has exceeded 10,000 US dollars, and has begun to demonstrate the demand constraint characteristics of the mature market economy. Thus, demand-side reform from the perspective of the dual circulation strategy is of great significance. Understanding the dual circulation strategy from the perspective of political economy focuses on opening up the production, circulation, consumption, and distribution links between domestic and foreign countries (3). In addition, some studies have provided relevant explanations for the dual circulation strategy from the perspective of empirical analysis at the macro level: Ding et al. examined the internal and external orientation choices of China's economic cycle from 1987 to 2017 by constructing an interprovincial transfer and export comparison preference index and found that China as a whole is currently dominated by the domestic large cycle (4); similarly, Yang studied the structural changes of China's economy from 1994 to 2019 from the perspective of the development pattern of the dual circulation strategy by constructing and measuring the indicator system reflecting the economic development situation (5). The theoretical analysis framework of domestic and international dual circulation strategies is constructed using input–output models that reveal the current situation and characteristics of the strategies. Accordingly, it can be seen that China's economic development has characteristics exhibited by domestic circulation (6).

With the advent of the Internet era, new generation information technologies such as big data and cloud computing have had a profound impact on the development of the medical industry. Stelzner et al. believe that with the continuous development of nanotechnology, medical technologies that cannot be realized due to the lack of the original refinement level can be realized under nano conditions, and it has a wide range of potential applications in medical communication (7). Dananjayan et al. believes that with the popularization and application of 5G technology, its characteristics across time and space can enable patients to realize "face to face" communication with doctors without the cost of long-distance commuting. Virtual consultation and remote consultation are becoming a new development direction of medical technology, and therefore play an irreplaceable role in the regional medical level (8). Wang et al. believe that supervised and unsupervised learning based on machine learning methods and data obtained from clinical or actual investigations can effectively improve the accuracy and scientific nature of disease prediction, construct intelligent medical scenarios, and realize effective application in practice (9).

The improvement of medical collaborative innovation efficiency is a process of exchange, collaboration, and collaborative innovation between various entities such as enterprises, colleges and universities, scientific research institutions, and government departments within the system. The collaborative utilization of resources and the joint development of technology are also realized in the region. Compared with the evaluation of innovation efficiency, the analytical perspective of collaborative innovation considers the correlation effect between various subjects within the innovation system and between various regional systems, which is more beneficial for achieving an innovation system. Current research on collaborative innovation mainly focuses on technological innovation, innovation efficiency, innovation ecosystems, innovation networks, and industry-university research; the methods used in collaborative innovation research in recent years are mainly system dynamics, evolutionary games, social network analysis, and other methods (10). Experts and scholars have conducted a lot of research on the regional collaborative innovation; specifically, scholars mainly from the connotation of collaborative innovation (11), the model of collaborative innovation (12), the mechanism of collaborative innovation (13), and other aspects of theoretical discussion (14) have also empirically examined the impact of the linkage relationship between enterprises, universities, research institutes, governments, and financial institutions within the regional innovation system and the efficiency of regional innovation.

Several relevant studies have been conducted in the academic community regarding the relationship between regional healthcare development and innovation. Most studies take innovation as the starting point and the core research area, to sort out its role in promoting regional healthcare development (15). Simultaneously, some studies believe that the relationship between innovation and regional healthcare development is more complicated, and their interaction and mutual influence form a coupled developmental relationship of mutual promotion and harmonious symbiosis (16). Scholars have studied the role of regional healthcare development in promoting innovation in terms of providing a good innovation environment (17), attracting talent (18), and providing better material conditions and financial input for innovative activities (19).

Thus, it can be surmised that the existing literature has carried out relevant research and analysis on the pattern of dual circulation strategy and medical collaborative innovation efficiency from the theoretical and empirical aspects. This provides an important reference for the research of this paper. However, the evaluation and measurement of regional dual circulation strategy are more effective, and the empirical analysis of the combination of strategy and medical collaborative innovation efficiency needs to be improved and expanded further.

2.2 Theory development

As a development deployment in the new era, the scientific connotation of the new development pattern lies in internal circulation as the mainstay, and external circulation as a supplement. From the perspective of the new development pattern, this study uses the framework of regional domestic and international economic cycles to analyze and discuss the impact of regional healthcare development on the efficiency of collaborative innovation.

The ideological origin of the new development pattern comes from the Marxist theory of the political economy. As Marx states in Capital, the expansion of reproduction of the entire society of production, distribution, circulation, and consumption of the capitalist economy is based on the domestic circulation of the capitalist economy. The production process of the capitalist economy is essentially the production of surplus value, but Marx's socialized large-scale production theory, based on the capitalist economy, applies to the analysis of the operation and circulation of the socialist market economy with Chinese characteristics as well. Therefore, using these concepts and logic to analyze the laws of the modern market economy, including the cycle of the socialist market economy, is also completely in line with Marxist positions and viewpoints (20).

Based on the above theoretical analysis, the essence of the national economic cycle is the social reproduction process, and the social reproduction theory is the basic tool for analyzing the domestic large cycle and the international economic cycle (21). Thus, there is a cyclical relationship between production, distribution, circulation, and consumption. Since these four processes cover most aspects of economic and social life, it provides a unified framework for the analysis of the economy and society. Therefore, the development of regional economies can be evaluated and interpreted from the perspective of the two major economic cycles in China and globally. Based on a collation and analysis of the existing literature, we believe that the specific links of the domestic and international dual circulation strategy can have an impact on the efficiency of regional innovation at the relevant level.

The improvement in the level of regional healthcare development is manifested in the production link as the improvement of the overall production capacity of the region, and production, as the starting point and foundation of social and economic activities. The improvement of its ability can naturally provide guarantee and support for the improvement of regional innovation efficiency. Specifically, the improvement of regional production levels can mainly affect regional innovation efficiency through the spillover effect of technical space (22), the improvement of the comprehensive support capacity of various undertakings and the progress of the management level and related systems (14).

In terms of distribution, the development of the regional economy is reflected in the more equal distribution of regional income, the structure and method of income distribution are more reasonable, and unequal income distribution is controlled and improved. The improvement in the income distribution pattern is also relatively clear for the improvement of regional innovation efficiency (23). On the demand side, unequal income distribution will significantly dampen consumer demand for innovative products, and thereby reduce domestic innovation and R&D investment (24). From an input perspective, maintaining the income gap at a high level, will reduce the total investment in research and development of the country, and damage its ability for independent innovation. While modest levels of inequality in income distribution can contribute to an increase in innovation levels, there is a consistent correlation between income distribution levels and regional innovation efficiency in the long run.

In terms of circulation, the development of the regional economy will inevitably be accompanied by the improvement of regional infrastructure and transportation accessibility. The developed regional commercial trade network and circulation system have also played an irreplaceable and important role in the improvement of regional innovation efficiency. Furthermore, developing the circulation industry can also effectively strengthen the region's independent innovation ability (25, 26).

Consumption, as the final link in the large-scale production of the domestic economic society, plays an important role in the field of economic development, and the vitality of regional consumption is also an important embodiment and evaluation indicator of the degree of development of the regional economy. The improvement in regional spending power can also promote innovation efficiency in the region in various ways. At the micro level, it will lead users to discover new needs in the market (27). Once the business adopts these market needs, it is applied to R&D and production, and then it will reap greater innovation performance. The development process of capitalist developed economies confirms the important role played by consumption levels and structures on the demand side in stimulating technological innovation and progress at the macro level (28).

Since joining the WTO in 2001, as an important member of the world economic system, China has actively participated in international trade and the international economic cycle and has established extremely close ties with the global economic system through decades of reform. Overall, a country's participation in the international economic cycle is mainly through import and export trade, foreign direct investment (FDI), and outward direct investment (OFDI). The impact of participation in the international economic cycle on innovation mainly comes from international technology spillover, and the main channels of international technology spillover are FDI and international import and export trade. Scholars have conducted a large amount of relevant research on theoretical mechanisms and empirical data focusing on the impact of FDI and import and export trade on innovation (29–31). Among them, FDI can influence the innovation of the host country through spillover and thus form two opposing hypotheses: the polluted paradise hypothesis and the pollution aura hypothesis (32). The former suggests that the transfer of low-end industries from developed countries to developing countries, and the locking of developing countries at the lower end of the value chain leads to the inhibition of innovation in developing countries. The latter suggests that developed countries will bring advanced technologies to promote innovation in developing countries. The ultimate effect depends on which effect is stronger, as both occur simultaneously. In addition, some scholars have studied the impact of international trade on innovation and found that the development of international trade plays a significant role in promoting and enhancing China's technological innovation ability.

Based on the above research and analysis, it can be observed that scholars have systematically analyzed and studied the impact of innovation and collaborative innovation from the perspectives of different parts of the domestic economic cycle and the international economic cycle. However, the empirical research on the systematic analysis of the impact mechanism of collaborative innovation from the overall perspective of the new development pattern has not yet been explored. In the era of global integration, any economy in the process of development has both a domestic cycle and a foreign cycle of two-cycle systems, the domestic market and the world market you have me, I have you, and the economic ties between the two are inseparable. Participating in the domestic and international economic cycles is mutually superficial, constituting a system of joint promotion of economic development. Therefore, it comprehensively reflects the specific level of regional economy under the current development pattern. Thus, this study considers the analysis framework of constructing a domestic and international economic cycle based on the new development pattern and studies its correlation with the efficiency of collaborative innovation.

3 Model and variables

3.1 Basic model setup and construction

The empirical part of this study focuses on identifying the impact of domestic and international dual circulation strategies on the efficiency of collaborative innovation. That is, the mechanism and intensity of the development level of various economic links in the city on the efficiency of collaborative innovation. The basic regression model was set as follows in Eq. (1):

$$Y_{it} = \alpha_0 + \alpha_1 E_{it} + \alpha_2 X_{it} + \alpha_3 C_{it} + \varepsilon_{it} \tag{1}$$

Among them, the explanatory variable *Yit* is the medical collaborative innovation efficiency of prefecture-level city i in *year t*, and the core explanatory variable is the economic development level of prefecture-level city i in year t. *EitXit* A is a set of variables that reflect the regional economy, and the domestic and international circulation level, including the variables that reflect the relevant levels of production, distribution, circulation, and consumption of the regional domestic economic cycle level, the total FDI of the region, and the total imports and exports of the region. These reflect the level of the regional economic cycle. *Cit* was another control variable. Since the medical collaborative innovation efficiency of a city is not only related to the innovation resources and environment of the city itself but is also affected by the spillover effect of the medical collaborative innovation efficiency of neighboring cities, the medical collaborative innovation efficiency of two cities that are geographically adjacent to each other will have a spatial correlation to a certain extent. Expanded model (1) introduces the effect of medical collaborative innovation efficiency in neighboring cities, and the expanded spatial regression model is Eq. (2)

$$Y_{it} = \alpha_0 + \alpha_1 \sum_{j=1}^{n} W_{ij} Y_{jt} + \alpha_2 E_{it} + \alpha_3 X_{it} + \alpha_4 C_{it} + \varepsilon_{it} \tag{2}$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^{n} w_{ij} \varepsilon_{it} + \mu_{it}$$

where *W* is the spatial weight matrix reflecting the connection of each city at the spatial level, and the element in the spatial weight matrix reflects the spatial connection between the cities. is the spatial lag coefficient and is the coefficient of spatial error, which reflects the spatial dependence of the sample observations and the spatial correlation that exists in the error structure, respectively. When the value is zero, the spatial econometric model is a spatial lag model; when the value is zero, the spatial econometric model is a spatial error model. The spatial lag coefficient and spatial error coefficient together reflect the interaction and effect of medical collaborative innovation efficiency between samples of neighboring cities, as well as their spatial spillover effects $w_{ij}\alpha_1\lambda\lambda\alpha_1$.

3.2 Spatial weights matrix

In contrast to traditional econometric research, spatial econometric research focuses on the processing of spatial data, and the so-called spatial data adds the position information or mutual distance of the cross-sectional units to the original cross-sectional or panel data (33). Therefore, the spatial weight matrix used to measure the spatial distance between regions must be introduced into the econometric analysis. Therefore, this study selects a geographic distance weight matrix based on the interregional geographic distance factor, such that that $W=\omega$, *where* ω represents the weight of the geographic distance spatial weight matrix, *and* W represents the geographic distance spatial weight matrix and its elements $_{wij.}$ It is the reciprocal of the absolute difference in geographical distance between city i and city j. The geographic distance data between cities is the straight-line distance between cities, calculated based on the longitude and latitude data obtained from the National Basic Geographic Information System 1:4 million terrain database.

3.3 Variable description

3.3.1 Dependent variables

Medical collaborative innovation efficiency (*innov*). The concept of "collaborative innovation" was first proposed by Gloor (34), and since then, researchers at home and abroad have conducted in-depth exploration and empirical analysis around its connotation, mode, mechanism, and effect evaluation. Based on the relevant research of Bai and Bian (35), the efficiency of collaborative innovation can be mainly divided into two types: intraregional and interregional. In this study, using the network DEA model, MaxDEA software was used to measure the performance of collaborative innovation in 283 cities from 2003 to 2018, and the average of their annual total efficiency was selected to represent the specific value of medical collaborative innovation efficiency.

Since collaborative innovation within the region involves many subjects and links, the research process in the innovation process will be ignored if the ordinary data envelopment analysis model is used, which can result in inaccurate calculation of the efficiency of collaborative innovation within cities. Through the network DEA theoretical system, the input and output in the innovation process can be quantified concretely, thus solving the problem of the input and output process as a "black box" and resulting in a lack of data in the intermediate links. The innovation triple spiral structure of enterprises, universities, and scientific research institutes in the city, and the interaction of innovative talents, capital, and other elements between various innovative subjects within it, are circular. The chain relationship between the innovative subjects can be divided into two stages: "learning to research" and "research to production." The two stages form a circular structure through the connection between the innovation subjects. "Learning to research" refers to the process in which universities obtain funds through cooperation with enterprises or government transfer payments, and use them as capital to cultivate the innovative talents needed for the next stage of output. "Research to production" refers to the process by which scientific research institutions transform the funds obtained from enterprises and the government, and the innovative talents absorbed from universities into scientific research results and put them into production and application. This study refers to the input–output index selection system in the relevant research of Wang (36) to quantitatively analyze the innovation efficiency in accordance with the order of "learning to research" and "research to production," decompose the cycle structure into a chain structure, and use the chain network DEA to quantify the medical collaborative innovation efficiency. Each city above the prefecture level is a decision unit DMUI ($i=1, 2, .., n$), assuming that there are s ($s=1, 2, ...,$) in the whole process S phase, the input variables and output variables of each stage are $_{Iis}$ and $_{Ois}$, respectively, and satisfy $Ii^{s} \in R_{+}^{\alpha s}$ and $_{Ois} \in R_{+}^{\beta s}$; the intermediate variables of the s and s + 1 phases are set to $Pi^{(s,s+1)}$ and satisfy $Pi^{(s,s+1)} \in R_{+}^{\gamma (s,s+1),}$ where α, β, and γ represent the number of input variables, output variables, and intermediate variables, respectively. $\alpha=1, 2, ..., x$, $\beta=1, 2, ..., y$, $\gamma=1, 2, ..., z$。 λS is the model weight, wS is the weight variable of the sth order throughout the process, and $\lambda S \in R_{+}^{n}$, μ^{s-}, and μ^{s+} are the relaxation variables of the input and output variables, respectively. The target θ of the network envelope analysis model can be expressed as in Eqs. (3, 4):

$$\theta=\min \frac{\sum_{s=1}^{S}\omega^{s}[1-\frac{1}{\alpha}(\sum_{x=1}^{\alpha}\frac{\mu_{x}^{s-}}{I_{x_0}^{s}})]}{\sum_{s=1}^{S}\omega^{s}[1+\frac{1}{\beta}(\sum_{y=1}^{\beta}\frac{\mu_{x}^{s+}}{O_{y_0}^{s}})]}$$
$$\begin{cases} I_0^s=\sum_{i=1}^{n}\lambda_i^s I_i^s+\mu^{s-} \\ O_0^s=\sum_{i=1}^{n}\lambda_i^s O_i^s+\mu^{s+} \\ P^{(s,s+1)}\lambda^{s+1}=P^{(s,s+1)}\lambda^{s} \\ \sum_{i=1}^{N}\lambda_i^s=\sum_{s=1}^{S}\omega^s=1 \\ \lambda^S,\mu^{s-},\mu^{s+},w^S\geq 0 \end{cases} \tag{3}$$

$$\theta_S=\frac{1-\frac{1}{\alpha}\left(\sum_{x=1}^{\alpha}\frac{\mu_x^{s-*}}{I_{x_0}^{s}}\right)}{1+\frac{1}{\beta}\left(\sum_{y=1}^{\beta}\frac{\mu_x^{s+*}}{O_{y_0}^{s}}\right)} \tag{4}$$

With reference to the data requirements of relevant research and network envelope analysis model, this paper selects the number of students in ordinary colleges and universities, the number of urban unit education practitioners and public finance education expenditure from the two aspects of human resources and capital to reflect the input of the first stage of "learning to research"; the number of scientific and technological practitioners of urban units is selected as the output of the first stage of learning and research. Then, the number of scientific and technological employees in urban units, public finance and scientific and technological expenditures, and the stock of fixed assets in the whole society are taken as the inputs for the second stage of research and production; the number of scientific research papers, patents, and GDP are used as the scientific research output and economic output of the second stage of "research and production."

3.3.2 Gravitational model

Since each region is not independent, the efficiency of collaborative innovation is affected not only by factors within the city but also by the flow of factors throughout the network of innovative cities. Collaborative innovation between industry, academia, and research also occurs in closed areas because of the flow and agglomeration of different types of innovation elements between cities. Therefore, it is necessary to measure the efficiency of collaborative innovation between regions from the spatial correlation perspective. The gravitational model is a successful application of the law of gravitation in physics to the social sciences and is mainly used to study the problem of spatial interaction in an economic society. Based on the gravitational model, medical collaborative innovation efficiency between cities is manifested as the collaborative development process of medical collaborative innovation efficiency within the city; whereby, there is an increase in the difficulty of absorption and spillover of innovation activities and a decrease in the collaborative innovation correlation between the two places when there is an increase in the economic gap between two places. For this reason, this study refers to the practice of Fan et al. (37) and others, constructs the following gravitational model from an economic point of view, and uses it to measure the efficiency of interregional collaborative innovation:

$$Inter\_innov_i = \sum_{j=1}^{n} \frac{Intra\_innov_i \times Intra\_innov_j}{d_{ij}^2} \qquad (5)$$

In Eq. (5), that is, the performance of city $Inter\_innov_i\, i$ in the inter-city collaborative innovation under the gravitational model, and the product of the $Intra\_innov_i \times Intra\_innov_j$ collaborative innovation performance between city i and city j, the geographical distance between city $d_{ij}^2 i$ and city j.

3.3.3 Independent variables

According to the theoretical analysis above, the domestic economic circulation system can be divided into four main parts: production, distribution, circulation, and consumption. These four parts complement each other and are indispensable, forming a closely connected circulatory system. This study starts with these four links and selects representative indicators to measure the relevant performance of the region in terms of domestic circulation.

Production (production), is an important regional economic measurement index. The gross industrial output value above a designated size intuitively reflects the economic production scale and capacity of the region, which can effectively measure the overall economic output level of the region. Therefore, it is widely used in related studies to evaluate the productivity level of the region. Thus, this study uses the total industrial output value above the designated size to characterize the regional production capacity.

Income was measured by the ratio of rural to urban income in the region. Relevant studies have shown that China's income gap is largely manifested as an urban–rural income gap. The level of the urban–rural income gap in the region is the distribution of output at the broadest level in the region, which reflects whether the output distribution in the region is reasonable (38). Referring to the relevant measurement methods of Xu et al. and Qian and Shen (39, 40), this study used the reciprocal ratio of *per capita* disposable income in urban areas to rural *per capita* net income to measure the relevant level of distribution in the region.

In terms of circulation (*transport*), modern innovation theory believes that innovation is the result of the interaction of various actors inside and outside the region (41); therefore, the selection of relevant indicators in circulation must reflect the mobility of production factors in the region. This was premised upon the relevant research by Tian et al. (42), who utilized the total amount of freight in the region to measure its circulation level.

In terms of consumption, the *per capita* consumption expenditure of the region, is the most intuitive embodiment of the consumption capacity of residents in the region, can be a good measure of the capacity and scale of the region in the field of consumption (43). Therefore, this study draws on the relevant research (44) and divides the total retail sales of social consumer goods by the total registered population of the region to obtain the *per capita* consumption expenditure of the region, and thereby measure the consumption level of the region.

Level of International Economic Circulation. Based on the above-mentioned research and theoretical analysis, the measurement and evaluation of the regional international economic cycle can be equivalent to the comprehensive systematic evaluation of the level of regional economic opening up. This study incorporates the level of attracting foreign investment (fdi) and regional import and export trade (trade) related to the international economic cycle, into the measurement analysis of the international economic cycle. This study selected the total annual FDI of the region and the total import and export trade of the region (45) as indicators to measure the level of attracting foreign investment (FDI) and the level of regional import and export trade (trade).

3.3.4 Threshold variable

Regional healthcare development level (*rhd*). The impact of domestic and international economic cycles on different regions and different periods in the same region is not the same, and the threshold effect characteristics are formed based on the regional healthcare development level in the region because of the heterogeneity between the economic development level and innovation activities between different regions, and the heterogeneity between the regional healthcare development level and innovation activities in different periods of the same region. The level of economic development plays an important role in the process of opening up all aspects of production, distribution, circulation, and consumption and forming a new development pattern (1). Therefore, the construction of a new development pattern must be effectively connected with the regional development strategy and the level of regional healthcare development (46). This study thus takes the regional healthcare development level (*rhd*) as the threshold variable and explores whether the impact of large domestic and international cycles under the threshold of different regional healthcare development levels may be manifested as different degrees of promoting or inhibiting the efficiency of regional collaborative innovation. In previous related studies, GDP has generally been used in the evaluation of regional healthcare development levels, but since it has been used in DEA analysis, this study draws on relevant research to avoid endogenesis (47, 48), which uses the average brightness of lights at night to indicate the level of regional healthcare development. As an objective alternative economic indicator, night light data have a high positive correlation with GDP, and can accurately reveal the local economic development level.

TABLE 1 Descriptive statistics of variables.

Variable type	Index selection	Symbol	Index	Data source
Explained variable	medical collaborative innovation efficiency	innov	Input–output ratio of innovation behavior	It is calculated by DEA method
Core explanatory variable	regional healthcare development	rhd	Government medical expenses	Chinese urban Statistical Yearbook
Explanatory variable	Production level	produce	Gross industrial output value above designated size	Chinese urban Statistical Yearbook (2004–2019)
	Distribution level	income	The reciprocal ratio of urban per capita disposable income to rural per capita net income	
	Circulation level	transport	Regional freight volume	
	Consumption level	consume	Regional consumption expenditure per capita	
	Level of attracting foreign investment	fdi	Total annual foreign direct investment	EPS database
	International trade level	trade	Total import and export trade	
Control variables	Economic vitality of manufacturing industry	electric	Electricity consumption	Chinese urban Statistical Yearbook (2004–2019)
	infrastructure	fixed	Total investment in fixed assets	
	Industrial structure	structure	Proportion of output value of tertiary industry to total output value of regional industry	

3.3.5 Control variables

This study refers to previous relevant studies on the efficiency of collaborative innovation at the city level (36) and controls some influencing factors related to innovation activities as control variables to join the model, including the total fixed asset investment (*fixed*) and electricity consumption in the region (*electric*) and regional industrial structure (*structure*) in terms of control variables to avoid the more serious bias of omission variables and to strip away the impact of regional healthcare development on the efficiency of urban collaborative innovation. The total investment in fixed assets in a region reflects the overall investment of the government in various construction projects in the region, and can effectively reflect the relevant level of infrastructure construction in the region. Electricity consumption represents the degree of economic vitality of manufacturing in a region, and the economic vitality of the manufacturing industry is inextricably linked to the innovation activities of the region (49). However, since most knowledge-intensive industries closely related to regional innovation belong to the tertiary industry, there should be a certain degree of correlation between the development and change of regional industrial structure and the efficiency of collaborative innovation (35). Therefore, this paper uses the proportion of tertiary industry output value as the tool of measurement. After controlling for the total amount of urban post and telecommunications business (*fixed*), electricity consumption (*electric*), and regional industrial structure (*structure*), it is more conducive to strip away the impact of regional healthcare development on the efficiency of urban collaborative innovation.

3.4 Data sources

The statistics used for the explanatory variables, explanatory variables, and control variables in this study are from the China Urban Statistical Yearbook (2004–2019) and the EPS database, and the parts with a small number of missing values are supplemented by linear smoothing. The number of scientific and technological papers used in the measurement of medical collaborative innovation efficiency consists of Chinese and English papers, Chinese papers, and English papers from CNKI and Web of Science (WOS) databases, and the number of three major patent applications (pieces) is retrieved from the "China Patent Full-text Database (CNKI Edition)." However, the variables used in the regression are logarithmic to eliminate the influence of heteroscedasticity on the study due to the existence of a comparative study of index mergers (Table 1).

4 Empirical results

4.1 Spatial correlation test of urban medical collaborative innovation efficiency

The Moran index reflects the degree of similarity in the values of the attributes of a spatially adjacent area cell, which is calculated as follows in Eq. (6):

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\left(x_i-\bar{x}\right)\left(x_j-\bar{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\left(x_i-\bar{x}\right)\left(x_j-\bar{x}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}} \tag{6}$$

n $_{xi}$ and xj represent the collaborative innovation efficiencies of city i and city j, respectively, and S^2 is the variance of $_i$ or $xj\bar{x}$, which is the mean of $_{xi}$ or xj. ω_{ij} is an element of the spatial weights matrix representing city i and city j neighbors. The Moran index has a range

TABLE 2 Moran-I index of collaborative innovation efficiency of 283 prefecture-level cities from 2003 to 2018.

Year	2003	2004	2005	2006	2007	2008	2009	2010
I	0.307	0.294	0.300	0.308	0.292	0.266	0.271	0.277
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Year	2011	2012	2013	2014	2015	2016	2017	2018
I	0.269	0.252	0.266	0.256	0.241	0.245	0.234	0.225
P value	0.000	0.000	0.000	0.000	0.003	0.030	0.008	0.096

of values of [−1, 1]; positive numbers indicate the existence of a spatial positive correlation, negative numbers indicate the existence of a spatial negative correlation, and 0 indicates a random distribution characteristic of the space, i.e., there is no spatial correlation. Taking 283 cities at the prefecture level and above in China as the research object and medical collaborative innovation efficiency as the observation, the Moran index for 2003–2018 was calculated separately (see Table 2). The Moran index in different years passed the significance test, indicating that the medical collaborative innovation efficiency of cities at the prefecture level and above in China had a significant spatial autocorrelation.

4.2 Endogenous problems

A bidirectional causal relationship between the explanatory variables can lead to endogeneity problems. Schumpeter's (50) theory of innovation and development regards innovation as the basic driving force of economic development. Thus, innovation efficiency can have an impact on economic development and economic development can provide a good material basis and environmental atmosphere for innovation, thereby promoting the development of innovation. Serious endogenous problems will make the least squares (OLS) estimation biased, and maximum likelihood estimation will fail when heteroscedasticity problems are present. Thus, the lag term of the explanatory variable can be selected as a tool variable to solve the problem of invalid estimation - the estimation is performed using the 2SLS method. However, considering the spatial spillover effect of innovation, we further selected the GS2SLS estimation, which selects each explanatory variable and its spatial lag term as the tool variable, and estimates the spatial panel model based on the 2SLS method while controlling the spatial correlation effects and endogenous problems in the model. The highest third-order spatial hysteresis term is selected as the tool variable for the datum regression, and the highest second-order spatial hysteresis term is selected as the tool variable for robustness testing.

4.3 Baseline regression analysis

Table 3 shows the GS2SLS estimates for the baseline model, and columns (1) and (2) are fixed-effects and random-effects model estimates that consider only the core explanatory variables and the model's fundamental variables. Columns (3) and (4) add other control variables to columns (1) and (2), respectively. Columns (1), (2), (3), and (4) of Table 3 all pass the 1% significance level, indicating that a fixed-effects model should be chosen. The coefficients of the spatial lag terms of medical collaborative innovation efficiency in Table 3 are significantly positive at the 1% level, indicating that collaborative innovation has a significant spatial spillover effect and that the flow and transfer of innovation elements between regions can improve the medical collaborative innovation efficiency of neighboring regions.

TABLE 3 GS2SLS regression results.

Explanatory variable	Geographical distance Spatial Weight Matrix (W1)			
	(1)	(2)	(3)	(4)
	FE	RE	FE	RE
W_1*lninnov	0.150***	0.029***	0.135***	0.014***
	(0.037)	(0.003)	(0.035)	(0.005)
lnproduce	0.001*	0.003***	0.001*	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
lnincome	0.009***	0.005***	0.004***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
lntransport	0.002***	0.001**	0.001	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
lnconsume	0.009***	0.012***	0.006***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
lnfdi	0.013***	0.014***	0.012***	0.013***
	(0.000)	(0.000)	(0.000)	(0.000)
lntrade	0.002***	0.004***	0.001***	0.004***
	(0.001)	(0.001)	(0.000)	(0.001)
Lnrhd	0.002***	0.005***	0.002***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
lnelectric			0.003***	0.004***
			(0.001)	(0.001)
lnfixed			0.005***	0.004***
			(0.001)	(0.001)
lnstructure			0.006***	0.007***
			(0.001)	(0.001)
Adjusted R^2	0.638	0.638	0.698	0.698
Wald test(p)	5416.211	5674.801	6341.145	6777.920
	(0.000)	(0.000)	(0.000)	(0.000)
Hausman test(p)	263.843 (0.000)		268.534 (0.000)	

***, ** and * represent significance levels of 1, 5 and 10% respectively. The value in square brackets below the coefficient is standard error; FE and RE represent fixed effects model and random effects model, respectively.

The influence of the interpreted variables representing the levels of various links in domestic and international economic cycles differs in terms of significance level and coefficient size. Specifically, among

TABLE 4 Robustness test results.

Variable	Replacement is replaced by explanatory variable	Replacement space weight matrix	Replacement of instrument variable
W_1*innov	2.437*** (0.164)	1.248*** (0.090)	1.205*** (0.021)
lnproduce	0.002** (0.001)	0.001* (0.001)	0.002*** (0.001)
lnincome	0.001 (0.001)	0.003** (0.001)	0.002** (0.001)
lntransport	0.004*** (0.001)	0.001* (0.001)	0.003*** (0.001)
lnconsume	0.004*** (0.001)	0.003** (0.001)	0.008*** (0.001)
lnfdi	0.012*** (0.000)	0.012*** (0.000)	0.013*** (0.000)
lntrade	0.001*** (0.001)	0.001* (0.000)	0.004*** (0.001)
lnrhd	0.003*** (0.001)	0.003*** (0.001)	0.002*** (0.001)
lnelectric	0.001 (0.001)	0.001 (0.001)	0.004*** (0.001)
lnfixed	0.000 (0.001)	0.002** (0.001)	0.004*** (0.001)
lnstructure	0.005*** (0.001)	0.004*** (0.001)	0.007*** (0.001)
Adjusted R^2	0.810	0.508	0.739
Wald test(p)	490.614 (0.000)	6204.111 (0.000)	6779.203 (0.000)

W represents W_1 in the replace interpreted variable, replace tool variable method, and W represents W_2 in the replace space weight matrix method.

TABLE 5 Regression by region.

Explanatory variable	Geographical distance spatial Weight Matrix (W_1)		
	Eastern region	Central region	Western region
W_1*lninnov	4.069*** (0.648)	1.203*** (0.277)	3.898*** (0.642)
lnproduce	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
lnincome	0.002** (0.001)	0.004*** (0.001)	0.001* (0.000)
lntransport	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
lnconsume	0.004*** (0.001)	0.007*** (0.002)	0.003*** (0.001)
lnfdi	0.011*** (0.001)	0.010*** (0.001)	0.011*** (0.001)
lntrade	0.002** (0.001)	0.001 (0.001)	0.001 (0.001)
lnrhd	0.003*** (0.001)	0.014*** (0.002)	0.022*** (0.002)
lnelectric	0.000 (0.000)	0.001 (0.001)	0.002** (0.001)
lnfixed	0.003*** (0.001)	0.001 (0.001)	0.001 (0.001)
lnstructure	0.001 (0.001)	0.003* (0.002)	0.003* (0.002)

***, ** and * represent significance levels of 1, 5 and 10% respectively; The values in square brackets below the coefficient are standard errors.

the variables representing the relevant levels of the four aspects of the regional economy's domestic cycle, the regional consumption level has the greatest effect on improving collaborative innovation performance. Consumption, as the final link of the economic cycle, is one of the troikas that drives the macroeconomy alongside investment and exports, and its important role in economic growth has been widely recognized (51, 52). Similarly, it also plays a very important role in promoting regional innovation, and this role is mainly reflected through feedback from a backward nature (53). In his theory of consumption, Marx affirmed the role of consumption in promoting social production, economy, and innovation. The continuous development of society has led to an increase in consumption demand. Therefore, enterprises must improve efficiency, optimize processes, and develop new products to meet people's increasing needs to survive in the face of fierce competition (54), which in turn will force all market participants to carry out more innovative activities. Among the variables representing the correlation level of the two aspects of the international cycle of the regional economy, the volume of FDI, and import and export trade have a significant positive impact on the efficiency of collaborative innovation, among which the positive impact of FDI on the efficiency of collaborative innovation is not only greater than the volume of import and export trade, but also greater than the explanatory variables representing the relevant level of the four aspects of the regional economy's domestic cycle. FDI mainly affects regional innovation through technology spillovers, indicating that city-level technology spillovers play a vital role in improving innovation efficiency.

4.4 Robustness test

The robustness test of the benchmark regression results is mainly performed in this study by replacing the interpreted variables, spatial weights matrix, and instrumental variables. This is done by replacing the geographic distance spatial weight matrix (*W1*) previously used in regression with a nested weight matrix of geographic and economic distance (*W2*). Based on GS2SLS regression, the highest second-order spatial hysteresis term was used to replace the highest third-order spatial hysteresis term used in the previous regression as a tool variable. Table 4 shows the regression results, where the spatial lag term is still significant and the positive relationship between the core explanatory variables and the efficiency of collaborative innovation is still significant. The results show that the benchmark regression in the preceding study has strong robustness.

4.5 Regional heterogeneity test

According to the gradient development theory of regional economics, China's economic regions are vertically divided into three major regions: the east, middle, and west (55)[1]. Since there are large economic development differences between these three regions, the 283 cities in the sample are divided into east, middle, and west according to the economic zones to which they belong, and spatial regression is carried out separately to explore whether there is a spatial spillover effect of regional healthcare development on the efficiency of collaborative innovation; the regression results are shown in Table 5. Comparing the regression results of various regions, we find that the

1 There are 115 cities in the eastern region, including 12 provinces, autonomous regions and municipalities directly under the central government in Hebei, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, Hainan, Beijing, Tianjin and Shanghai; there are 109 cities in the central region, including nine provinces and autonomous regions in Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan and Inner Mongolia; and 59 cities in the western region, including Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Ningxia, Qinghai, and Xinjiang, eight provinces, and autonomous regions.

role of distribution and consumption level in improving the efficiency of collaborative innovation is significant in the three regions with respect to the four aspects of the domestic economic cycle; this is consistent with the conclusions reached by the benchmark regression results. Specifically, the improvement of distribution and consumption levels plays the most obvious role in improving the efficiency of collaborative innovation in the central region, followed by the eastern region, and finally the western region. From the perspective of economic development, owing to the early opening up of the eastern region and the high level of economic development, the collaborative innovation of industry, education, and research has formed a relatively mature model, with the most significant spatial spillover effect. The central region is in an important stage of transformation and upgrading; therefore, the demand for innovation in all aspects of domestic economic development is more urgent, and the role of domestic economic development in promoting innovation is more obvious. However, because most western cities are limited by a weak foundation of local economic development and are late in opening up to the outside world, the level of economic development has lagged behind that of the central and eastern regions. In recent years, the western region has benefited from the internal transfer of industries supported by the policy of large-scale development in the western region. The western region has thus taken a leading position in the country in terms of economic development speed in recent years. However, due to the late development of the western region, the relevant supporting facilities and mechanisms still need to be improved, and the level of economic marketization is insufficient. Thus, the inequality of income distribution and the lack of consumption vitality have a greater restrictive effect on regional innovation.

Among the two aspects of the international economic cycle, attracting foreign investment has maintained a positive and significant state in the three regions in improving the efficiency of collaborative innovation, and its coefficients are significantly greater than the four aspects of the domestic economic cycle. From the perspective of innovation, the regression results prove that there is an obvious positive spillover effect of FDI on the improvement of the efficiency of China's industry-university-research collaborative innovation and affirm the role of foreign investment in promoting China's innovative development.

4.6 Different stage test

Through the division of the overall period and the comparative changes, combined with the relevant theories, the phased characteristics of regional healthcare development for the performance improvement of collaborative innovation can be better analyzed and verified. The Eighteenth National Congress of the Communist Party of China held in 2012 clearly pointed out that scientific and technological innovation is a strategic support for improving social productivity and comprehensive national strength, and must be placed at the core of the overall development of the country. The Congress emphasized "that we must adhere to the path of independent innovation with Chinese characteristics and implement the innovation-driven development strategy." The significance of the innovation-driven development strategy is to clarify that the direction of China's future economic development will change from traditional labor and resource-driven model to an innovation-driven model, and that innovation must better serve development and economic construction. Under the guidance of the innovation-driven development strategy, China's innovation industry has reached new heights, and the development of China's economy is gradually transforming and upgrading in the direction of high quality and sustainability under the impetus of innovation. Therefore, this study takes 2012 as an important node of regional collaborative innovation and development, and divides 2003–2018 into two time periods: 2003–2012 and 2013–2018 for comparative analysis of benchmark regression. The regression results are presented in Table 6.

The coefficient of the spatial lag term of medical collaborative innovation efficiency in Table 6 was significantly positive at the 1% level in both the 2003–2012 and 2013–2018 time periods, of which the coefficient of 2013–2018 was significantly greater than that of 2003–2012, indicating that the spatial spillover effect of medical collaborative innovation efficiency showed a gradually increasing trend. In terms of specific dual circulation strategy links, the coefficients of consumption level and distribution level in 2013–2018 increased significantly compared to 2003–2012, while the coefficient of foreign investment attraction and international trade level in 2013–2018 decreased compared to 2003–2012. This shows that in terms of promoting the efficiency of collaborative innovation, the various links in the circulation of the regional economy have gradually begun to play a more important role following the introduction of the innovation-driven strategy.

4.7 Threshold effect test

We will use the threshold regression model to conduct further research here to further explore the impact of domestic and international large cycles on the efficiency of collaborative innovation at different levels of economic development in different regions. "Threshold regression" tests for significant differences in the parameters of a sample group divided according to the threshold

TABLE 6 Results of regression by stages.

Explanatory variable	Geographical distance spatial Weight Matrix (W_1)	
	2003–2012	2013–2018
W_1*lninnov	1.199***	2.167***
	(0.120)	(0.182)
lnproduce	0.001 (0.001)	0.001 (0.001)
lnincome	0.002** (0.001)	0.004*** (0.001)
lntransport	0.001 (0.001)	0.001 (0.001)
lnconsume	0.003*** (0.001)	0.007*** (0.002)
lnfdi	0.011*** (0.001)	0.007*** (0.001)
lntrade	0.002** (0.001)	0.001* (0.001)
lnrhd	0.003*** (0.001)	0.006*** (0.001)
lnelectric	0.000 (0.000)	0.001 (0.001)
lnfixed	0.003*** (0.001)	0.001 (0.001)
lnstructure	0.001 (0.001)	0.003* (0.002)

***, ** and * represent significance levels of 1, 5 and 10%, respectively.

value. The threshold regression model developed by Hansen (56) can intrinsically divide data intervals according to the characteristics of the data themselves, avoiding the arbitrariness of artificially dividing the sample intervals. Therefore, this study adopts Hansen's threshold regression model, takes the economic development level as the threshold variable, and combines the logarithmic form in the benchmark model to set the following single-threshold regression model in Eq. (7):

$$\begin{aligned} \ln innov_{it} &= \alpha X_{it} + \beta_1 \ln rhd_{it} \times I\left(\ln rhd_{it} \le \gamma_1\right) \\ &+ \beta_2 \ln rhd_{it} \times I\left(\gamma_1 < \ln rhc_{it} \le \gamma_2\right) \\ &+ \beta_3 \ln rhd_{it} \times I\left(\gamma_2 < \ln rhd_{it} \le \gamma_3\right) + C + \varepsilon_{it} \end{aligned} \quad (7)$$

where Y represents the domestic large cycle level of region i in year t; X is the control variable including environmental governance, industrial structure, and urban form; and Ecoit is the threshold variable for regional high-quality development. Where γ is a fixed threshold value, α is the coefficient of influence of X_{it} on the efficiency of collaborative innovation, β_1 and β_2, the threshold variables Ecoit are γ_1 and Ecoit ≤, respectively, the coefficient of influence on medical collaborative innovation efficiency at $>\gamma_1$, C is a constant term, ε it a random perturbation term, and $I(\cdot)$ is a schematic function. Similarly, the formula for the double-threshold test is as follows (β_2 and β_3 have a meaning similar to β_1):

Through the threshold regression model in the Stata 15 software, the regional production, distribution, circulation, consumption, foreign investment attraction, and international trade level are taken as the core explanatory variables. The single-threshold assumption and the double-threshold assumption are tested, and the test results are shown in Table 7. It can be seen that the results of the single-threshold test are more significant than those of the double-threshold test, so the results of the single-threshold regression were selected for further analysis. Thresholds 1 and 2 for each core explanatory variable were both 0.830 and 3.140, but there were still minor differences in the confidence intervals for each threshold. The results of the threshold test show that the regional healthcare development level is greater than 0.83 and less than 0.83, which will lead to different effects of domestic and international cycles on the efficiency of collaborative innovation.

Table 8 presents the regression results of the panel sill model. According to the threshold values of different regional healthcare development levels and the corresponding coefficients of the core explanatory variables, the impact of domestic and international economic cycles on the efficiency of collaborative innovation can be analyzed under the economic development levels of two different regions. Specifically, when the regional healthcare development level is [0, 0.830], 78.82% of the samples of the regional healthcare development level of each city in the past years are in this range, which is the scope of the largest impact of the domestic and international economic cycles on the efficiency of collaborative innovation. Among them, samples in the central region accounted for 40.91%, samples in the western region accounted for 33.34%, and samples in the eastern region accounted for 25.75%. In this range, compared with other factors, FDI stock has the most obvious role in promoting the efficiency of collaborative innovation, and for every unit increase in the logarithmic value of regional FDI stock, medical collaborative innovation efficiency will increase by 0.014 units accordingly. The coefficient of influence of the allocation level is second only to FDI stock, but only about one-third of the latter coefficient, indicating that for every 1 unit increase in the value of the allocation level, the efficiency of collaborative innovation will increase by 0.004 units. The remaining coefficients are positive, indicating that domestic and international economic cycles improve medical collaborative innovation efficiency. When the regional healthcare development level was 0.830 or above, 21.18% of the samples in the regional healthcare development level of each city in the calendar year were in this range, which is smaller than the sample range below the threshold value. Among them, the sample from the eastern, central, and western regions accounted for 72.68, 14.60, and 12.72%, respectively. In this range, the coefficients of influence of various parts of the domestic and international economic cycles on the efficiency of collaborative innovation did not change in the order of size, but the specific coefficient values increased to varying degrees.

Based on the analysis results, the impact of the level of economic development on the efficiency of collaborative innovation is positive in each link above and below the threshold value, but the specific coefficient size is different. After the regional healthcare development level crossed the threshold value of 0.830, the regression coefficients of the core explanatory variables in the regression increased significantly. When the allocation level is used as the core explanatory variable, the elasticity coefficient of the allocation level to the efficiency of collaborative innovation increases from 0.004 to 0.006 after crossing the threshold value, while the consumption level, the level of attracting foreign investment, and the level of international trade are used as the core explanatory variables. Similarly, the elastic coefficient of medical collaborative innovation efficiency also increased from 0.003, 0.014, and 0.001 to 0.006, 0.019, and 0.002, respectively, after crossing the threshold. When the production level and flow level are the core

TABLE 7 Threshold regression test results.

	lnproduce	lnincome	lntransport	lnconsume	lnfdi	lntrade
Single threshold	39.710***	34.060***	41.300***	47.370***	47.810***	38.71***
Double threshold	8.440	6.670*	6.930	14.320	13.340	7.630
Threshold value 1	0.830	0.830	0.830	0.830	0.830	0.830
Threshold value 2	3.140	3.140	3.140	3.140	3.140	3.140
Confidence interval 1	[0.740,0.840]	[0.820,0.840]	[0.820,0.840]	[0.750,0.840]	[0.750,0.840]	[0.715,0.840]
Confidence interval 2	[2.885,3.385]	[2.885,3.300]	[2.885,3.300]	[2.885,3.300]	[2.885,3.300]	[2.885,3.385]

The data in the table are F statistics corresponding to the threshold test. ***, ** and * are significant at the level of 1, 5 and 10%, respectively.

TABLE 8 Coefficient estimation results of threshold regression model.

	lnproduce	lnincome	lntransport	lnconsume	lnfdi	lntrade
lnproduce		0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
lnincome	0.004*** (0.001)		0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)
lntransport	0.001 (0.001)	0.001 (0.001)		0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
lnconsume	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)		0.003*** (0.001)	0.003*** (0.001)
lnfdi	0.014*** (0.000)	0.014*** (0.001)	0.014*** (0.001)	0.014*** (0.000)		0.014*** (0.001)
lntrade	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.001)	
lnelectric	0.004*** (0.001)	0.004*** (0.002)	0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.002)
lnfixed	0.005*** (0.001)	0.005*** (0.002)	0.006*** (0.001)	0.006*** (0.001)	0.005*** (0.001)	0.005*** (0.001)
lnstructure	0.025*** (0.002)	0.025*** (0.006)	0.026*** (0.002)	0.025*** (0.003)	0.025*** (0.002)	0.025*** (0.003)
$(\text{lnrhd} \leq \gamma_1)$	0.001 (0.001)	0.004*** (0.001)	0.001 (0.001)	0.003*** (0.001)	0.014*** (0.001)	0.001*** (0.001)
$(\text{lnrhd} > \gamma_1)$	0.001 (0.001)	0.006*** (0.001)	0.001 (0.001)	0.006*** (0.001)	0.019*** (0.001)	0.002*** (0.001)
R^2	0.792	0.791	0.788	0.794	0.793	0.792

***, ** and * represent significance levels of 1, 5 and 10%, respectively.

explanatory variables, the regression coefficients of the core explanatory variables above and below the threshold value are not significant, and there is no significant size change. Overall, the domestic and international economic cycles in regions with higher levels of regional healthcare development have a more obvious role in promoting the efficiency of collaborative innovation, which may stem from the closer relationship between regional industry-university-research collaborative innovation and regional healthcare development with a better level of regional development, while the domestic and international economic cycles reflect regional healthcare development from the perspective of specific links.

5 Conclusion and policy recommendations

Starting from the perspective of the dual circulation strategy, this study uses the relevant statistics of 283 cities in China from 2003 to 2018 to use the GS2SLS spatial econometric model to view the real circulation strategy of the new development pattern. The spatial spillover effect of medical collaborative innovation efficiency improvement is empirically analyzed, and the threshold effect of "domestic and international economic cycles "on medical collaborative innovation efficiency is further explored. The results of the study show that: (1) overall, after considering the spatial spillover effect of medical collaborative innovation efficiency and controlling endogeneity, there is a significant spatial positive correlation between the regional healthcare development level and medical collaborative innovation efficiency. (2) From the perspective of the regional dual circulation strategy, the role of attracting foreign investment in the regional economic international cycle is the most obvious, and the role played by the domestic economic cycle has been significantly improved after the launch of the innovation-driven strategy. (3) The results of the threshold regression show that the factors of the dual circulation strategy will show different degrees of promotion effect on the efficiency of collaborative innovation above and below the threshold value of 0.83 in the regional healthcare development level, and the promotion effect under the higher regional healthcare development level is more obvious. Combined with the analysis results, this study proposes the following policy suggestions:

First, from the perspective of the dual circulation strategy, the development of the regional economy is necessary to promote innovative development in China. The development of innovative activities must be supported by a strong regional economy, and innovation without economic activities will become a source of water and wood. Therefore, it is not possible to separate regional healthcare development and innovation-driven development strategy, and it should be rationally planned and implemented for the development of local innovation undertakings according to local conditions. However, it is necessary to be aware of the significant spatial spillover effect of innovation, the role of innovation leadership in central cities, and the need to strengthen innovation cooperation and collaboration among various regions to better achieve the balanced development of innovation in various regions.

Second, from the empirical results, since the introduction of the innovation-driven strategy, the improvement of the domestic economic cycle level has played an increasingly important role in promoting the efficiency of collaborative innovation, therefore, under the new development pattern of "dual circulation strategy," the regional healthcare development idea of taking the domestic economic cycle as the main body and participating in the international cycle will help promote the improvement of medical collaborative innovation efficiency. With the improvement in China's economic development level, economic growth will be more dependent on endogenous innovation inputs, and the dependence on the introduction of innovation will be relatively weakened. Against the background of the new era and the pattern of economic development, all aspects of domestic economic development are of great significance to innovation, therefore, it is necessary to better grasp and make good use of the positive externalities brought about by regional healthcare development. China's economic development has entered a new stage of speed reduction and quality improvement, and independent innovation and development are not only urgently needed for China's economic development and industrial transformation and upgrading. Moreover, its effects are bound to inevitably appear in China after decades of rapid development and the construction of the entire industrial chain system to the current stage. However, China should always adhere to the principle of open and inclusive development, improve the quality and efficiency of opening up, and continue to promote a high level of opening up to further play an increasingly active role in global economic governance and actively participate in the international economic cycle.

Third, there are still huge differences in the level of development between various regions in China, and the practical problems and development directions faced under the new development pattern will inevitably be different. It is necessary to consider the implementation of differentiated policies to promote the improvement of medical collaborative innovation efficiency. The eastern region, which has better economic development, must adhere to high-quality development, achieve a high level of openness, take the initiative to participate in the international economic cycle, and give full play to the leading role of national economic development and innovation. The central region, which is in a state of rapid development and a period of industrial transformation, should continue to pay attention to the follow-up construction of various institutional guarantees while maintaining economic growth, and avoiding imbalance and inadequacy of development, so that the broadest masses of people can effectively enjoy the dividends brought by regional healthcare development, so as to promote the improvement of local medical collaborative innovation efficiency through all-round and inclusive economic performance. The western region, which is still in an underdeveloped state, must recognize its shortcomings in terms of regional healthcare development and innovation, focus on improving the local economic development level and the living standards of residents, actively promote the implementation of the rural revitalization strategy, and consolidate the fruits of the battle against poverty to compensate for the shortcomings and deficiencies in the development of local people's livelihood while ensuring the local economic development level, so as to better achieve innovative development.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: https://www.stats.gov.cn/sj/zxfb/index.html.

Author contributions

LC: Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. JH: Conceptualization, Data curation, Formal analysis, Methodology, Writing – review & editing. XG: Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing.

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Spatial distribution and influencing factors of CDC health resources in China: a study based on panel data from 2016–2021

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Background: Measuring the development of Chinese centers for disease control and prevention only by analyzing human resources for health seems incomplete. Moreover, previous studies have focused more on the quantitative changes in healthcare resources and ignored its determinants. Therefore, this study aimed to analyze the allocation of healthcare resources in Chinese centers for disease control and prevention from the perspective of population and spatial distribution, and to further explore the characteristics and influencing factors of the spatial distribution of healthcare resources.

Methods: Disease control personnel density, disease control and prevention centers density, and health expenditures density were used to represent human, physical, and financial resources for health, respectively. First, health resources were analyzed descriptively. Then, spatial autocorrelation was used to analyze the spatial distribution characteristics of healthcare resources. Finally, we used spatial econometric modeling to explore the influencing factors of healthcare resources.

Results: The global Moran index for disease control and prevention centers density decreased from 1.3164 to 0.2662 ($p < 0.01$), while the global Moran index for disease control personnel density increased from 0.4782 to 0.5067 ($p < 0.01$), while the global Moran index for health expenditures density was statistically significant only in 2016 ($p < 0.1$). All three types of healthcare resources showed spatial aggregation. Population density and urbanization have a negative impact on the disease control and prevention centers density. There are direct and indirect effects of disease control personnel density and health expenditures density. Population density and urbanization had significant negative effects on local disease control personnel density. Urbanization has an indirect effect on health expenditures density.

Conclusion: There were obvious differences in the spatial distribution of healthcare resources in Chinese centers for disease control and prevention. Social, economic and policy factors can affect healthcare resources. The government should consider the rational allocation of healthcare resources at the macro level.

KEYWORDS

healthcare resources, spatial autocorrelation, spatial econometric model, influential factors, China

Introduction

Adequate healthcare resources are the cornerstone of a functioning health system and a prerequisite for ensuring that effective health services are available to different groups (1, 2). Healthcare resources allocation refers to the manner in which healthcare resources flow between health care institutions (sectors) or regions, and can reflect the level of health services (2). Healthcare resources affect the residents' access to health care services, and studies show a positive correlation between healthcare resources and access to health care (3, 4). To optimize the allocation of healthcare resources in rural areas and contribute to more convenient access to health services for local residents (4). Rational healthcare resources allocation helps people achieve more desirable health outcomes (5, 6). For example, it has been found that adequate healthcare resources are conducive to reducing child COVID-19 mortality and morbidity (7). Health professionals are able to provide quality health services to tuberculosis patients, improving their quality of life and health outcomes (8).

The uneven distribution of healthcare resources is a long-standing challenge in China. It is also prevalent in other countries (regions), such as the United States (9), Portugal (10), Japan (11), Kenya (12), and Southeast Asia (13). As the largest developing country with a vast land area and a large population, China faces the challenge of maximizing the provision of comprehensive health care services given the constraints on available healthcare resources (14). A number of studies had evaluated healthcare resources allocation in China, but focused more on the entire health care system (15), Traditional Chinese Medicine (14), maternal and child health care (16), and primary health care system (17). Little attention is paid to the disease prevention and control system.

Chinese Centers for Disease Control and Prevention (CCDC) are an important part of China's public health system. It has a mission to create a healthy and safe living environment, maintain social stability and promote people's health by preventing and controlling disease, injury and disability (18). CCDC began in the 1940s and has been developing for more than 70 years. Nowadays, a unique four-tier disease prevention and control system has been formed, which contains national, provincial, municipal and county-level disease prevention and control centers (19). In 2016, the Healthy China 2030 plan emphasized adherence to prevention as the mainstay and prevention and control of major diseases, highlighting the importance of the CCDC in promoting the process of Healthy China (20). In 2019, the COVID-19 outbreak gave the public a more direct understanding of CCDC's critical role in public health incident response. After the epidemic, the government of China accelerated the development and construction of the disease prevention and control system, with particularly focusing on optimizing the allocation of healthcare resources in regional CCDC (21). In 2023, the State Council of China issued the Guiding Opinions on Promoting the High-Quality Development of the Disease Prevention and Control Business, which particularly emphasized the necessity of promoting the reform of the CCDC system and building a strong public health system (22).

Healthcare resources affect the capacity and capability of CCDC to provide preventive health services (23). Health workforce is the most dynamic and critical element of the CCDC system, determining the level and quality of health services and influencing citizens' opportunities to access preventive care (24). Health material resources are the essential condition for the provision of preventive health services to citizens and the basic indicator of the level of public health service. Health financial resources represent the impact of healthcare resources allocation on the health of the population (25). In summary, healthcare resources are crucial to the development of CCDC. Adequate healthcare resources will not only be conducive to promoting the high-quality development of CDC, but will also facilitate the achievement of the strategic goal of Healthy China. Therefore, it is necessary to conduct a detailed study of CCDC healthcare resources.

Currently, scholars mostly use equity analysis methods to analyze healthcare resources, such as the Gini coefficient, the Theil index and the Health Resource Density Index(HRDI), etc. (26). Ao et al. used the Gini coefficient, the Theil index and HRDI to evaluate the equity of rural healthcare resources in China (27). Jian sun used the concentration index to analyze the equity in the distribution of health materials and health human resources (28). Liu et al. used the Gini coefficient combined with spatial autocorrelation to analyze the inequality of healthcare resources in Traditional Chinese Medicine hospitals (29). These methods analyzed equity in the regional allocation of healthcare resources only in terms of population and geographic area. Although spatial autocorrelation analysis was applied, the distribution of healthcare resources was not spatially analyzed in depth. In addition, most of the studies on CCDC only used descriptive analysis methods such as rates and composition ratios to make a simple quantitative analysis of human resources for health (30–32). Fewer studies have addressed financial and material resources for health and have not been analyzed using more specialized statistical methods.

Based on panel data from 2016 to 2021, this study aims to use spatial autocorrelation analysis to explore the characteristics of the distribution of healthcare resources in CCDC and use spatial econometric models to assess the factors influencing health resources in CCDC from four major aspects: social, economic, health, and policy. To provide a theoretical basis for the health department to carry out the next health system reform and to gain a more comprehensive understanding of the factors affecting the development of the CDC from multiple perspectives.

Abbreviations: CCDC_D, Chinese Centers for Disease Control and Prevention density; DCP_D, disease control personnel density; HE_D, health expenditures density; PD, population density; UR, urbanization rate; PTHE, *per capita* total health expenditure; GDP, *per capita* GDP; IID, incidence of infectious diseases; EP, proportion of older adult population (aged over 65); GF, proportion of government finance.

Materials and methods

Data sources and variable selection

Data sources

This study used panel data for 31 provinces in China from 2016 to 2021. Hong Kong, Macau and Taiwan provinces are not included because of inconsistent statistical standards for the data. All data are from the China Health and Family Planning Statistical Yearbook, China Health Statistical Yearbook and China Statistical Yearbook.

Healthcare resources indicators

Based on the configuration of the population served and with reference to other studies, the number of disease control personnel per 10,000 population (disease control personnel density), the number of CCDC per 10,000 population (CCDC density), and *per capita* health expenditures (health expenditures density) were selected as indicators of healthcare resources in this study (33–36). The calculation method is as follows.

$$Disease\ control\ personnel\ density = \frac{Number\ of\ disease\ control\ personnel}{Population\ at\ the\ end\ of\ the\ year}$$

$$CCDC\ density = \frac{Number\ of\ CCDC}{Population\ at\ the\ end\ of\ the\ year}$$

$$Health\ expenditures\ density = \frac{Health\ expenditures\ of\ CCDC}{Population\ at\ the\ end\ of\ the\ year}$$

Independent variables

As health systems develop, health resources are influenced by a variety of factors, such as geographic differences (17) economic levels (37), and topographic conditions (38). Based on previous studies and data availability, we chose to explore four factors that may influence CCDC healthcare resources development in terms of social development, economic conditions, health factors, and policy factor. Table 1 shows the meaning and abbreviation of the variables.

Social development

Urbanization can reflect the level of public health services in a region (39). A higher level of urbanization means more developed transportation and easier access to health care services (40). The population density is used to measure the demand for healthcare resources in an area, which also benefits the government in measuring how to allocate health expenditures (41).

Economic conditions

Per capita GDP is often used as an indicator of the level of economic development (41). The distribution of human resources for health is influenced by *per capita* GDP, with higher *per capita* GDP attracting more health professionals (42). In both urban and rural areas, *per capita* health care expenditures are correlated with the amount of healthcare resources available in the neighborhood (43).

Health factors

Aging and infectious diseases can increase health expenditure, leading to financial burden on the country (44–46). The older adult have more and more urgent needs for healthcare services due to the deterioration of their natural physiological functions, such as reduced mobility and resistance (47). The outbreak of infectious diseases not only threatens the health of population, but also seriously affects the utilization of health care resources (42).

Policy factors

In China, health expenditures of the CCDC are composed of government financial input, income from healthcare services, and social funds. In fact, government finances make up a larger proportion. When the financial proportion is low, it affects the scope of health services provided by health care institutions (48).

Methods

Spatial weight matrix

In this study, we use the queen collinearity matrix (49), and regions with common points or common edges are adjacent to each other. Since there is no neighboring province in Hainan Province, it is set that Hainan Province and Guangdong Province are mutually neighboring according to previous studies (50, 51). The assignment rules are as follows:

TABLE 1 Variables and their definitions, abbreviations.

Variables	Definitions	Code
Dependent variables		
Disease control personnel density	the number of disease control personnel per 10,000 population	DCP_D
CCDC density	the number of CCDC per 10,000 population	CCDC_D
Health expenditures density	*per capita* health expenditures	HE_D
Independent variables		
Social development	Population density	PD
	Urbanization rate	UR
Economic conditions	*Per capita* total health expenditure	PTHE
	Per capita GDP	GDP
Health factors	Incidence of infectious diseases	IID
	Proportion of older adult population (aged over 65)	EP
Policy factor	Proportion of government finance	GF

$$W_{ij} = \begin{cases} 1, \text{If there is a common edge or common point} \\ \quad\quad \text{between province i and province j.} \\ 0, \text{If there is no common edge or common point} \\ \quad\quad \text{between province i and province j.} \end{cases}$$

Spatial autocorrelation analysis

The global Moran index and the local Moran index are usually used to analyze the spatial correlation of the studied indicators (52, 53). The global Moran index is used to characterize the spatial aggregation and distribution of overall health indicators, but it cannot clearly indicate the spatial aggregation area. Therefore, local spatial autocorrelation is used to measure the regions where spatial aggregation occurs (54). The formula is as follows:

$$Global\ Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2}$$

$$Local\ Moran's\ I = \frac{n\left(x_i - \bar{x}\right)\sum_{j=1}^{n}W_{ij}\left(x_j - \bar{x}\right)}{\sum_{j=1}^{n}\left(x_i - \bar{x}\right)^2}$$

where x_i and x_j denote HP_D or CCDC_D or HE_D in provinces i and j, respectively, $\bar{x}$ is the average value, and W_{ij} denotes the spatial weight matrix between provinces i and j.

The standardized statistic *z*-value is used to determine whether the global Moran index and local Moran index pass the test. The formula is as follows:

$$Z = \frac{I - E[I]}{\sqrt{\text{var}[I]}}$$

where $E[I]$ and $\text{var}[I]$ are the mathematical expectation and variance, respectively.

The global Moran index has a range of values from-1 to 1. When the global Moran index $I > 0$, it indicates spatial positive correlation; when the global Moran index $I < 0$, it indicates spatial negative correlation; when $I = 0$, it indicates spatial random distribution. If the local Moran index >0, it means that the health indicators tend to cluster together (high values are adjacent to high values or low values are adjacent to low values), and if the local Moran index <0, it means that the health indicators do not tend to cluster together (high values are adjacent to low values or low values are adjacent to high values).

Spatial econometric model

Traditional OLS regression models do not consider spatial factors. Therefore, this study uses spatial econometric models to explore the factors influencing healthcare resources. There are three common traditional spatial econometric models: spatial error model (SEM), spatial lag model (SLM), and spatial Durbin model (SDM).

The SLM model is often used to explore whether the value of a spatial unit is influenced by its neighboring spaces, while the SEM model is often used to analyze the case where the dependent variable is related to a set of variables and a spatial autocorrelation error term. However, the SDM model is used to analyze the case where the dependent variable is influenced by the independent variables of this spatial unit and the neighboring spatial units. The SEM, SLM and SDM models constructed in this study are formulated as follows:

SEM:

$$\begin{aligned} \ln Y_{it} = {} & \beta_1 lnPD_{it} + \beta_2 lnUR_{it} + \beta_3 lnPTHE_{it} + \beta_4 lnGDP_{it} \\ & + \beta_5 lnIID_{it} + \beta_6 lnEP_{it} + \beta_7 lnGF_{it} + \alpha + \mu_i + \gamma_t + \varepsilon_{it} \end{aligned}$$

$$\varepsilon_{it} = \lambda W \varepsilon_{it} + \delta_{it}$$

SLM:

$$\begin{aligned} \ln Y_{it} = {} & \rho WlnY_{it} + \beta_1 lnPD_{it} + \beta_2 lnUR_{it} + \beta_3 lnPTHE_{it} + \beta_4 lnGDP_{it} \\ & + \beta_5 lnIID_{it} + \beta_6 lnEP_{it} + \beta_7 lnGF_{it} + \alpha + \mu_i + \gamma_t + \varepsilon_{it} \end{aligned}$$

SDM:

$$\begin{aligned} \ln Y_{it} = {} & \rho WlnY_{it} + \beta_1 lnPD_{it} + \beta_2 lnUR_{it} + \beta_3 lnPTHE_{it} \\ & + \beta_4 lnGDP_{it} + \beta_5 lnIID_{it} + \beta_6 lnEP_{it} + \beta_7 lnGF_{it} + \theta_1 WlnPD_{it} \\ & + \theta_2 WlnUR_{it} + \theta_3 WlnPTHE_{it} + \theta_4 WlnGDP_{it} + \theta_5 WlnIID_{it} \\ & + \theta_6 WlnEP_{it} + \theta_7 WlnGF_{it} + \alpha + \mu_i + \gamma_t + \varepsilon_{it} \end{aligned}$$

where Y_{it} denotes the dependent variable (CCDC_D, DCP_D, or HE_D) in province i in year t; W denotes the spatial weight matrix; ρ is the spatial autoregressive coefficient; α denotes the intercept of the regression; $\propto_i$ and γ_t denote the individual and time effects, respectively; ε_{it} denotes the random error term; λ is the spatial effect of the random error; β_i denotes the effect of the explanatory variable in province i on the explained variable; θ_i denotes the effect of the explanatory variable in neighboring provinces on the explained variable in province i.

This study uses a logarithmic transformation to reduce heteroskedasticity, implying that the effect of the independent variable on the dependent variable is explained in percentage form (55). If the correlation coefficient is less than 0.85, there is no multicollinearity in the regression model. Table 2 shows the correlations among the variables, all of which are less than 0.85, which indicates that there is no problem of multicollinearity in this study.

To select the optimal spatial econometric model, we used the Lagrange multiplier test statistic (LM), robust Lagrange multiplier statistic (RLM), and likelihood ratio test (LR) to determine the appropriate model, and then performed the Hausman test to determine whether to choose a fixed-effects model or a random-effects model. Finally, the Goodness-of-Fit (R^2) as the main basis for determining the model. All analyses were performed in STATA 16.0. $p < 0.05$ was considered statistically significant in this study.

Results

Basic information

From 2016 to 2021, DCP_D and HE_D showed an overall increasing trend, while CCDC_D showed a decreasing trend year

TABLE 2 Pearson correlation analysis between variables.

	CCDC_D	DCP_D	HE_D	lnPD	lnUR	lnPTHE	lnGDP	lnIID	lnEP	lnGF
CCDC_D	1.000									
DCP_D	0.832***	1.000								
HE_D	0.103	0.180**	1.000							
lnPD	−0.643***	−0.648***	−0.342***	1.000						
lnUR	−0.665***	−0.540***	0.258***	0.205***	1.000					
lnPTHE	−0.002	0.124*	0.584***	−0.299***	0.619***	1.000				
lnGDP	−0.331***	−0.293***	0.373***	0.105	0.807***	0.771***	1.000			
lnIID	0.444***	0.375***	−0.148**	−0.311***	−0.470***	−0.268***	−0.384***	1.000		
lnEP	−0.662***	−0.582***	0.030	0.534***	0.561***	0.185**	0.368***	−0.659***	1.000	
lnGF	0.238***	0.167**	−0.469***	−0.270***	−0.162**	−0.070	−0.135*	0.103	−0.166**	1.000

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
CCDC_D, the number of CCDC per 10,000 population; DCP_D, the number of disease control personnel per 10,000 population; HE_D, per capita health expenditures; PD, population density; UR, urbanization rate; PTHE, per capita total health expenditure; GDP, per capita GDP; IID, incidence of infectious diseases; EP, proportion of older adult population (aged over 65); GF, proportion of government finance.

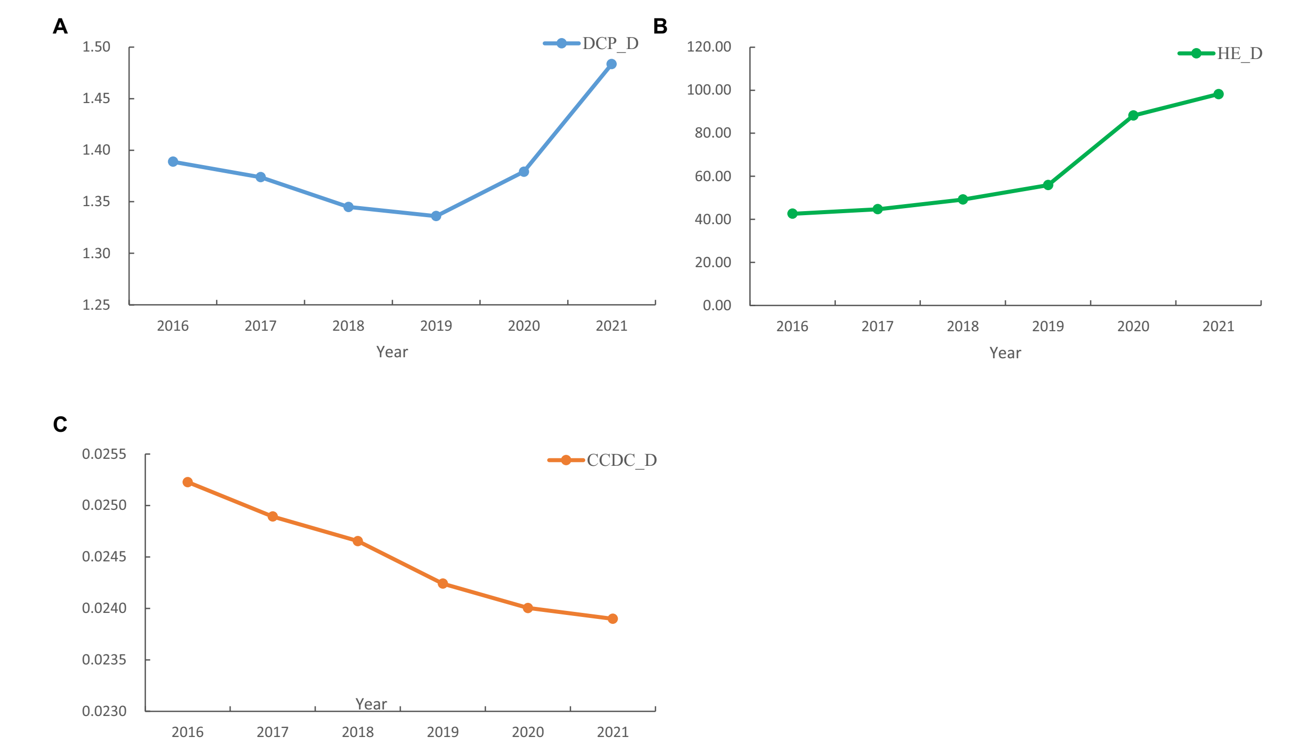

FIGURE 1
Changes of CCDC Healthcare Resources, 2016–2021.

by year (Figure 1). The descriptive statistical analysis of each dependent and independent variable in this study was shown in Table 3. The mean values of CCDC_D, DCP_D and HE_D for 2016–2021 were 1.58, 0.04 and 11.07, respectively (Table 3). It should be noted that CCDC_D and DCP_D in the western region were significantly more than those in the central and eastern regions, with Tibet having the highest CCDC_D and DCP_D. Beijing has the highest HE_D of all provinces. Compared to the policy's disease control personnel density standards, only eight provinces qualified in 2021, and mostly located in the western region (Supplementary Table S1).

Spatial correlation analysis

Besides HE_D and lnPD, other variables showed significant spatial autocorrelation (Tables 4, 5). The global Moran index of CCDC_D decreased from 0.1364 to 0.2662 in 6 years. However, the global Moran index of DCP_D increased from 0.4782 to 0.5067, which indicated a gradually increasing spatial autocorrelation. In addition, we mapped the spatial distribution of CCDC_D, DCP_D, and HE_D (Figures 2A–C). Overall, the three types of healthcare resources showed a trend of gradually decreasing from west to east, and the provinces with lower healthcare resources density were mainly in the eastern coastal areas.

TABLE 3 Variables and descriptive statistics.

Variable	Mean	SD	Min	Max
CCDC_D	0.04	0.04	0.01	0.25
DCP_D	1.58	0.59	0.74	4.15
HE_D	11.07	18.74	0.87	113.65
PD	2653.05	1705.31	194.71	7461.18
UR	60.99	11.72	29.60	89.30
PTHE	4671.44	1934.25	2374.79	13834.01
GDP	67080.47	30743.43	27457.70	183980.00
IID	225.03	92.29	80.80	659.75
EP	11.75	2.75	5.00	17.40
GF	71.60	26.47	3.38	100.00

CCDC_D, the number of CCDC per 10,000 population; DCP_D, the number of disease control personnel per 10,000 population; HE_D, per capita health expenditures; PD, population density; UR, urbanization rate; PTHE, per capita total health expenditure; GDP, per capita GDP; IID, incidence of infectious diseases; EP, proportion of older adult population (aged over 65); GF, proportion of government finance.

TABLE 4 Dependent variable Moran index.

year	CCDC_D	DCP_D	HE_D
2016	0.3164***	0.4782***	0.1826*
2017	0.3190***	0.4590***	0.0261
2018	0.3146***	0.4534***	0.0185
2019	0.2931***	0.4391***	−0.0157
2020	0.2721***	0.4733***	0.0322
2021	0.2662***	0.5067***	0.0348

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
CCDC_D, the number of CCDC per 10,000 population; DCP_D, the number of disease control personnel per 10,000 population; HE_D, per capita health expenditures.

TABLE 5 Independent variable Moran index.

year	lnPD	lnUR	lnPTHE	lnGDP	lnIID	lnEP	lnGF
2016	0.1537	0.4084***	0.2573***	0.3638***	0.4335***	0.3692***	0.2550**
2017	0.1523	0.4097***	0.2318**	0.4139***	0.4394***	0.4507***	0.1354
2018	0.1514	0.4009***	0.2172**	0.3876***	0.4243***	0.4164***	0.2147**
2019	0.1506	0.3954***	0.2099**	0.3574***	0.4632***	0.4054***	0.1118
2020	0.1609*	0.3774***	0.1672*	0.3617***	0.5017***	0.4203***	−0.0239
2021	0.1633*	0.3767***	0.1671*	0.3574***	0.4628***	0.4203***	0.0996

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
PD, population density; UR, urbanization rate; PTHE, per capita total health expenditure; GDP, per capita GDP; IID, incidence of infectious diseases; EP, proportion of older adult population (aged over 65); GF, proportion of government finance.

The spatial agglomeration of healthcare resources density was presented as maps (Figures 2D–F). In general, high-high cluster was mainly distributed in the western and northeastern regions, including Xinjiang, Tibet, Qinghai and Heilongjiang. Eastern region (Shandong, Jiangsu and Zhejiang, etc.) and central region (Anhui, Jiangxi and Shanxi, etc.) dominated by low-low cluster.

Regarding the DCP_D, high-low cluster was mainly distributed in Henan and Fujian, while low-low cluster was mainly distributed in the central and eastern regions, and most provinces were located near the Yangtze River basin. In terms of the CCDC_D, only Sichuan showed low-high cluster, while high-high cluster was mainly distributed in the west and low-low cluster was concentrated in the east. In terms of HE_D, only a few provinces showed spatial aggregation, with Heilongjiang showing high-high cluster and the other four provinces showing low-low cluster.

Spatial econometric analysis

The results of the statistical tests used to determine the best spatial econometric model were shown in Table 6. As an example of constructing a spatial econometric model of CCDC_D, LM (error) was significant, and the LR test judged that the SDM model would degenerate into SEM and SLM models, and the Hausman test indicated that the choice of random effects was more appropriate. In summary, the SEM model with random effects was chosen for the

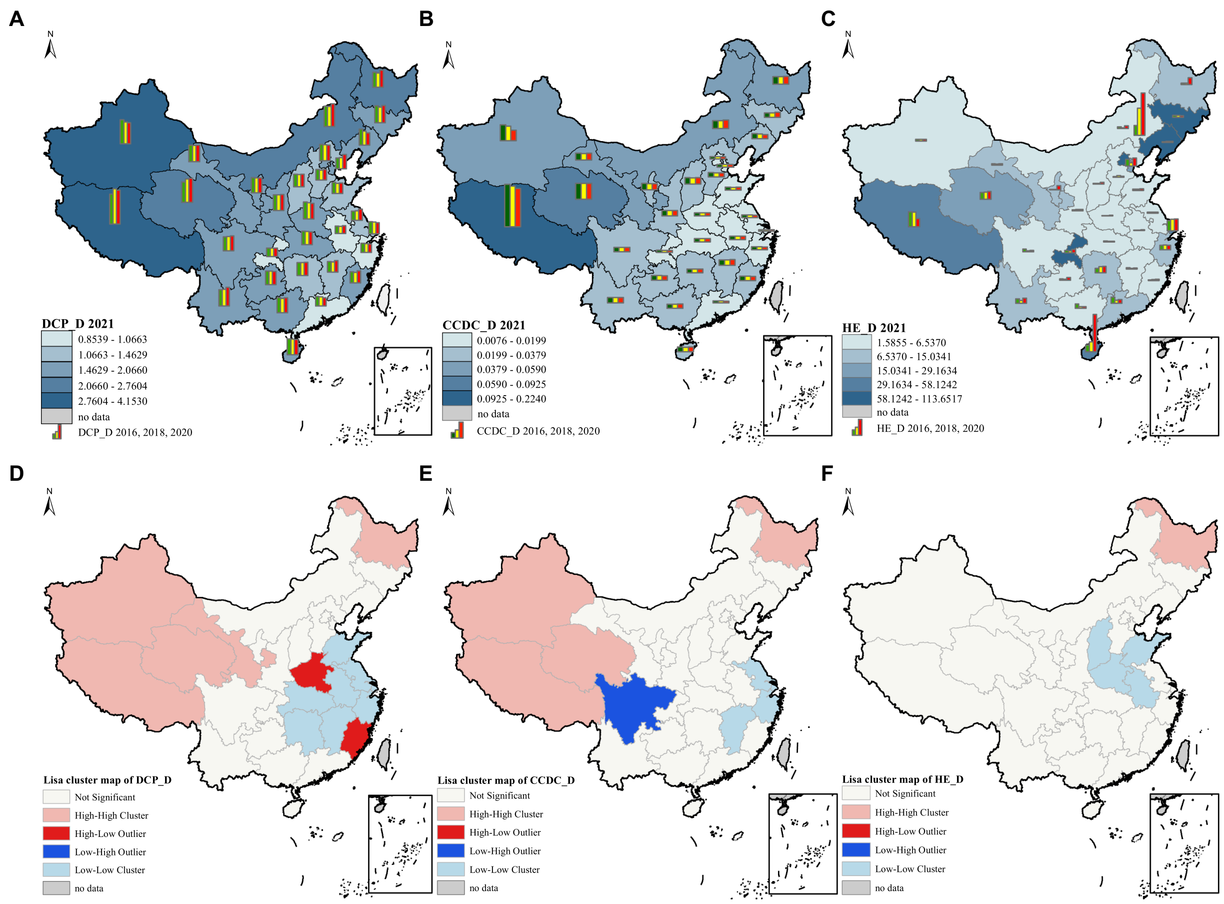

FIGURE 2
(A) spatial distribution of DCP_D; **(B)** spatial distribution of CCDC_D; **(C)** spatial distribution of HE_D; **(D)** univariate local indicator of spatial association cluster map of DCP_D in 2021; **(E)** univariate local indicator of spatial association cluster map of CCDC_D in 2021; **(F)** univariate local indicator of spatial association cluster map of HE_D in 2021. The average value of DCP_D, CCDC_D and HE_D in **(A–C)** was divided into five levels based on natural breaks (Jenks). These figures are drawn based on the standard map from the National Center for Basic Geographic Information (https://ngcc.cn/ngcc).

TABLE 6 **Statistical indicators of the spatial econometric model.**

Test	CCDC_D	DCP_D	HE_D
Moran's I	8.6170***	8.1600***	3.7400***
LM(error)	61.0690***	54.3970***	9.7820***
LM(lag)	3.7470*	24.9630***	0.1990
RLM(error)	66.9310***	29.4400***	14.5000***
RLM(lag)	9.6090***	0.0070	4.9170**
LR(lag)	10.3700	55.2000***	19.4400***
LR(error)	12.5700*	61.7100***	20.5200***
Hausman	9.5800	89.4800***	51.1400***

*$p < 0.1$; ***$p < 0.01$.
CCDC_D, the number of CCDC per 10,000 population; DCP_D, the number of disease control personnel per 10,000 population; HE_D, per capita health expenditures.

spatial effect analysis of the CCDC_D. Through LM test, LR test and Hausman test, we chosen the SDM model with fixed effects to analyze the spatial effects of DCP_D and HE_D.

We calculated the Goodness-of-Fit(R^2) to determine individual effects, time effects, and two-way fixed effects. The bigger the R^2 value, the better the model fit. As shown in Table 7, time effects were selected for both DCP_D and HE_D. Since there might be inter-individual differences among provinces over time, we chosen two-way fixed effects for further analysis of CCDC_D.

The spatial econometric models for three healthcare resources density were shown in Table 8. In the spatial error model of CCDC_D, population density and urbanization were negatively correlated with CCDC_D, with each 1% increase in population density decreasing CCDC_D by 0.03%. However, each 1% increase in infectious disease

TABLE 7 The Goodness-of-Fit (R^2) of the spatial econometric models.

R^2	CCDC_D	DCP_D	HE_D
time	0.5923	0.7778	0.6712
ind	0.5923	0.2816	0.0030
both	0.5923	0.3493	0.0026

CCDC_D, the number of CCDC per 10,000 population; DCP_D, the number of disease control personnel per 10,000 population; HE_D, per capita health expenditures.

TABLE 8 Spatial econometric models of healthcare resources density.

variables	CCDC_D	DCP_D	HE_D
lnPD	−0.0277***	−0.1423***	−6.5272***
lnUR	−0.0392***	−2.3901***	−22.9843**
lnPTHE	0.0043	0.7234***	40.0911***
lnGDP	−0.0025	0.3103**	−4.3025
lnIID	0.0068***	0.1758*	−4.0537
lnEP	0.0082*	−0.1002	6.4237
lnGF	0.0003	0.0132	−14.6053***
WxlnPD		−0.1109	5.1469
WxlnUR		1.6467***	37.4240**
WxlnPTHE		0.1305	−8.331
WxlnGDP		−1.1561***	−11.3396
WxlnIID		−0.6465***	−5.4014
WxlnEP		−0.8721***	−20.3898
WxlnGF		0.0417	−1.5393
RE or FE	RE	FE	FE
Observations	186	186	186
R-squared	0.592	0.778	0.671
Number of provinces	31	31	31

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
CCDC_D, the number of CCDC per 10,000 population; DCP_D, the number of disease control personnel per 10,000 population; HE_D, per capita health expenditures; PD, population density; UR, urbanization rate; PTHE, per capita total health expenditure; GDP, per capita GDP; IID, incidence of infectious diseases; EP, proportion of older adult population (aged over 65); GF, proportion of government finance; RE, random effect; FE, fixed effect.

TABLE 9 Direct, indirect, and total effects of dependent variables on DCP_D.

	Direct	Indirect	Total	Spillover effect
lnPD	−0.1448***	−0.1467	−0.2915*	No
lnUR	−2.3766***	1.4951***	−0.8816**	Yes
lnPTHE	0.7398***	0.2006	0.9404	No
lnGDP	0.2868*	−1.2122***	−0.9253**	Yes
lnIID	0.1416	−0.6999***	−0.5583**	Yes
lnEP	−0.1195	−1.0470***	−1.1665***	Yes
lnGF	0.0173	0.0481	0.0654	No

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
DCP_D, the number of disease control personnel per 10,000 population; PD, population density; UR, urbanization rate; PTHE, per capita total health expenditure; GDP, per capita GDP; IID, incidence of infectious diseases; EP, proportion of older adult population (aged over 65); GF, proportion of government finance.

prevalence and aging increased the CCDC_D by 0.01 and 0.01%, respectively.

Since there are total, direct and indirect effects in the SDM model, the respective effects of DCP_D and HE_D are shown in Tables 9, 10. In term of DCP_D, population density, *per capita* GDP, *per capita* total health expenditure, and urbanization had different degrees of influence on local disease control personnel density. Urbanization and *per capita* total health expenditure increased by 1%, resulting in 2.38% decrease and 0.74% increase in the DCP_D in the province, respectively. In terms of spillover effects, aging, infectious disease prevalence, and *per capita* GDP increased by 1%, resulting in 1.05, 0.70, and 1.21% decrease in

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TABLE 10 Direct, indirect, and total effects of dependent variables on HE_D.

	Direct	Indirect	Total	Spillover effect
lnPD	−6.5499***	4.8474	−1.7026	No
lnUR	−24.1832***	36.9194**	12.7362	Yes
lnPTHE	40.5638***	−11.4827	29.0811	No
lnGDP	−3.9678	−9.7247	−13.6925	No
lnIID	−4.7497	−5.1865	−9.9362	No
lnEP	6.9353	−22.2412	−15.3059	No
lnGF	−14.4624***	−1.1853	−15.6477***	No

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
HE_D, per capita health expenditures; PD, population density; UR, urbanization rate; PTHE, per capita total health expenditure; GDP, per capita GDP; IID, incidence of infectious diseases; EP, proportion of older adult population (aged over 65); GF, proportion of government finance.

DCP_D in neighboring provinces, respectively. However, each 1% increase in urbanization was followed by a 1.50% increase in DCP_D in neighboring provinces (Table 9). Population density, urbanization and government financial share had negative effects on HE_D in the province, with each 1% increase decreasing HE_D in the province by 6.55, 24.18 and 14.46%, respectively. Urbanization only had significant spillover effect, with each 1% increase in local urbanization increasing the HE_D of neighboring provinces by 36.92% (Table 10).

Discussion

This study aims to determine the characteristics of the spatial distribution of healthcare resources in Center for Disease Control and Prevention in China and to explore the influencing factors of health resources, which will help the health department to develop a reasonable resources allocation plan. The results showed that there was a significant spatial autocorrelation of health human resources and health physical resources, and the spatiality of health financial resources was not significant. Social, economic, policy, and health factors all had various degrees of impact on the healthcare resources of the Chinese center for disease control.

We found differences in CCDC density between provinces and the national average, in addition to marked regional differences in health expenditures density. By 2021, disease control personnel density was still below the basic requirements set by the government, with a national average disease control personnel density of 1.48 in 2021, while the government set a standard of 1.75 (56). In general, health professionals and recent medical graduates are reluctant to work at the CCDC. They prefer to work in hospitals or pharmaceutical companies with good development prospects and high salaries. This may have contributed to the shortage of health human resources in CCDC (23). In order to respond the crisis of future disease pandemics, more attention should be paid to developing the quantity and quality of disease control personnel.

This study analyzed the characteristics of the spatial distribution of disease control personnel density, CCDC density, and health expenditures density. The density of CCDC and disease control personnel showed a gradual decrease from west to east, with the highest in western regions such as Tibet, Xinjiang and Qinghai, and the lowest in eastern regions such as Shanghai, Guangdong and Jiangsu. The government of China stipulated that only one CDC should be set up in administrative districts at the county level and above (57). Western provinces such as Xinjiang and Tibet cover a wide area, and have more counties, so more CDC have been established. Moreover, the number of permanent residents in the western provinces is small, both of which make for a high CCDC density in the west. Previous studies had shown that the western region has an adequate health workforce (27, 52, 58), which was made a variety of national recruitment programs to attract talented people to work in the west (59).

However, in the developed regions of eastern China, disease control personnel density is low due to the huge local population base and the limited number of disease control personnel. The treatment of the CCDC may not match the local consumption level, leading to the flow of health talent to hospitals or companies with high salaries (60). Based on the distribution of health expenditures density, it is reasonable to infer that health expenditures are related to the severity of the epidemic in each province. In 2021, the COVID-19 epidemic is more serious in several provinces such as Tibet, Hainan and Liaoning. The government also spent significantly more on health in these provinces than in other provinces with more stable epidemics. Therefore, each province should make a strategic plan for the development of health human resources in the CCDC that is suitable for its own development, and appropriately adjust the size of CCDC personnel on the basis of the actual situation. Healthcare resources should be allocated scientifically to improve the accessibility of health services, taking into account various factors such as the number of inhabitants, geographic environment and public health events.

Spatially, the global Moran index of CCDC_D decreases, indicating that the number of CCDC gradually tends to be evenly distributed in space. Since China began a new round of health care reform in 2009, the public health system had accelerated the construction of CCDC to ensure that preventive health services are fully available (57). However, the global Moran index of disease control personnel density increased, which showed a strong spatial autocorrelation, which was similar to the results of other studies (61). Dong et al. found that the global Moran index of healthcare resources (e.g., doctors, nurses, technicians, etc.) increased to a certain extent from 2010 to 2016 (62). Cheng et al. found that the average density of health personnel increased from 1.60 in 2016 to 1.88 in 2019 (50). These studies implied a gradually expanding spatial aggregation of human resources for health. The high-high aggregation type of the density of CCDC and disease control personnel were mainly distributed in the western region, such as

Xinjiang, Tibet and Qinghai, while the low-low aggregation type was distributed in the eastern region, such as Jiangxi, Zhejiang and Jiangsu. Policy changes, population mobility, and flexible employment of health workers may have contributed to this spatial aggregation. There is a necessity for the health sector to have a better understanding of the factors affecting the distribution of healthcare resources in order to be able to formulate an effective regional healthcare resources allocation policy.

In general, healthcare resources are closely linked to social development, economic conditions, policies, and so on. Urbanization, as one of the factors representing social development, has a significant impact on each of the three healthcare resources in this study. The impact of urbanization on health expenditure density is much greater than the impact on the density of CCDC and the density of disease control personnel. This may be due to that the higher the urbanization, the higher the income from health expenditures, which then has a greater impact on the density of health expenditures. In health, disease control personnel density and CCDC density are positively affected by the incidence of infectious diseases. Other scholars have also concluded that during epidemic periods, a large and well-trained health workforce is necessary to actively carry out epidemiological investigations, and so on (63).

In addition, aging has a positive effect on CCDC density. This may be due to the fact that, as the level of awareness increases and aging becomes more serious, people pay more attention to preventive health care, and local governments increase their investment in preventive health care services for the older adult population (64). At the same time, this means that the need for the CCDC is also increasing. Among the economic factors, GDP *per capita* and *per capita* health care expenditures have a positive impact on disease control personnel density, and *per capita* health care expenditures have twice the impact of GDP *per capita*. In terms of regional impacts, social development, health factors and economic factors have spillover effects on disease control personnel density in neighboring provinces. The GDP of the province is negatively correlated with the density of disease control personnel in the surrounding provinces. Each 1% increase in the province's GDP leads to 1.21% decrease in disease control personnel density in the surrounding provinces.

Areas with higher economic levels are more likely to attract health personnel from neighboring areas who choose to work across districts (65). Particularly, as the economic level rises, it stimulates the demand for health services among the population (66), and it also increased the local demand for disease control personnel. Aging has a negative spillover effect on the density of disease control personnel in neighboring provinces. Studies have confirmed that the higher the aging, the greater the need for health workforce (67). This may be attributed to a greater need for more and more specialized health care services for the local older adult, which has led to a reduction in the number of disease control personnel in the neighboring provinces. Urbanization has a positive spillover effect on the density of disease control personnel in neighboring provinces, and we believe that urbanization has a spillover effect on health manpower, as confirmed by previous studies (68). Increasing urbanization is conducive to accelerating the mobility of human resources for health across regions. While focusing on the development of urbanization, the government should also pay attention to the impact of urbanization on healthcare resources of CCDC, and actively promote the high quality development of urbanization and CCDC.

In terms of spillover effects of health financing density, only urbanization development has a positive spillover effect on health expenditures density. Increasing urbanization in the province by 1% will cause the health expenditures density in the surrounding provinces to increase by 36.92%. It can be understood that the better developed the city, the higher the level of the health economy, causing the government to redirect investment to neighboring poorer provinces.

This study also has some limitations. Firstly, we calculated healthcare resources density based on population size only and conducted a study on spatial distribution and influencing factors. In the next study, healthcare resources density can be calculated based on land area. Secondly, other factors such as education levels and salary levels may have an impact on healthcare resources (69, 70). However, due to the availability of data, it was not possible to include the level of education and salary level in the study of influencing factors.

Conclusion

In conclusion, our study identified significant spatial variation in healthcare resources allocation of CDC in China. Moreover, the spatial aggregation of health human and health financial resources increased positively over the study period, which reflects the expansion of spatial variability. Social development, economic conditions, health factors and policy factors had impacts on the allocation of healthcare resources not only in the province but also in neighboring provinces.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: https://www.stats.gov.cn/.

Author contributions

YiY: Writing – original draft, Writing – review & editing. JL: Writing – review & editing. XD: Writing – review & editing. YaY: Writing – review & editing. LZ: Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2024.1331522/full#supplementary-material

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Development of an assessment tool for designated medical institutions in China——Based on the application of an online assessment system

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Background: Due to the expanding coverage of medical insurance and the growth of medical expenses, the ability to assess the performance of designated medical institutions (DMIs) in supporting the delivery of high-quality patient care and the standardized use of funds represents a priority in China. Despite such interest, there has yet to be an operable standard and labor-saving method for assessing DMIs in China.

Objective: The main objectives include two aspects: (1) establishing an evaluation index system for DMIs based on contracts; (2) designing and developing an online evaluation platform.

Methods: A group of 20 experts with theoretical and practical expertise in medical insurance regulation and performance evaluation were invited to select available indicators. A combination weighting method based on analytic hierarchy process and entropy method was used to determine the weight coefficient. Shanghai was taken as the sample area, and 760 DMIs were included in the empirical research. The test-retest reliability method and criterion-related validity method was used to test the reliability and the validity of the evaluation result.

Results: An assessment index system that included 6 domains and 56 indicators was established in this study. Furthermore, we developed an online platform to assist in the implementation of the assessment. The results showed that the average score of assessment was 94.39, the median was 96.92. The test-retest reliability value was 0.96 ($P \leq 0.01$), which indicated high stability of the assessment. In addition, there was a significant negative relationship between assessment score and the penalty amount of DMIs ($R = -0.133$, $P < 0.001$). After adjusting for the basic characteristics of medical institutions, the number of visits and revenue, the negative relationship was still significant ($B = -0.080$, $P < 0.05$). These results are consistent with expectations, indicating that the assessment had good criterion-related validity.

Conclusions: This study established an operable assessment measure and developed an online platform to assess the performance of DMIs. The results showed good feasibility and reliability in empirical research. Our research findings provided an operable Chinese solution for DMI assessment that saves manpower and time, which would have good enlightening significance in other regions of China and in low-income and middle-income countries internationally.

KEYWORDS

basic medical insurance, designated medical institutions, online assessment system, medical insurance supervision, medical service agreement

Highlights

- An assessment standard based on medical insurance service agreements was established to supervise the performance of contracted medical service providers, and the results showed good feasibility and reliability in empirical results.
- An online platform was developed to assist in the implementation of assessment, which helps save time and manpower in the assessment of medical insurance agencies.

Introduction

To improve the quality, efficiency, and responsiveness of medical services, market competition mechanisms have been introduced in healthcare industry. In the context of marketization of medical services, contract management is an important management method to improve the performance and accountability of medical institutions in recent years, and has been widely applied in the healthcare field in various countries around the world. In China, the main elements of the basic medical insurance system include medical service providers, medical insurance agencies, medical insurance administrative departments and insured persons (1). Among them, the medical insurance agencies and medical service providers are interrelated through contract. Specifically, the medical insurance agencies play the role of medical service purchasers—they select qualified medical service providers and sign contracts with them, and these contracted medical service providers should provide medical services to the insured persons accordance with the contract requirements. These contracted medical service providers are named designated medical institutions (DMIs) in China. The medical expenses can be partially or fully reimbursed by medical insurance. Therefore, the medical insurance agencies have been exploring how to effectively play the role of contract management and how to strengthen the performance evaluation of DMIs.

Based on the theory of incomplete contracts, the contract between the medical insurance agencies and the medical service provider is a typical incomplete contract, characterized by unpredictability, difficulty in contracting, and difficulty in verification (see Table 1) (2, 3). Due to human's limited rationality and opportunistic behavior, the complexity and uncertainty of the external environment, as well as the asymmetry and imperfection of information, it is impossible to take all possible future scenarios into account when signing the contract, making it difficult for the medical insurance agency to clearly specify the quantity and quality of medical services that DMIs need to provide in contracts, resulting in a lack of effective evaluation criteria for contract execution. In recent years, the default rate of DMIs in China has been high, and the overall implementation of agreements has been poor, seriously endangering the security of medical insurance funds. According to the statistics of the National Healthcare Security Administration, in 2019, a total of 815,000 DMIs were inspected, of which more than 264,000 (approximately 32%) were punished for violating the agreement, and 11.56 billion yuan of medical insurance funds were recovered. In 2020, a total of 627,000 DMIs were inspected, of which 401,000 (64%) were punished, and a total of 22.31 billion yuan was recovered throughout the year (4). Therefore, it is urgent to design effective performance evaluation standards from the perspective of contract management, intuitively reflecting the performance of DMIs, so as to supervise and restrict their behavior and improve the security and efficiency of medical insurance funds.

TABLE 1 Characteristics of contracts between medical insurance agencies and DMIs.

Characteristics	Causes
Unpredictability	The bounded rationality of contract subjects such as medical insurance agencies and DMIs The unpredictability of disease, doctor's behavior and medical service effectiveness
Difficulty in contracting	The low measurability of medical service leads to high contracting cost for designing detailed terms
Difficulty in verification	Lack of professional third-party evaluation agency Lack of operational standards for measuring service outcomes

In an effort to reduce expenditures, improve health outcomes and enhance patient experience, private and public payers have experimented with an array of programs, including hospital report cards, accountable care organizations (ACOs), and pay-for-performance (P4P) programs (5). Hospital report card policies refer to governments publishing quality indicators of hospitals mainly including health outcome indicators such as risk-adjusted mortality rates or readmission rates (6). The ACO model (7) ensures that medical services meet certain quality standards while medical expenses are lower than pre-set cost standards. The more medical expenses saved, the more economic rewards ACO members receive (8–10). In this model, 34 nationally recognized quality measures (four quality domains of patient/caregiver experience, care coordination and patient safety, preventive health and clinical

Abbreviations: DMIs, designated medical institutions; AHP, analytic hierarchy process.

care for at-risk populations) are used to control quality. P4P programs, also known as value-based purchasing (VBP), link provider's reimbursement with performance on a set of defined quality measures (11). For example, the UK National Health Service introduced the Quality of Outcomes Framework (QOF) in 2003, which includes three domains (clinical, public health, quality improvement) of indicators. That same year, the US Centers for Medicare & Medicaid Services (CMS) began the Hospital Quality Incentive Demonstration (HQID), 34 quality measures were established by the CMS across 5 clinical conditions addressing acute care (12). However, the above influential evaluation methods for medical service providers in developed countries are based on solid medical information and professional third-party evaluation institutions (13–17), making it difficult to apply them to low-income and middle-income countries or regions with relatively underdeveloped medical information support facilities and third-party evaluation.

In China, medical insurance payers are increasingly paying attention to the evaluation of medical service providers. In previous studies, research has mainly focused on topics such as performance evaluation, credit evaluation, medical cost detection and identification of abnormal behaviors. For example, a study established a credit evaluation system for public hospitals that included five dimensions—honest procurement, honest charging, honest medical insurance, honest diagnosis and treatment, and honest practice, and tested it in three tertiary medical institutions (18). Another study improved clustering-based local outlier factor methods to detect abnormal medical fees and utilized rule-based methods to identify abnormal medical behavior, such as hospitalization decomposition (19). These studies provide valuable contributions to the supervision and decision-making of medical insurance payers. However, the existing literature on the performance evaluation of contracted medical service providers is mostly limited to specific aspects such as medical quality, medical behavior, and medical expenses, and there is a lack of comprehensive consideration based on contracts. Besides, most studies were conducted mainly in public tertiary hospitals with complete medical information infrastructure, resulting in limited generalizability of the evaluation indicators. The other types of medical service providers may be difficult to implement due to operational difficulties such as data collection and insufficient on-site assessment manpower (20). Therefore, this study aims to construct an evaluation index system to identify the compliance level of DMIs, providing reference for medical insurance supervision. Based on this, an online evaluation platform was designed and developed to collect, calculate, and analyze evaluation data, solving the problem of insufficient manpower in medical insurance contract management.

Methods

Participants

The procedure of this study is shown in Figure 1. Firstly, we established an evaluation index system for DMIs based on contracts. Secondly, we designed and developed an online platform to implement the evaluation. Thirdly, we conducted empirical research on 760 DMIs and tested the reliability and validity of the indicator system.

In the empirical research, we took Shanghai as the sample area. The inclusion criteria for the evaluated institutions were as follows: (1) should remain in business by December 31, 2020; (2) should be the headquarters of the contracted institutions. The exclusion criteria were as follows: (1) internal medical institutions affiliated with enterprises, schools, and other institutions, which do not provide health services to the public; (2) branch medical institutions, such as the branch hospital of a public medical institution. According to the above inclusion and exclusion criteria, 760 contracted health providers in Shanghai were included in the study.

Determine the evaluation goal and dimensions

Based on contract theory and performance management theory, we analyzed the elements of the contract-based medical service providers evaluation system and the logical relationships between them through literature review and expert interviews. Then we constructed a conceptual framework (see Appendix 1) including evaluation subject, evaluation object, evaluation goal, evaluation dimensions, and evaluation tool for evaluation. Specifically, the evaluation subjects refer to medical insurance agencies, the evaluation objects refer to DMIs and the evaluation tool refer to online platform. The determination of evaluation goals and evaluation dimensions was as follows:

Firstly, we systematically collected policy documents published from 2009 to 2020 on official platforms such as the Chinese government website, the National Health Commission, and the National Healthcare Security Administration. A total of 23 national policy documents and 114 local policy documents were collected. After sorting and analyzing, we summarized the development stages and goals of basic medical insurance and contract management in China, and analyzed the main goals of contract management at the current stage.

At the same time, semistructured interviews with 12 experts (consisting of five medical insurance administrators, four hospital managers and three scholars) were conducted with the following questions being asked: "What do you think are the goals of contract-based assessment for designated medical institutions?" and "What requirements do you think designated medical institutions should meet?"

Based on the results of the above two parts, we have determined the goals and dimensions for evaluating the compliance level of DMIs.

Building the preliminary indicator pool

A literature review of on the performance of contracted medical service providers was performed by searching PubMed, CNKI and Wanfang databases to collect preliminary evaluation indicators. We collected literatures from 2000 to 2021, and gathered a total of 660 articles. After excluding the duplicates, conference reports, and

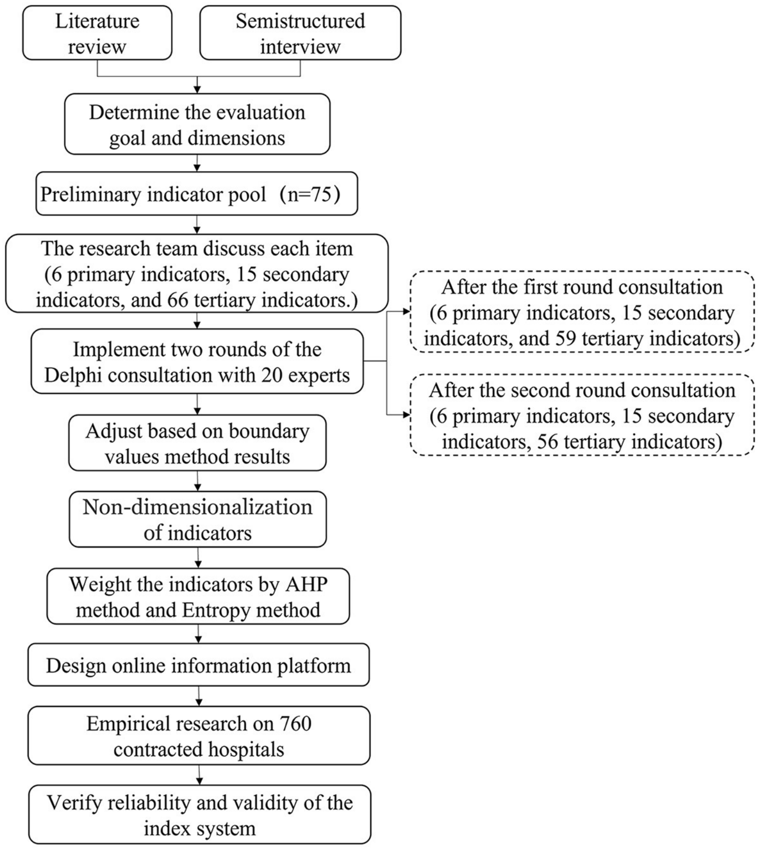

FIGURE 1
Study procedure for constructing an evaluation index system of DMIs.

papers without any indicators, 120 papers were left. Besides, we also included 33 local medical insurance contracts from different regions for in-depth review together. After reviewing the above materials, a total of 75 indicators were identified. The research team discussed each item one by one, deleted the duplicate ones, and classified them to form a hierarchical index system consisting of six primary indicators, 15 secondary indicators, and 66 tertiary indicators.

Using the Delphi method to build an index system

Two rounds of the Delphi consultation were conducted to collect experts' opinions on the preliminary index system. We selected 20 experts including medical insurance administrators, hospital managers and scholars to participate in the Delphi consultation, and invited them to score the importance and feasibility of each candidate indicator on a 1–10 scale.

And then, we used the boundary values of two important statistics (arithmetic mean and coefficient) to screen the indicators. The inclusion criteria were as follows: (1) the arithmetic mean of the importance and feasibility of candidate indicators is >7; (2) the coefficient of variation is ≤0.25. Otherwise, the indicators will be deleted.

To ensure the scientific soundness and rationality of the Delphi method, the experts' positive coefficient, authority coefficient and coordination coefficient were calculated. The experts' positive coefficient reflects the positive input from the experts, which can be expressed by the effective response rate. An effective response rate above 70 is considered a very good standard. The expert authority coefficient is generally determined by two factors: the judgment basis coefficient, denoted by Ca, and the familiarity coefficient, denoted by Cs. The calculation formula for expert authority coefficient is $C_r = \frac{C_a+C_s}{2}$. Generally, the higher Cr is, the higher the prediction accuracy. A Cr value <0.7 is considered to indicate acceptable reliability. The coordination of the experts' opinions reflects the consistency of evaluation of all experts, which guarantees the scientific of the index system, and can be calculated by Kendall's W concordance coefficient.

Exploring the quantitative calculation method

Dimensionless methods

Dimensionless methods were explored based on the data type to obtain the standard value of each indicator. The assignment methods for standard values in this study were as follows (21–24): (1) "0–1" assignment method, which is applicable to binary classification indicators with the answer of "yes" or "no". (2) Multi-condition assignment method, which is applicable to indicators that need to meet more than one requirement. (3) Proportional assignment method, which is applicable to indicators expressed as a percentage. (4) Segment assignment method, which is applicable to indicators with an acceptable range, with a value of 0 assigned outside the acceptable range and a proportional value assigned within the acceptable range. (5) Min-max normalization, which is applicable to indicators lacking reference values and without extreme outliers. The calculation formula is as follows when the indicator is positive in direction (which means the higher the indicator value is, the better the evaluation will be):

$$y_i = \frac{x_i - \min(X_i)}{\max(x_i) - \min(x_i)}$$

The calculation formula is as follows when the indicator is negative (which means the lower the indicator value is, the worse the evaluation will be):

$$y_i = \frac{\max(x_i) - x_i}{\max(x_i) - \min(x_i)}$$

Where x_i is the original value of the indicator, y_i is the standard value of the indicator.

(6) Horizontal comparison assignment, which assigns values by comparing the scores of the evaluated institution with the mean of all assessed objects, is used for indicators lacking reference values and with extreme outliers. The calculation formula is as follows when the indicator is positive in direction:

$$y_i = \frac{X_i}{\overline{X}}$$

The calculation formula is as follows when the indicator is negative direction:

$$y_i = \frac{\overline{X}}{X_i}$$

Where x_i is the original value of the indicator, y_i is the standard value of the indicator, X is the average value of similar medical institutions at the same level.

Combination weighting method

A combination weighting method based on analytic hierarchy process (AHP) method and entropy method was used to determine the weight coefficient.

Using the AHP to assign subjective weights

AHP method was used to determine the subjective weight coefficient. Twenty experts who participated in consultation compared the relative importance of the indicators in each domain, scored them and formed a judgment matrix A= $(a_{ij})_{n\times n}$ (25). Yaahp11.2 was used to input the judgment matrix of each expert and calculate the subjective weight coefficient of each indicator.

Using the entropy method to assign objective weights

Entropy method was used to determine the objective weight coefficient, and the calculation formula was as follows (26).

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{1}$$

P_{ij} means the proportion of the index value of medical institution i of index j.

$$e_j = -k \sum_{i=1}^{m} P_{ij} \ln P_{ij} \tag{2}$$

e_j means the entropy of index j.

$$g_j = 1 - e_j, (j = 1, 2, 3 \ldots n) \tag{3}$$

g_j means the difference coefficient of index j.

$$\mu_j = \frac{g_j}{\sum_{j=1}^{n} g_j} (j = 1, 2, \ldots, n) \tag{4}$$

μ_j means correction coefficient of index j.

$$\theta_j = \frac{\mu_j w_j}{\sum_{j=1}^{n} \mu_j w_j} \tag{5}$$

w_j means the initial weight obtained by AHP method, θ_j means the weight obtained by adjusting w_j with the correction coefficient μ_j.

The combination weight W is calculated by the initial weight (w_j) obtained by AHP method and the adjusting weight (θ_j) obtained by entropy method. The formula is as follows, and the value of ρ is usually 0.5.

$$W_j = \rho w_j + (1 - \rho)\,\theta_j \tag{6}$$

W_j means the combination weight calculated by w_j and θ_j.

Reliability and validity analysis

Reliability analysis

We used the test-retest reliability method to test the reliability of the indicator system. The correlation coefficient of the assessment scores obtained online and on site was calculated as the retest reliability value to test the stability of the assessment.

Validity analysis

We use criterion-related validity to test the consistency between the measured value and the true value of the evaluation result. The criterion is usually represented by a recognized, reliable

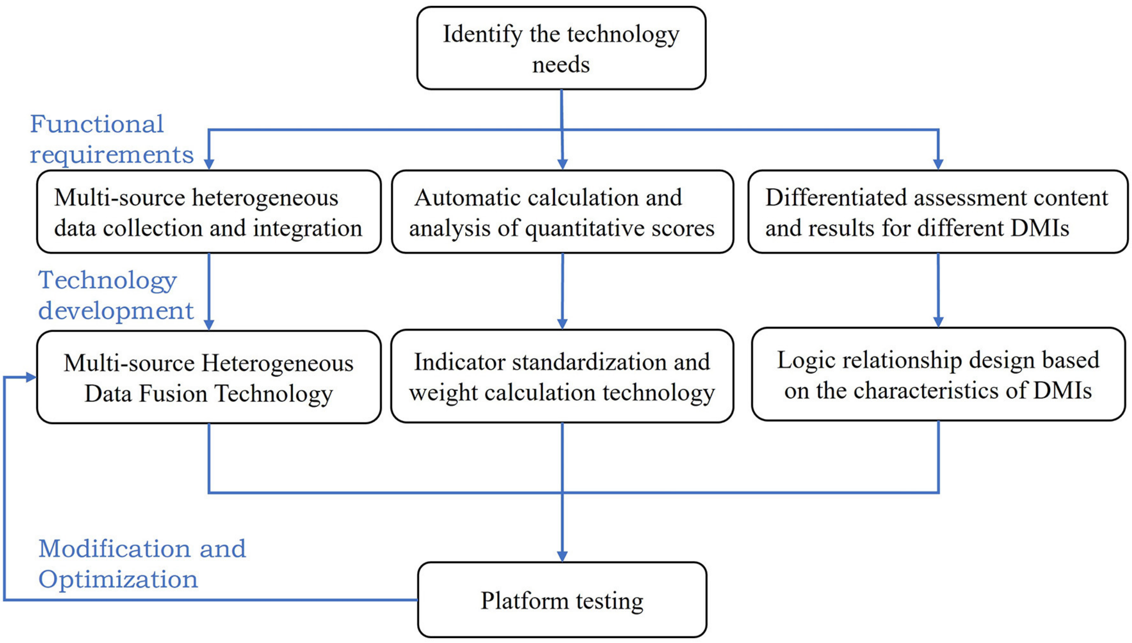

FIGURE 2
Technical development of the assessment platform for DMIs.

and authoritative indicator. The higher the correlation between evaluation results and the criterion, the more authentic and reliable the evaluation results are. In this study, the criterion indicator is represented by the penalty amount for medical insurance supervision of DMIs. The research hypothesis is that when there is a significant negative correlation between the evaluation value and the criterion value (which means the higher the evaluation score, the lower the penalty amount of contracted medical providers), it indicates that the evaluation result is consistent with the true value, and the assessment result is reliable. We used spearman correlation analysis and linear regression analysis to analyze the relationship between evaluation results and the criterion indicator.

Design of the online assessment platform

The online assessment platform mainly aims at solving the following problems: (1) the number of DMIs to be assessed is large, and the manpower for assessment is insufficient; (2) the assessment data comes from multiple departments and 760 DMIs, which means that the data sources are diverse and the data volume is large. Thus, it is difficult to integrate, process and analyze the data; (3) different levels and types of medical institutions would be assessed by different indicators, which makes manual data collection and calculation prone to errors.

Based on the above problems, the design of the information platform was as follows: (1) Automatic calculation and analysis of quantitative scores. Based on the indicator standardization and weight calculation method obtained from the above research, a score calculation program was designed to automatically calculate the assessment scores. (2) Technology for the collection and integration of multisource heterogeneous data. As the data came from multiple sources, the research group developed the integration and standardized technology of multisource heterogeneous data for the assessment platform. (3) The logical correlation design based on the characteristics of medical institutions. Due to the differences in the medical insurance settlement level, nature and type of evaluated institutions, the platform established a logical association between the assessment content, assessment results and characteristics of medical institutions, which made it possible to implement differentiated assessments for different medical institutions (see Figure 2).

Statistical analysis

The arithmetic mean, standard deviation and coefficient of each indicator's importance and feasibility scores were used to screen the indicators. The experts' positive coefficient, authority coefficient and the Kendall W coefficient were used to determine whether the Delphi expert consultation results were scientific and reliable. An analytic hierarchy process (AHP) method and entropy method was used to determine the weight coefficient. The Cronbach's α reliability coefficient method and the criterion-related validity were used to test the reliability and validity of evaluation. All the above analysis were conducted in SPSS 27.0, Excel 2021 or Yaahp11.2. A two-sided p-value <0.05 was considered statistically significant in this study.

TABLE 2 Six main domains and connotations of the assessment index system.

Domains	Connotation
Medical insurance management	Refers to the infrastructure configuration and completion of basic business required for medical insurance management
Medical insurance settlement	Refers to the management and settlement of medical insurance funds by DMIs comply with regulations
Medical service quality	Refers to the medical service quality and safety of DMIs
Medical service efficiency	Refers to the convenience and efficiency of diagnosis and treatment provided by DMIs
Medical expense control	Including the growth of medical expenses and the rationality of medical fees
Experience of the insured persons	Refers to the protection of the rights of the insured and the subjective experiences of the insured persons

Results

Definition of assessment objectives and dimensions

According to the policy document review and interviews results, the compliance level of DMIs was defined as the performance evaluation of medical service providers conducted by medical insurance management departments or third-party organizations based on contracts. The aim is to use limited health insurance funds to purchase better quality services, and improve the medical experience of insured persons. Thus, the assessment objectives mainly include three aspects: standard use of medical insurance funds, providing high-quality, efficient and affordable medical services, and improving the medical experience of insured persons. On this basis, six assessment dimensions are further formed, including medical insurance management, medical insurance settlement, medical service quality, medical service efficiency, medical expense control, and experience of the insured persons. The specific definitions of each assessment dimension are shown in Table 2.

Results of the Delphi consultation

Basic information of experts

Among the experts participated in the Delphi consultation, the majority had a master's degree or above (95%), 80% had been engaged in relevant work for more than 10 years, and 85% of them held senior professional title. Thus, they had authoritative opinions on management of medical service providers. More details are shown in Table 3.

Experts' positive coefficient

In the first round of the Delphi consultation, all 20 questionnaires were recovered, with a response rate of 100%. In the second round, 20 questionnaires were distributed and 19 were collected back, with a response rate of 95.00%. The response rate of all the two rounds of the Delphi consultations were both above 70%, indicating that the experts' feedback was positive.

TABLE 3 Basic information of experts ($N = 20$).

Participants' information	*N*	%
Gender		
Male	13	65.0
Female	7	35.0
Age		
30–39	6	30.0
40–49	8	40.0
≥50	6	30.0
Education		
Bachelor	1	5.0
Master	12	60.0
PhD	7	35.0
Occupation		
Hospital manager	5	25.0
Medical insurance administrators	6	30.0
Health department administrators	3	15.0
Scholar	6	30.0
Professional title		
Senior	17	85.0
Middle	3	15.0
working years		
0–9	4	20.0
10–19	5	25.0
20–29	5	25.0
≥30	6	30.0

Expert authority coefficient (Cr)

The values of the expert authority coefficient Cr from the two rounds of expert consultations were 0.85 and 0.86 respectively, >0.7, indicating that the expert consultation results were accurate and reliable.

Coordination of experts' opinions

The coordination of experts' opinions is shown in Table 4. In both two rounds of the Delphi consultations, Kendall's W coefficients ranged between 0.150 and 0.426, and the importance and feasibility scores in both rounds were all effective ($P < 0.001$), suggesting the consistency among experts.

TABLE 4 Kendall's W concordance coefficient test results.

	First round		Second round	
	Importance	Feasibility	Importance	Feasibility
Kw	0.308	0.150	0.426	0.153
χ^2	633.480	306.811	853.746	312.418
P	<0.001	<0.001	<0.001	<0.001

Indicators' screening

We calculated the boundary values of all indicators. According to the screening criteria, the primary and secondary indicators met the retention criteria, and the tertiary indicators were adjusted after the consultation. Seven indicators were deleted in the first round, and three were deleted in the second round (see Appendix 2).

The adjusted assessment index system for DMIs included 6 domains and 56 indicators. The 56 indicators and their descriptions, data sources, and directions were shown in Appendix 3. The data sources for the assessment mainly included the following: (1) hospital self-reported data, which was collected from the assessed DMI reporting the required data and uploading supporting materials on the information platform; (2) Data records from the relevant administrative department, which were collected from the relevant administrative department supplying daily work data and previous inspection data related to the assessed DMI.

Results of the quantitative calculation method

Dimensionless results

Based on the above criteria, in this study, the dimensionless method and assignment criterion for each indicator were chosen according to the data type, and the standard values were calculated. The specific results are shown in Appendix 4.

Results of the combination weight coefficient

Table 5 shows the combination weighting coefficients calculated by the AHP and entropy methods. The weight of the six domains of agreement enforcement assessment were ranked from high to low as follows: medical service quality, medical expense, medical service efficiency, medical insurance settlement, experience of the insured, and medical insurance management. Improving the quality of medical services and reducing expenditures are the most important aspects of performance evaluation for DMIs.

Construction of the online assessment platform

The overall structure and functions of the online information platform are shown in Figure 3.

The main user groups of the platform include municipal level medical insurance management department, district-level medical insurance management department and contracted medical service

TABLE 5 Weight coefficients of indicators.

Indicators	w_j^a	θ_j^b	W_j^c
1. Medical insurance management	0.0748	0.0295	0.0521
1.1 Basic construction	0.0133	0.0013	0.0073
1.1.1 Establish medical insurance department	0.0105	0.0009	0.0057
1.1.2 Build bylaws and policies	0.0028	0.0004	0.0016
1.2 Human resource management	0.0066	0.0028	0.0047
1.2.1 Records management of physicians	0.0019	0.0019	0.0019
1.2.2 Records accuracy of physicians	0.0007	0.0007	0.0007
1.2.3 Insurance settlement personnel	0.0040	0.0002	0.0021
1.3 Information system	0.0247	0.0041	0.0144
1.3.1 Establish medical insurance information management department	0.0050	0.0002	0.0026
1.3.2 Connect medical insurance network	0.0093	0.0005	0.0049
1.3.3 Equip auxiliary equipment in computer room	0.0012	0.0001	0.0006
1.3.4 Equip intelligent monitoring system of basic medical insurance	0.0014	0.0014	0.0014
1.3.5 Establish doctor (nursing) workstation	0.0020	0.0011	0.0016
1.3.6 Internet security	0.0047	0.0007	0.0027
1.3.7 Contingency plan for information system	0.0012	0.0001	0.0006
1.4 Medical insurance business	0.0262	0.0148	0.0205
1.4.1 Sign of designated medical institution	0.0021	0.0010	0.0015
1.4.2 Monitoring equipment in medical insurance service area	0.0013	0.0006	0.0010
1.4.3 Medical insurance policy consulting service	0.0031	0.0031	0.0031

(Continued)

TABLE 5 (Continued)

Indicators	w_j^a	θ_j^b	W_j^c
1.4.4 Medical insurance policy training for medical personnel	0.0043	0.0009	0.0026
1.4.5 Publicity of medical insurance complaint channels	0.0043	0.0002	0.0023
1.4.10 Implementation of additional agreements of specific institutions	0.0111	0.0090	0.0100
1.5 Drug procurement	0.0038	0.0065	0.0052
1.5.1 Purchase, sales and deposit record	0.0007	0.0001	0.0004
1.5.2 Application of national procurement platform	0.0020	0.0020	0.0020
1.5.4 Completely product authorization information	0.0003	0.0003	0.0003
1.5.5 Proportion of centralized procurement drugs	0.0008	0.0042	0.0025
2. Medical insurance settlement	0.1088	0.139	0.1241
2.1 Claims settlement requirement	0.0347	0.0223	0.0285
2.1.1 Claims settlement materials	0.0145	0.0051	0.0098
2.1.2 Scope of claim settlement	0.0089	0.0089	0.0089
2.1.3 Issue settlement bills	0.0032	0.0002	0.0017
2.1.4 Settlement of agreed diagnosis and treatment items	0.0081	0.0081	0.0081
2.2 Reconciliation management	0.0744	0.1167	0.0956
2.2.1 Overdue days of reconciliation	0.0189	0.0016	0.0103
2.2.2 Proportion of daily reconciliation deduction amount	0.0555	0.1151	0.0853
3. Medical service quality	0.4004	0.4471	0.4272
3.1 Medical service management	0.1110	0.1142	0.1127
3.1.1 Identify the insured correctly	0.0144	0.0144	0.0144
3.1.2 Qualified medical record	0.0167	0.0050	0.0109

(Continued)

TABLE 5 (Continued)

Indicators	w_j^a	θ_j^b	W_j^c
3.1.3 Medical expense inquiry service	0.0102	0.0102	0.0102
3.1.4 Registration and filing of external inspection and treatment	0.0044	0.0002	0.0023
3.1.5 Standard use of family sickbeds	0.0079	0.0079	0.0079
3.1.8 Outpatient prescription outsourcing service	0.0043	0.0043	0.0043
3.1.11 Hospitals reject patients without justifiable reasons	0.0322	0.0322	0.0322
3.1.12 Scoring of bad practice of medical institutions	0.0210	0.0400	0.0305
3.2 Health care quality management	0.2961	0.3329	0.3145
3.2.1 Qualified rate of inspection	0.0526	0.0185	0.0356
3.2.2 Proportion of default amount of drugs with payment limitation	0.1880	0.2647	0.2263
3.2.4 Mortality of cases in low-risk group	0.0555	0.0497	0.0526
4. Medical service efficiency	0.1095	0.0761	0.0896
4.1 Convenient medical treatment	0.0261	0.0153	0.0207
4.1.1 Average waiting time after appointment	0.0199	0.0150	0.0175
4.1.2 Convenience Services and Facilities	0.0062	0.0003	0.0032
4.2 Efficient diagnosis and treatment	0.0771	0.0608	0.0689
4.2.1 Outpatient return visit rate	0.0171	0.0178	0.0174
4.2.2 Re admission rate within 15 days after discharge	0.0449	0.0242	0.0346
4.2.5 Inpatient outpatient ratio	0.0151	0.0188	0.0169
5. Medical expense	0.2306	0.2797	0.2569
5.1 Growth rate of medical expenses	0.0931	0.1817	0.1374
5.1.1 Proportion of medical service income	0.0289	0.1037	0.0663

(Continued)

TABLE 5 (Continued)

Indicators	w_j^a	θ_j^b	W_j^c
5.1.2 Increase in average outpatient cost per time	0.0227	0.0371	0.0299
5.1.3 Increase in average hospitalization cost per time	0.0232	0.0212	0.0222
5.1.4 Increase in average drug cost per outpatient	0.0083	0.0040	0.0061
5.1.5 Increase in average drug cost per hospitalization	0.0100	0.0157	0.0129
5.2 Reasonable medical charges	0.1411	0.098	0.1195
5.2.5 Cost shifting of exceeding medical insurance settlement	0.0525	0.0132	0.0328
5.2.6 Implementation of copay rate of medical insurance	0.0748	0.0710	0.0729
5.2.9 Standardizing charge for newly increased medical service	0.0138	0.0138	0.0138
6. Experience of the insured	0.0760	0.0286	0.0503
6.1 The insured's rights	0.0294	0.0193	0.0244
6.1.1 Signing of informed consent	0.0198	0.0120	0.0159
6.1.2 Information security	0.0096	0.0073	0.0085
6.2 Evaluation of the insured	0.0425	0.0093	0.0259
6.2.1 Subjective satisfaction of the insured	0.0167	0.0030	0.0098
6.2.2 Complaints of the insured	0.0258	0.0063	0.0161

[a] w_j, means subjective weight obtained by AHP method.
[b] θ_j means objective weight obtained by entropy method.
[c] W_j means combined weight obtained by AHP method and entropy method.

institutions. The functions of the platform designed for each user group were as follows: (1) for municipal level medical insurance management department, the main functions of platform include uploading the relative regulatory inspection and work record data, collecting assessment data from medical institutions, automatically calculating the assessment scores, and analyzing, ranking and publishing the assessment results; (2) for district-level medical insurance management department, the main functions of platform include supervising the progress of the assessment, uploading the on-site spot checks data and analyzing the assessment results within the jurisdiction; (3) for contracted medical service institutions, the main functions of platform include uploading the required data of assessment online and querying the assessment results. Therefore, the platform designed the following functional modules: (1) information filling module; (3) scoring module; (4) information release module. Based on the above design, the platform was used to achieve convenient and efficient data collection and integration, automate data calculation and analysis, and visualize assessment results to improve the operability of the assessment.

Results of empirical research

The arithmetic mean of the assessment score was 94.39, the median was 96.92, the highest score was 100, and the lowest was 60.64.

The study analyzed the assessment scores of contracted medical service providers with different administrative levels, natures and types, and found significant differences in assessment scores between evaluated institutions with different administrative levels ($F = 45.233$, P 0.001) (Table 6).

Validation of the assessment score

Reliability test

The study ensured the stability and repeatability of the assessment results through the following methods: (1) the interference of manual calculation errors was eliminated through an automatic calculation program, which ensured the accuracy of the data calculation. (2) using the method of complete random sampling, 145 institutions were selected from all evaluated institutions, and data was collected on-site again, and the evaluation results were calculated by experts. The correlation coefficient of the assessment scores obtained online and on site was calculated as the retest reliability value to test the stability of the assessment. The test-retest reliability value was 0.96 ($P \leq 0.01$), which indicated high stability of the assessment.

Results for criterion-related validity

The relationship between the penalty amount and the assessment score of DMIs are shown in Table 7. The correlation analysis result shows that there is a significant negative relationship between the assessment score and the penalty amount of DMIs ($R = -0.133$, $P < 0.001$). This result is consistent with the hypothesis, and it can be considered that the evaluation results can better reflect the real situation with high validity.

In regression analysis, we adjusted administrative level, medical institution type, the number of medical visits and revenue, and found that the relationship between the assessment score and the penalty amount of DMIs was still significant ($P < 0.001$). Besides, we analyzed the relationship between the assessment score and the penalty amount of DMIs in different levels of medical institutions, and found that the relationship between the assessment score and the penalty amount of DMIs was significant

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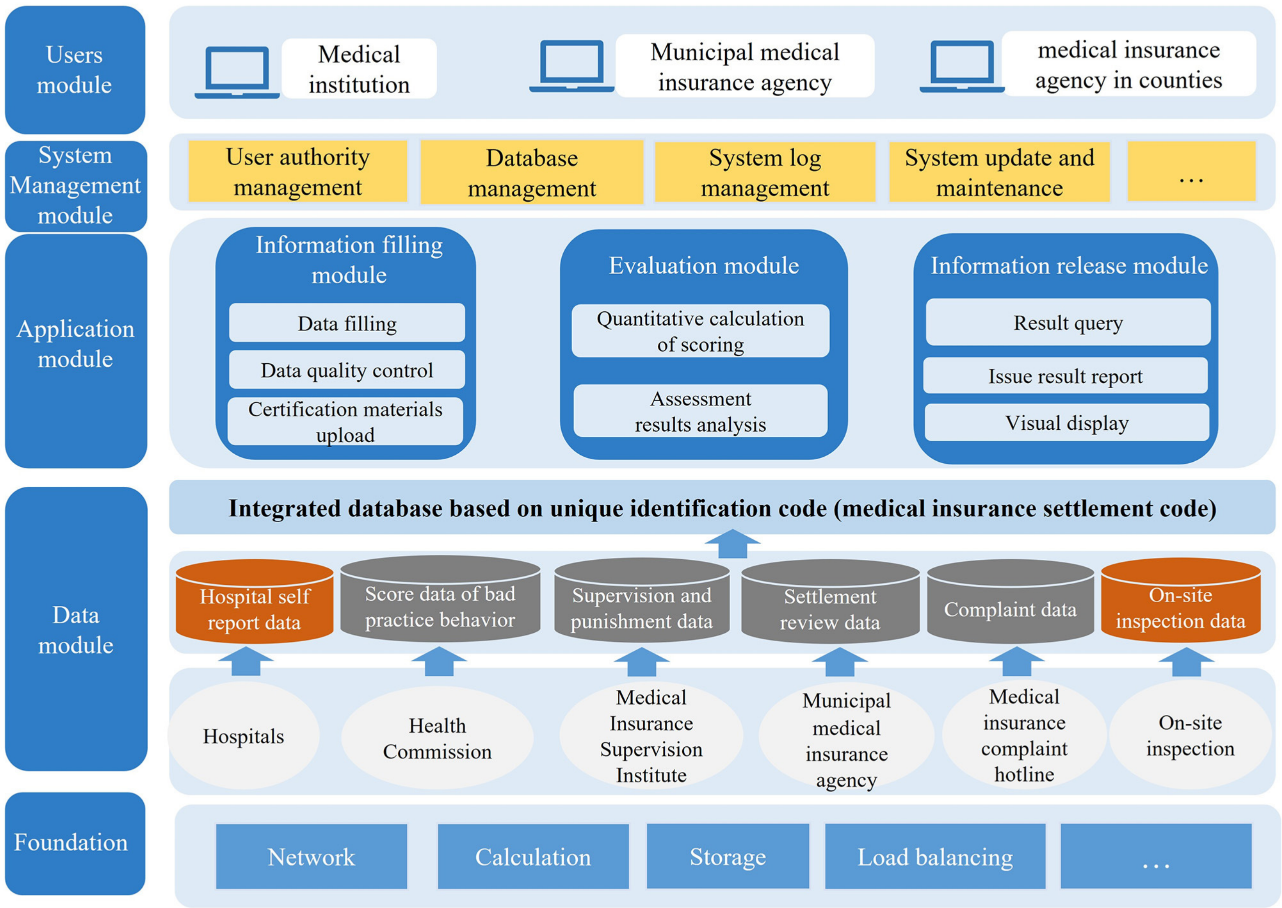

FIGURE 3
The structure and functions of the assessment information platform.

in first-level and third-level medical institutions ($P < 0.001$), see Table 8.

Discussion

The main contributions of this study include two aspects: (1) established a unified and operable assessment standard for medical insurance agencies to assess the performance of DMIs; (2) designed and developed an online assessment platform to assist in data collection, submission of supporting materials, score calculation, results analysis and results reporting, which help to improve the efficiency of assessment and save manpower.

In 2020, the coverage of medical insurance reached 95% in China, including over 1.36 billion people (27). Basic medical insurance is highly important for residents' health. Due to the expanding coverage of medical insurance and the growth of medical expenses, the ability to assess the performance of DMIs in supporting the delivery of high-quality patient care and the standardized use of funds represents a priority for all health care systems. In China, such interests are growing. However, the lack of standards and manpower makes it challenging to assess the medical service providers. Most related studies focused on medical insurance payment reform (28–31), credit evaluation of DMIs (32, 33), medical insurance fraud behavior (34, 35) and high medical expense warnings (36, 37). However, most of them reported limitations of data collection (37) and sample's representativeness (32).

In this study, we established an online assessment platform that combined online data reporting with integrated data from relevant administrative departments. Through this platform, we have addressed the data collection issues caused by incomplete medical information infrastructure and insufficient regulatory manpower. First, the construction of information system made it possible to collect data more efficiently. The data of DMIs and relevant administrative departments could be collected through self-reporting and uploading required data records and attachment materials, avoiding the high manpower and low efficiency issues of traditional on-site inspection, which made it possible to assess all the 760 DMIs in Shanghai. Second, the online assessment system integrated data from different departments to ensure the comprehensiveness of data collection. The data collection includes the hospitals' self-report data, hospitals' supportive materials, relevant government administrative departments data (the municipal health commission, health supervision institute, food and drug administration and so on) and daily work records of medical insurance agency.

TABLE 6 The assessment scores of DMI.

Variables	$\chi \pm \sigma$	t/F	*P*
Administrative level			
First-level and below	95.43±6.15	**45.233**	**<0.001**
Second-level	93.37±6.54		
Third-level	87.15±10.26		
Nature of ownership			
Social-run institutions	94.43±7.12	0.108	0.982
Public institutions	94.37±6.96		
Medical institution type			
comprehensive institutions	94.03±7.40	5.205	0.082
Specialized institutions	94.94±6.37		

The bold values means statistically significant.

TABLE 7 Correlation analysis between assessment scores and penalty amount of DMIs.

Variables	Assessment scores	Penalty amount of DMIs
Assessment scores	1	-0.133^{***}
Penalty amount of designated medical institutions	-	1

$^{***}P < 0.001$.

Based on analysis of the agreement terms, we constructed an index system that includes six dimensions: medical service quality, medical expense, medical service efficiency, medical insurance settlement, experience of the insured, and medical insurance management. The selection of the above dimensions combined the opinions of different stakeholders, in order to reach consensus on performance balance from different perspectives. The Delphi method was used to screen indicators, which had also been well applied in other related studies in China. In addition, in order to prevent possible intentional concealment or non-reporting by hospitals, this study adopted various methods to ensure data quality: (1) intelligent identification of abnormal data in hospital filled out data; (2) Self reporting data needs to be synchronously uploaded with supporting materials for verification; (3) Spot check the evaluated institution and verify the evaluation results through on-site inspection by experts. The empirical results indicate that the assessment tool developed in this study has high feasibility and reliability. In future research, the evaluation platform will be further developed as a workstation for medical insurance agencies to collect daily work records of hospitals, in order to achieve scheduled tracking and dynamic management of DMI.

The main significance of performance assessment is to identify the problems existing in contracted medical service providers. Based on the assessment results, how to motivate medical service providers to continuously improve quality is the next step that needs to be addressed when applying the research outcomes to practice. We suggest that further research and policy development are needed to build based on our research. For example, in empirical research in Shanghai, we attempted to use the assessment results for decision-making by medical insurance agencies as a basis for renewing their contracts with DMIs. A qualification line was set up according to the analysis of assessment scores. Only those qualified institutions could renew agreements with medical insurance agency, and those unqualified ones should suspend the renewal until they were qualified. In future research, more applications based on assessment should be designed, such as grading the institutions and associating the medical insurance payment proportion and inspection frequency with the grade.

Limitations

The main limitations of this study were as follows. First, the medical service agreement between DMIs and medical insurance agencies may change with the adjustment of medical insurance policies, so in future applications, it is necessary to fine tune the indicators according to policy changes. Second, we selected Shanghai as the sample region for this study. There may be differences in medical insurance requirements among different regions, which may limit the extrapolation of research results. We compared and analyzed service agreements in different regions and found that due to the consistency of medical insurance regulatory goals, the agreement terms in most regions are highly consistent, and only a few terms may have differences. Therefore, our research findings still have good enlightening significance in other regions of China and in low-income and middle-income countries internationally. In subsequent research, the online platform will be further optimized to assist in establishing a continuous quality improvement mechanism for DMIs. All evaluation results of DMI in the past will be stored in the database of the information system, and medical insurance institutions can monitor the quality improvement of DMI through regular inspections.

Conclusions

The reform of China's medical insurance system has entered a new stage after more than 20 years of practice, which has brought with increasing requirements on the high-quality patient care and the standardized use of funds provided by DMIs. Based on the agreements assigned by medical insurance agency and DMIs, this study established an operable assessment measure and developed an online platform to assess the enforcement of medical service agreements of DMIs. The empirical results of Shanghai indicated that our assessment measures performed well in feasibility and reliability. Besides, the development of online platform improved the efficiency and convenience of assessment, which provided an operable

TABLE 8 Linear regression results between assessment scores and penalty amount of DMIs.

Variables	Administrative level							
	All DMIs		First level and below		Second level		Third level	
	Beta	T	Beta	T	Beta	T	Beta	T
Administrative level	−0.153***	−3.455						
Medical institution type	0.039	1.127	0.018	0.353	0.002	0.021	0.147	1.198
Number of Outpatients	−0.127	−1.838	−0.005	−0.106	−0.240*	−2.216	−0.120	−0.574
Number of inpatients	−0.213***	−4.832	−0.076	−1.823	−0.097	−0.933	−0.140	−0.678
Outpatient Revenue	−0.322**	−3.117	0.086	1.828	0.140	1.611	−0.293*	−2.470
Inpatient Revenue	0.249*	2.413	−0.229***	−4.885	0.153	1.736	−0.297	−2.522
Penalty amount of contracted medical providers	**−0.086***	**−2.452**	**−0.087***	**−2.037**	0.005	0.058	**−0.236***	**−2.013**
R^2	0.143		0.056		0.091		0.255	

*P < 0.05, **P < 0.01, ***P < 0.001. The bold values means statistically significant.

solution to save time and manpower in the supervision of DMIs.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

QW: Conceptualization, Funding acquisition, Methodology, Project administration, Writing – original draft, Writing – review & editing. RD: Methodology, Validation, Visualization, Writing – review & editing. QY: Writing – review & editing. TZ: Conceptualization, Funding acquisition, Project administration, Resources, Visualization, Writing – review & editing. BW: Software, Visualization, Writing – review & editing.

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Conflict of interest

BW was employed by Shanghai Haiyul Information Technology Co. Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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Research on the effect of charitable donations on regional medical level

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As the main vehicle for the tertiary distribution, charity has a certain regulating effect on regional medical level. However, the improvement of regional medical effect of charity has yet to be tested. Based on provincial panel data from 1997 to 2019, this study analyzes the impact of charitable donations on regional medical level. The empirical results show that charitable donations widen the gap of overall regional medical level in China, which not only results from the current period but also from charity accumulation in the past. The regional heterogeneity analysis show that charitable donations have expanded the regional medical level of the eastern and western regions, while have no significant effect on the regional medical level gap in the central region. The widening effect in the eastern region of charitable donations is the largest. In addition, charitable donations expand the regional medical level gap between urban and rural areas in China. Charity, as the regional medical development mechanism, has not yet played its due role and advantages in regulating regional medical level gap. Formulating and adjusting the corresponding charity promotion policies is necessary.

KEYWORDS

charitable donations, regional medical level, Gini coefficient, provincial panel data, China

1 Introduction and literature review

Report to the 20th Communist Party of China National Congress states that the regional medical level gap is still wide, which is an important issue China is facing. According to the National Healthcare Administration, People's Republic of China, the proportion of residents' medical spending in total consumer spending will rise from 6.7 percent in 2002 to 8.6 percent in 2022. More than 70% of China's residents have less than 70% of the reimbursement rate within the scope of the policy, and patients with serious diseases are more likely to use innovative drugs and other drugs outside the medical insurance catalog, and the personal burden is more heavy. According to the Statistics and Information Center of the China Health Commission, the total out-of-pocket rate of hospitalization expenses for patients with basic medical insurance was only 44.6 percent in 2018, and the out-of-pocket rate for rural patients was as high as 47.2 percent. Among hospitalized patients, 24.2% voluntarily left the hospital due to financial difficulties. However, due to the mutual offsetting dynamics of widening and narrowing the regional medical gap, the development medical gap of China has been hovering high for a period, which will be a basic trend of regional medical level in China (1).

Faced with serious income distribution situation in China, China government to improve the regional medical system and build a well-coordinated institutional framework, with a view to not only making the pie bigger but also improving the way the pie is divided up. As a major form of the current regional medical level gap in China (2), charity has become an important force in narrowing the gap between the high level of regional medical and the low level of regional medical, which is a great historical mission entrusted by the times.

After more than three decades of downturn, China's philanthropy has grown considerably. The total amount of charitable donations has risen from 1.4 billion yuan in 1997[1] (3) to 225.313 billion yuan in 2020 (4). Thus, what is the regional medical level of the rapidly growing philanthropy in China? Has it had an impact on narrowing the regional medical gap? And to what extent has it had an impact? This study intends to address the above issues to providing empirical evidence for the formulation and optimization of charity promotion policies.

Considering the complexity and versatility of the factors that affect regional medical level and how the effects are produced, factors that impact regional medical level need to be sorted out. Since Lewis (5) put forward the dual sector model, research on the causes of regional medical level gap has been advanced. Ranis and Fei (6) further revised and improved Lewis' model, constructing a more complete theoretical system to explain the regional medical level gap. Beyond the 1980s, scholars mainly explained the factors of regional medical level gap from economic growth, technological progress, education, labor transfer, and economic globalization (7–9). Since the 1990s, Chinese scholars have also conducted many useful explorations on the causes of the regional medical level gap in China. Many scholars believe that China's long-standing urban–rural dual economic structure (10) and the urban-biased institutional arrangements interacted with it (11, 12) are important factors contributing to the widening regional medical level gap in China. Zhan and Zhou (13) examined medical insurance reimbursement policy; total medical expenses, income level and aging society are the key factors that cause the gap in China's medical development level. Their analysis showed that the impact of economic growth on the regional medical level gap is not equivalent between urban and rural areas. The education variable in public goods significantly widen the regional medical level gap, while institutional factors such as marketization reduce it. Other research has analyzed the impact of income of household (14), higher education policies (15), and social security (16) on the regional medical level of urban and rural residents.

At the current stage of China's development, regional disparity has become a common problem (17–19). With the development of philanthropy, charity, especially charitable donations, as a gentle hand in regulating on regional medical level, has come to public attention along with the improvement of regional medical policies. In China, donation has an important impact on the development of medical treatment in various forms. For example, through the establishment of special projects, deep cooperation with enterprises and medical institutions, and a variety of relief agencies, these are important ways to realize the contribution of donations to medical development. At the theoretical and logical level, the idea that charity can reduce regional medical level gap is widely accepted. According to modern philanthropic economics, public goods theory and warm glow theory (see text footnote 1) are the two major theoretical cornerstones for explaining philanthropic behavior (20, 21), which provide philanthropic behavior with lasting motivation together with the goodness contained in traditional religions such as Buddhism, Christianity, and Taoism. Driven by this motivation, the role of charity in regulating regional medical level is also extremely unique. Firstly, it is a hybrid form of regional medical level that, depending on its source of funding, can have an impact on regional medical level[2] in a way that no other form of distribution can (22–24), and the important role of charity in the improvement of regional medical level is widely recognized (25–28). Secondly, the mechanisms and paths of charitable donations in regulating regional medical level gap are characterized by directness, specificity, and complementarity. Charitable donations can directly regulate the gap between the rich and the poor through non-profit charitable organizations and transfer wealth between social groups with different levels of regional medical level (29, 30), which is a direct transmission mechanism that is difficult to achieve in other forms of distribution. And the earmarked characteristics of charitable donations ensure that donations are transferred to specific beneficiary groups. The function of government's direct transfer payment in regional medical field is similar, but it is not so specific.[3] Complementarity is characterized more by the fact that charity complements the regulating effects of regional medical level by taking personal emotional resonance and ethical and moral drives as its starting point (14, 31–33).

Due to the speculation and malfunction of charitable donations, its actual regional medical level gap have yet to be empirically tested. However, empirical research in this area is not very numerous and has not come to a consensus. Developed countries, represented by the United States, have more empirical research and more available data due to the earlier start of their philanthropy. Jackson (34) analyses the autonomous philanthropic institutions of the African Americans in Chicago during the period of rapid urbanization and segregation, which affirms the important role these institutions played in raising income levels and improving the quality of life for African Americans. Brest's (35) research on outcome-oriented philanthropy came to a similar conclusion, suggesting that this new type of philanthropy works well to help the poor and needy. Drawing on the constructing history of Ford Foundation and its recent goals, Soskis (36) explores whether the foundation can eliminate inequality, arguing that although there exists no definitive answer, it is better than doing nothing at all. On the contrary, some scholars believe that the development of charity will not lead to a narrowing gap of regional

1 In 1997, China received charitable donations totaling140,159,000yuan, including 415,146,000yuan in cash and 986,449,000 yuan in donations of clothing and quilts.

2 Enterprises and other market entities' donations become a part of the primary distribution by entering the donor's production and operation cost. The government's grants, donations, and purchase of social organization services belong to the category of secondary distribution by entering the fiscal budget. As for individual members of society, their voluntary donations belong to the tertiary distribution after obtaining the share of primary and secondary distribution of social products.

3 Beneficiary groups of social welfare, social assistance and benefits do not have to pay for receiving direct assistance, which is different from the social insurance system. Although their mechanism is essentially similar to that of charity, they are subject to national coordination, which weakens their specificity.

medical and may even produce some bad consequences. Reich (37) found that charity in the United States is not as well-developed as it appears to be. Contrarily, issues such as where, to whom, and how much charitable funds are invested can lead to potential fail of charity under the intervention of public policy, thereby exacerbating social inequality. The literature on the relationship between charity and regional medical level in China is relatively few, and most of them are normative studies with inconsistent views. At present, there is a big gap in the overall level of regional medical development due to the poor connection of relevant medical security systems in China, the need to standardize charitable medical behaviors, the lack of charitable mobilization capacity, and relevant institutional constraints. Most studies infer by logical deduction that the development of philanthropy in China can reduce the regional medical level gap to a certain extent (38–40). However, skeptics argue that charity does not necessarily reduce inequality, and that it may disregard the status quo of inequality or even be the cause of increased inequality (41, 42).

According to previous studies, there is a certain consensus on the significance and value of charitable donations in regulating regional medical level and narrowing the gap between the rich and the poor. However, empirical research on the effect of charitable donations on regional medical level is relatively weak, and the conclusions of these research are divergent. Therefore, research on this issue, especially empirical research based on Chinese data, needs to be strengthened. The possible marginal contributions of this paper are as follows: First, from the perspective of previous research, there is a certain consensus on the significance and value of charitable donations in standardizing regional medical standards and narrowing the gap between the rich and the poor. This paper studies the impact of charitable donations on regional medical standards, especially based on empirical data from China. Second, this paper uses a two-way fixed-effect panel model to analyze the impact of *per capita* charitable donations in each province on the regional medical level gap from 1997 to 2019, and conducts robustness test and heterogeneity analysis.

2 Data sources, variables, and model

2.1 Data sources

All raw data in this study are from the China Statistical Yearbook, the China Civil Affairs' Statistical Yearbook, the statistical yearbooks of provinces, autonomous regions and municipalities from 1998 to 2020,[4] and the statistical communiqué on economic and social development of provinces, autonomous regions and municipalities from 1997 to 2019.

2.2 Variables and descriptive statistics

2.2.1 Explained variable

In this study, Gini coefficient (*Gini*) is chosen as the explained variable to measure the regional medical level gap. The measurement and calculation of Gini coefficient is very important and cumbersome, which needs to be explained in detail. The estimation of Gini coefficient in China, especially for the urban–rural decomposition of Gini coefficient under China's dual economic structure has always been an important area of research, and many scholars have carried out a lot of exploration (43–45). However, no consensus has been reached. In addition, provincial data are more likely to be missing. Accordingly, provincial Gini coefficients are much less commonly measured in China. Using the non-equal grouping Gini coefficient, Chen (46), for the first time in a more complete way, calculated and analyzed the Gini coefficients for urban and rural residents in 21 provinces in China for the period 1995–2004. However, the urban and rural regional medical level data in China's statistical yearbook have been grouped in different ways, such as interval grouping, quintile grouping, and non-equal groups, which causes the calculation caliber of the results to be inconsistent. In other literature estimating provincial Gini coefficient, only a single year is measured, or only a single and several provinces are observed, which is difficult to provide us with a comprehensive source of data and measurement methods (47). After comparing the literature on the measurement of provincial Gini coefficients, urban, rural, and the overall Gini coefficients of China's 27 provinces from 1995 to 2010 tallied by Li and Zhao (48) are finally used. The use of area ratio formula can better solve the problem of inconsistent calculation caliber for Gini coefficient, while the data and time span coverage are more considerable. The specific calculations are as follows:

$$\mathrm{Ginic} = 1 - \frac{1}{\mathrm{P_c W_c}} \sum_{\mathrm{I}=1}^{\mathrm{n}} \left(\mathrm{w_{ci-1}} + \mathrm{w_{ci}} \right) \times \mathrm{P_{ci}} \tag{1}$$

$$\mathrm{Ginir} = 1 - \frac{1}{\mathrm{P_r W_r}} \sum_{\mathrm{I}=1}^{\mathrm{n}} \left(\mathrm{w_{ri-1}} + \mathrm{w_{ri}} \right) \times \mathrm{P_{ri}} \tag{2}$$

$$\begin{aligned} \mathrm{Gini} = {} & \mathrm{RP_C^2} \frac{\mathrm{U_C}}{\mathrm{U}} \mathrm{Ginic} + \mathrm{RP_r^2} \frac{\mathrm{U_r}}{\mathrm{U}} \mathrm{Ginir} \\ & + \mathrm{RP_c RP_r} \frac{\mathrm{U_C} - \mathrm{U_r}}{\mathrm{U}} \end{aligned} \tag{3}$$

whereas equation (1) and (2) are formulas for calculating urban and rural Gini coefficients, respectively. P_C, P_r, W_{ci}, and W_{ri} are the urban sample population, the rural sample population, the regional medical level of urban subgroup *i*, and the regional medical level of rural subgroup *i*, respectively. Equation (3) is the Sundrum formula for calculating the overall Gini coefficient for urban and rural areas,[5] in which RP_C, RP_r, U_C, U_r, and U are the proportion of the urban population, the proportion of the rural population, regional medical level of the urban population *per capita*, regional medical level of rural

4 Hebei Economic Yearbook for Hebei Province and Gansu Development Yearbook for Gansu Province.

5 Sundrum formula cannot effectively solve the situation if the urban and rural income grouping data overlap, which is common in China's urban and rural income survey data. Although scholars make a lot of explorations for solving this problem, no consensus has been reached. To remain consistent with the data calculated by Zhai et al. (19), this study still chooses the Sundrum formula to calculate the overall urban and rural Gini coefficient after referring to other research practices.

population *per capita*, and the overall regional medical level *per capita*, respectively.

Further, considering the missing values in some provinces, data accessibility of other variables, and the calculation caliber, eight provinces out of 27 provinces[6] are excluded. Finally, a total of 19 provinces (autonomous regions or municipalities) has been reserved, including Beijing, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong, Shanxi, Jiangxi, Henan, Hubei, Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Shaanxi, Gansu, and Xinjiang.

In addition, in the robustness tests section, this study employs the Theil's index (*Theil*) as a substitute for the explained variables to measure the inequality of regional medical level (49). In the urban–rural heterogeneity section, the urban–rural regional medical level ratio (*incomeratio*) is introduced as an explained variable to measure the urban–rural regional medical level gap. The urban–rural regional medical level ratio is equal to the disposable regional medical level of urban residents *per capita* divided by the disposable net regional medical level of rural residents *per capita*.

2.2.2 Explanatory variable

Charitable donations *per capita* (*pcharity*) is the core explanatory variable in this study. The data for 2010–2015 are calculated by the provincial social donations data from the China Statistical Yearbook divided by the population of the province in that year. Since the China Statistical Yearbook does not provide data by province before 2010 and after 2015, to ensure the consistency of the data,[7] this study selected the sum of social donations (mainly reflecting donations received by the civil affairs departments) and the fund-raising regional medical level or added values of foundations, charitable associations, and social organizations by province in the current year (mainly reflecting donations received by charitable organizations) from the China Civil Affairs' Statistical Yearbook, which is then divided by the population of that year. In the regression, the amount of charitable donations *per capita* are standardized to avoid the estimated coefficients being too small (*z pcharity*). In the robustness tests, the amount of charitable donations *per capita* received by the civil affairs department (*CApdonation*) is used as an alternative explanatory variable to re-estimate the results of the baseline model.

2.2.3 Control variables

Based on previous research, the control variables are categorized into two groups. One is variables that measure the level of provincial philanthropic development, such as the number of foundations (*LNfoundation*). The other is provincial characteristic variables affecting regional medical level, such as the level of economic development (*LNpgdp*), which is deflated using the 1997 provincial GDP *per capita* as the base and then taken logarithms. The squared term of economic development (*LNpgdp2*) is also added to test the Kuznets hypothesis. The level of urbanization (*LNrcity*) is calculated by dividing the urban population by the population of the province in logarithmic terms. Since the population of long-term residents is not considered in China Statistical Yearbooks before 2004, the urbanization level is revised mainly referring to Zhou and Tian (50). The data for 2005–2019 are from the China Statistical Yearbook. The level of economic openness (*LNropen*) is obtained by converting the total amount of imports and exports of each province using the average USD to RMB exchange rate for the year, dividing it by GDP and then taking the logarithm. The level of financial development (*LNrfinance*) is calculated by dividing the loan balance of financial institutions in each province by GDP and taking the logarithm. Average years of education (*LNredu*) is calculated using the formula: (population of college degree and above education *16 + population of upper secondary education*12 + population of lower secondary education*9 + population of primary education*6)/ total population aged 6 years and above. Endowment insurance coverage rate (*LNrss1*), health insurance coverage rate (*LNrss2*), and unemployment insurance coverage rate (*LNrss3*) are calculated as the ratio of the number of endowment insurance participants to the working-age population plus the older adult population, the ratio of the number of health insurance participants to the total population, and the ratio of the number of unemployment insurance participants to the working-age population, with the logarithms taken at the end, respectively.[8]

2.2.4 Descriptive statistics

Table 1 reports the descriptive statistics for each variable. The mean value of Gini coefficient, which measures the disparity in regional medical level, is 0.38, very close to the Gini coefficient international alertness line level of 0.4. Its standard deviation is 0.05, which is relatively large, suggesting that income disparity fluctuates greatly between different provinces and years. Thiel's index, alternative explained variable in the robustness test, has the same characteristics. The mean of explanatory variable, charitable donations *per capita*, is 31.73 yuan, which is relatively low. Charitable donations *per capita* in different provinces and years fluctuates largely, with the lowest charitable donation *per capita* amounting to only 0.14 yuan and the highest to 458 yuan. The charitable donations *per capita* received by civil affairs, which is the alternative explanatory variable in the robustness tests, has a mean value of 6.11 yuan, with the lowest being 0.04 yuan and the highest being 85.83 yuan, suggesting that the charitable donations *per capita* received by civil affairs also has the same characteristics. From the descriptive statistics of the variables, it can be concluded that the level of charitable development remained low and regional medical level disparity are evident during the sample period.

6 The provinces excluded are Liaoning, Tianjin, Heilongjiang, Anhui, Hunan, Ningxia, Yunnan, and Qinghai.

7 A rough calculation is conducted to ensure that the sum of provincial donations for the year is close to the national donation volume of the Annual Report on China's Philanthropy Development.

8 The number of endowment insurance participants in rural areas has been counted in the China Statistical Yearbook since 2006 (being merged into urban and rural basic endowment insurance since 2010), which is included in the calculation of this study. The working-age population is the population aged 15–64 based on data of age distribution of the population given by each province and the definition of International Labor Organization, of which no direct data are given for 2001. It is estimated based on the population aged 15 or older minus the population aged 65 or older.

TABLE 1 Descriptive statistic of variables.

Variables	Mean	Median	Std. Dev.	Min.	Max.	Obs.
Gini	0.38	0.38	0.05	0.23	0.49	437
Theil	0.12	0.11	0.06	0.02	0.28	380
pcharity	31.73	6.41	64.95	0.14	458	437
LNfoundation	4.15	4.16	1.20	0.69	7.08	316
CApdonation	6.11	1.59	11.46	0.04	85.83	433
LNpgdp	11.11	11.29	1.63	7.70	14.03	437
LNrcity	3.84	3.85	0.34	3.13	4.50	437
LNropen	2.94	2.61	1.01	1.05	5.12	437
LNrfinance	3.57	3.50	0.68	2.15	5.26	437
LNpedu	2.12	2.13	0.14	1.69	2.54	437
LNrss1	3.36	3.38	0.88	1.34	4.63	437
LNrss2	2.91	3.52	1.92	−3.53	4.77	437
LNrss3	2.57	2.46	0.55	1.25	4.35	437
Incomeratio	2.75	2.68	0.55	1.60	4.59	431

2.3 Model

A two-way fixed-effects panel model is used to analyze the regional medical level gap of charitable donations, focusing on the impact of charitable donations *per capita* on regional medical level gap. The baseline model of this study is set as follows:

$$\mathrm{Gini}_{it} = \beta_0 + \beta_1 \mathrm{pcharity}_{it} + \beta_2 \mathrm{X}_{it} + u_i + year_t + e_{it} \quad (4)$$

whereas *Gini* is the Gini coefficient for each province, which measures the regional medical level gap across provinces. *pcharity* is charitable donations *per capita* in each province, which indicates the level of charitable donation in each province. *X* is a series of control variables. One group is variables measuring the level of philanthropic development, calculated by the number of foundations in each province. The other group is provincial characteristic variables affecting the regional medical level gap, including GDP *per capita*, the proportion of urban population, the share of total imports and exports, the percentage of loan balances of financial institutions, average years of education *per capita*, and the coverage rate of endowment insurance, medical insurance, and unemployment insurance. i denotes province; t denotes year; u_i is a province fixed effect; $year_t$ is a year fixed effect; e_{it} is the error term. β_1 in equation (4) is the core coefficient of this study. β_1 greater than 0 indicates that the charitable donations *per capita* has a positive effect on provincial regional medical level gap (i.e., charitable donations *per capita* widens the provincial regional medical level gap). Conversely, charitable donations *per capita* narrows the provincial regional medical level gap.

3 Empirical results and analysis

3.1 Benchmark regression

Firstly, the applicability of random effects and the fixed effects model are analyzed using the Hausman Test, which rejects the null hypothesis at 1% significance level, implying that there is a correlation between the unobservable fixed effects and other variables in the model. Thus, the fixed effects model is chosen. The results of the two-way fixed effects model are reported in Table 2, where column (1) shows the result of only adding the number of foundations, which measures the level of philanthropic development. Column (2) is the results only adding provincial characteristic variables. Column (3) is the result of adding both the number of foundations and the provincial characteristic variables. As the effect of charitable donations *per capita* on the regional medical level may not necessarily come exclusively from the current period, column (4) shows the result of adding one-period lagged term of the core explanatory variable on top of column (3).

Table 2 shows that the estimated coefficients of charitable donations in four columns are all positive and significant at the 1% level, indicating that charitable donations *per capita* widens the regional medical level gap. Column (3) shows that the Gini coefficient improves by 0.011 for each standard deviation increase in charitable donations *per capita* (the core explanatory variables are standardized) after controlling other variables. The addition of a one-period lagged term of explanatory variable in column (4) increases the Gini coefficient by 0.009 for each standard deviation increase in charitable donations *per capita*, which is smaller than the estimated coefficient in column (3), suggesting that the accumulation of charitable donations in previous period has some impact on the regional medical level in the current period.

The results of the benchmark regression may be due to the following reasons: Firstly, in terms of the receipt of charitable resources. Although the volume of charitable donations in China is growing rapidly, the absolute amount of charitable donations *per capita* is still small, and the resource mobilization capacity of the charitable sector is still very limited. National charitable donations totaled 137.974 billion yuan in 2019 (51), merely 0.14% of the national GDP[9] (52), compared to 2.10% in the United States[10] (53, 54). According to the World Giving

9 GDP for China in 2019 is 9,908.65 billion yuan.

10 The charitable donations of the United States totaled $449.64 billion in 2019, and GDP was $21.433trillion.

TABLE 2 The impact of *per capita* charitable giving on income distribution.

Variables	Explained variable: gini coefficient			
	(1)	(2)	(3)	(4)
z pcharity	0.004*** (3.03)	0.007*** (3.87)	0.011*** (5.43)	0.009*** (3.33)
LNfoundation	−0.010*** (−3.05)		−0.007** (−1.98)	−0.007** (−2.03)
Lz pcharity				0.003 (1.10)
LNpgdp		0.031 (1.37)	−0.047 (−1.39)	−0.048 (−1.41)
LNpgdp²		−0.001 (−1.63)	0.002 (1.62)	0.002 (1.63)
LNrcity		0.039** (1.98)	0.110*** (3.03)	0.104*** (2.90)
LNropen		−0.015*** (−4.34)	−0.009** (−2.34)	−0.009** (−2.38)
LNrfinance		0.014* (1.85)	0.030*** (3.02)	0.029*** (2.95)
LNpedu		−0.022 (−0.52)	−0.072 (−1.54)	−0.069 (−1.48)
LNrss1		−0.004 (−0.71)	−0.007 (−1.06)	−0.007 (−1.02)
LNrss2		0 (−0.10)	0.005 (1.44)	0.004 (1.31)
LNrss3		−0.017*** (−2.71)	−0.029*** (−3.49)	−0.028*** (−3.41)
cons	0.436*** (37.80)	0.103 (0.71)	0.419** (2.03)	0.397* (1.91)
Province FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	316	437	316	316
Adj R²	0.548	0.624	0.601	0.602

The *t* values are given in parentheses. *, **, and *** represent significance levels of 10, 5, and 1%, respectively.

Index 2021 published by the United Kingdom Charities Aid Foundation in 2021, China ranked 95th in the Giving Index among 114 countries surveyed in 2020, and 85th in charitable donations (55). Low levels of charity donations, especially the level *per capita*,[11] have led to a weak impact of charitable donations on regional medical level gap. Secondly, in terms of the allocation of charitable resources. The allocation of charitable resources will affect its regulating effect. In recent years, there have been frequent charity scandals, mismatches and inefficient allocation of charitable funds and goods, which have caused adverse social impacts, dampened public enthusiasm for donations, and further weakened the regulating effect of charity. Thirdly, in terms of the tools used to incentivize charitable donations. Tax benefits for charitable donations are used by governments to incentivize social giving, which are also highly controversial. Critics argue that tax benefits for donations are essentially a government's subsidy to donors, with higher level of regional medical benefiting more than lower level of regional medical. Thus, tax benefits are therefore an inverted subsidy that increases inequality (56, 57). Accordingly, charitable donations are likely to widen the regional medical level gap and offset the regulating effect of charitable donations on regional medical level gap.

In terms of variables measuring the level of philanthropic development, columns (1), (3), and (4) show that the number of foundations reduces the regional medical level gap. Column (4) shows that 1 unit increase in the logarithm of the number of foundations reduces the regional medical level gap by 0.007 unit, which is significant at the 5% level. The main reason is that, with the guidance and support of policies, the rapid growth of corporate and community foundations and the consequent expansion of the scale of endowments and charitable assets will significantly narrow the regional medical level (58).

In terms of control variables: (1) The estimated coefficient of the level of urbanization (*LNrcity*) is significantly positive, indicating that

11 Due to inconsistence of statistical caliber and data collection, the total amount of charitable donations in China may be seriously underestimated. However, it is indisputable that the amount of charitable donations is not large in China.

urbanization has widened inequality in regional medical level, mainly due to the fact that China's traditional path of urbanization paid too little attention to social equity issues and inequities in education, healthcare, and older adult care services under the urban–rural hukou system, which should be improved with the process of urbanization toward the right side of the inverted U-shaped curve (59). (2) The estimated coefficient of the level of financial development (*LNrfinance*) is significantly positive, indicating that financial development has widened the regional medical level gap. An important reason is that there are certain cost thresholds and credit constraints in accessing financial market and enjoying financial services in China. The affluent class, due to its accumulated wealth and good reputation, can enjoy more financial services than the poor class, thereby obtaining higher investment returns, which widens the gap between the rich and the poor (60). Thus, it is recommended to vigorously promote the development of inclusive financing (61). (3) The estimated coefficient of the level of economic openness (*LNropen*) is significantly negative, suggesting that trade openness and economic globalization contribute to reducing inequality in regional medical level. Previous research has indicated that trade globalization will exacerbate regional medical level gap in the short run but narrow it in the long run (62). Therefore, China should participate in the process of economic globalization in a more active role, expand the degree of economic openness, and improve the income disparity. (4) The estimated coefficient of unemployment insurance (*LNrss3*) is significantly negative, indicating that the development of unemployment insurance reduces the regional medical level gap. Thus, the coverage rate of unemployment insurance should be expanded by paying attention to the low-income groups with unstable employment status and high unemployment rate, thereby gradually including them in the insurance coverage (63). Other control variables, including the level of economic development, average years of education, and endowment and health insurance coverage, have no significant effect on the regional medical level gap.

3.2 Robustness tests

3.2.1 Using the sub-period of 2008–2019

After the Wenchuan Earthquake in 2008, people's enthusiasm for charity soared in China. Thus, 2008 is also called the first year of China's philanthropy, after which China's public welfare and charity began to develop in specialized, organized, and synergic direction. Therefore, the development of charity after 2008 is different from that before 2008. The sample for 2008 and later is remained and the regression is conducted again to verify the robustness of the benchmark results, which is shown in columns (1) and (2) of Table 3. Column (2) reports the results of adding one-period lagged term of the explanatory variable.

3.2.2 Replacing explanatory variables

The core explanatory variable of this study, charitable donations *per capita*, comes from the sum of charitable donations received by civil affairs, foundations, charitable associations and social organizations. The core explanatory variable is replaced with the amount of charitable donations *per capita* received by civil affairs (*CApdonation*) to verify the robustness of the benchmark results, which is shown in columns (3) and (4) of Table 3. Column (4) reports the results of adding one-period lagged term of the explanatory variable.

3.2.3 Replacing explained variables

The explained variable is replaced with Theil's index (*Theil*) to verify the robustness of the results, which is shown in columns (5) and (6) of Table 3. Column (6) also reports the results of adding one-period lagged term of the explanatory variable.

Table 3 reports the results of robustness tests. After using the sub-period and retaining data only from 2008 and later years for the regression, the basic findings are consistent with the benchmark regression. Charitable donations *per capita* widens the regional medical level gap, with the Gini coefficient increasing by 0.009 for each standard deviation increase in charitable donations *per capita*, which is significant at the 1% level [column (4)]. After replacing the core explanatory variables with the amount of charitable donations *per capita* received by the civil affairs, the basic findings are consistent with the benchmark regression. The amount of charitable donations *per capita* received by the civil affairs sector widens the regional medical level gap, and a one standard deviation increase in the amount of charitable donations *per capita* received by the civil affairs sector increases the Gini coefficient by 0.007, which is significant at the 1% level [column (4)]. After replacing the explained variable with Theil's index, the basic findings are still consistent with the benchmark regression. The amount of charitable donations *per capita* widens the regional medical level gap, and a one standard deviation increase in charitable donations *per capita* is associated with a 0.008 increase in the Theil's Index, which is significant at the 1% level [column (6)]. Therefore, the benchmark regression results are robust.

3.2.4 Endogenous test

Considering the possible endogeneity problem between charitable donations and regional medical level, the 2SLS method is used to test, referring to the study of Gu and Ouyang (64), which adopts charitable donations lagged by one period [pcharity(t−1)] as the instrumental variable (IV), and the results are shown in Table 4. The first-stage estimation results show that the IV has a better explanatory power for the endogenous variables. The Kleibergen-Paaprk LM test rejects the original hypothesis of under-identification of IV, while the Kleibergen-Paap rk Wald F statistic is significantly larger than the critical value of the Stock-Yogo in the test of weak identification of IV. The second-stage estimation results show that the estimated coefficient of charitable giving on regional healthcare levels remains significantly positive after accounting for endogeneity, further corroborating the findings of the benchmark regression.

3.3 Heterogeneity analysis

3.3.1 Regional heterogeneity

Considering China's traditional division standards of three major regional of East, Central and West, the impact of charitable donations *per capita* on regional medical level is examined.[12] Consistent with the

12 There are 19 provinces available in this study. The eastern region includes seven provinces (municipalities): Beijing, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, and Guangdong. The central region includes four provinces: Shanxi, Jiangxi, Henan, and Hubei. The western region includes eight provinces (autonomous regions): Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Shaanxi, Gansu, and Xinjiang.

TABLE 3 Robustness tests.

Variables	Gini coefficient				Theil's index	
	Using sub-period after 2008		Replacing explanatory variables		Replacing explained variables	
	(1)	(2)	(3)	(4)	(5)	(6)
z pcharity	0.007*** (2.97)	0.009*** (4.21)			0.005*** (3.36)	0.008*** (7.20)
Lz pcharity		0.002 (0.79)				0.005*** (3.17)
z CApdonation			0.006*** (4.16)	0.007*** (4.88)		
Lz CApdonation				0.004*** (2.65)		
Other control variables	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	225	225	308	312	316	316
Adj R^2	0.604	0.605	0.597	0.592	0.916	0.913

The *t* values are given in parentheses. *, **, and *** represent significance levels of 10, 5, and 1%, respectively.

TABLE 4 Endogenous test.

Variables	The first stage	The second stage
IV	0.003*** (4.21)	
pcharity		0.008*** (7.20)
Kleibergen-Paaprk LM	45.426***	
Kleibergen-Paaprk Wald F	62.952 {16.38}	
Other control variables	Y	Y
Province FE	Y	Y
Year FE	Y	Y
N	297	297
Adj R^2	0.605	0.592

Figure in {} is the Stock-Yogo test thresholds.

previous section, Hausman test is used to reject the random effects model. Thus, fixed effects model is chosen. Table 4 reports the basic results for different regions, as well as the results of adding one-period lagged term of the explanatory variable.

Table 4 shows that the East [Columns (1) and (2)] and the West [Column (6)] are consistent with the nation (i.e., the amount of charitable donations *per capita* significantly widens income distribution gap). Column (2) and (6) indicate that after the addition of one-period lagged term, Gini coefficient in eastern region increases by 0.013 for each standard deviation increase in the amount of charitable donations *per capita*, which is significant at the 1% level. Column (6) shows that after the addition of one-period lagged term, Gini coefficient in the western region increases by 0.006 for each standard deviation increase in charitable donations *per capita*, which is significant at the 5% level. Although charitable donations *per capita* expand the regional medical level gap in both regions, the estimated coefficient in the eastern region is larger than that of western region. Although the coefficients in the central region are not significant, they are also positive and are smaller than the estimated coefficient in the eastern and western regions, which indicates that charitable donations *per capita* to expand the regional medical level gap in the eastern region has the largest effect.

Explanation for the results above can be made as follows. Currently, most of China's charitable donations come from the affluent class. According to relevant statistics, the top 100 enterprises donators in 2018 accounted for 34.8% of the overall donations, while the top 100 individual donators accounted for 29.2%, which accounted for 64% of the total together. Other donators only account for 36%, indicating that the head donators are the main force of social donations (51). The level of economic development in the eastern region is superior to that of the central and western regions, and most of the enterprises and individuals who make the most donations are also clustered in the eastern region. According to the theory of elite philanthropy, although the affluent class makes large donations, they receive more substantial returns, of which scale is staggering (65, 66). Thus, while elite philanthropy ostensibly boasts of fairness, justice and giving back to community (67, 68), their charitable donations do not play a role in narrowing regional medical level gap, which widens inequality contrarily (69, 70). Therefore, the widening effect of charitable donations *per capita* on regional medical level is more prominent in the eastern region. Therefore, the widening effect of charitable donations *per capita* on regional medical level is more pronounced in the Eastern region of China.

3.3.2 Urban–rural heterogeneity

The urban–rural regional medical level ratio is used as an explained variable to examine the effect of charitable donations *per capita* on the urban–rural regional medical level gap. Similar to the previous section, Hausman test is used and fixed effects model is chosen finally. Table 5 reports the results of urban–rural heterogeneity. Columns (2) reports the regression results by adding a one-period lagged term of explanatory variable.

Table 5 shows that charitable donations *per capita* widens the urban–rural regional medical level gap. As shown in column (2), an increase of one standard deviation in charitable donations *per capita* increases the urban–rural regional medical level ratio by 0.048, which is significant at the 1% level. That is, the larger the charitable donations *per capita*, the larger the urban–rural regional medical level gap. Although disposable regional medical level *per capita* in the rural area of China is growing, disposable income *per capita* in China's urban area is growing much more.

TABLE 5 Regional heterogeneity.

Variables	Explained variable: Gini coefficient					
	East		Central		West	
	(1)	(2)	(3)	(4)	(5)	(6)
z pcharity	0.011** (2.59)	0.013*** (4.32)	0.001 (0.35)	0.001 (0.70)	0.005 (1.24)	0.006** (2.28)
Lz pcharity		0.004 (0.80)		0.001 (0.56)		0.002 (0.35)
Other control variables	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	154	161	88	92	198	207
Adj R^2	0.604	0.661	0.713	0.753	0.602	0.645

The *t* values are given in parentheses. *, **, and *** represent significance levels of 10, 5, and 1%, respectively.

The reason for this is that towns and cities have a higher level of economic development, a larger number of high net worth individuals, and a larger number of powerful corporations, thereby increasing the volume of charitable donations. According to the theory of elite philanthropy mentioned above, enterprises and individuals that donate the most are keen to donate, thereby receiving more corresponding returns, which is conducive to their career development and income increase. In rural areas, however, where the level of economic development is relatively lower, and the location is remote, enterprises and residents here donate little or nothing, and their incomes grow slowly or stagnate. Thus, the regional medical level gap between urban and rural areas is getting wider and wider (Table 6).

TABLE 6 Urban–rural heterogeneity.

Variables	Explained variable: urban–rural regional medical ratio	
	(1)	(2)
z pcharity	0.033* (1.67)	0.048*** (3.23)
Lz pcharity		0.024 (1.13)
Other control variables	Y	Y
Province FE	Y	Y
Year FE	Y	Y
N	316	316
Adj R^2	0.791	0.790

The *t* values are given in parentheses. *, **, and *** represent significance levels of 10, 5, and 1%, respectively.

4 Conclusion and suggestions

Through the empirical analysis of provincial panel data from 1997 to 2019, it is concluded that the current charitable donations *per capita* in China expands the regional medical level gap. And this effect does not only come entirely from the current period but also from the accumulations of past charitable donations. In terms of regional differences, the amount of charitable donations *per capita* expands the regional medical level gap of the east and west regions, and the impact is not significant in the central region. In addition, the charitable donations *per capita* in the eastern region has the greatest expanding effect of the regional medical level gap. In terms of the difference between urban and rural areas, charitable donations *per capita* widens the regional medical level gap between the urban and rural areas, also promotes the increase in the disposable regional medical level *per capita* of the urban areas.

Charitable donations, as the main tool of the tertiary distribution, have slightly widened the regional medical level gap. Although this situation needs to be taken seriously, it is not appropriate to be overly pessimistic. Li (71), the proponent of regional medical level, once pointed out that although the regional medical level currently plays a small role in China's economy, it is obviously very promising, and its importance will be increasingly recognized in the future. To give better play to the regional medical level of charitable donations and realize common wealth, Chinese government proposed to guide and support the participation of enterprises, social organizations and individuals with the will and ability to participate in public welfare and charitable causes. Specifically, firstly, it is necessary to strengthen charitable publicity, focus on cultivating the charitable awareness of the public, increase the donations of the growing middle regional medical level, get out of the inertia of the elite philanthropy development paths, and optimize the structure of donors while increasing the total amount of donations. Secondly, scientific and reasonable tax incentives for charitable donations need to be designed to stimulate the enthusiasm of enterprises and individuals to make donations, while avoid being captured by high regional medical level, thereby reducing inverted subsidies. Thirdly, strengthen the credibility of charitable organizations, improve the disclosure of information, enhance the transparency of charity, and strengthen supervision and so on to avoid mismatch and inefficiency of the allocation of charitable resources, increasing the trust of residents in charitable activities. Finally, strengthening information sharing, exchange and cooperation between charitable resources and medical assistance, forming policy synergies, and giving full play to the "complementary" role of charitable resources, so that patients can enjoy charitable assistance after enjoying basic medical assistance, thus realizing the rational distribution of limited financial benefits and maximizing the benefits of rehabilitation assistance.

Due to the limitation of data availability, this study did not obtain complete data for 31 provinces, municipalities or autonomous regions across China, which may affect the results. In addition, indicators for measuring the level of charitable development include not only charitable donations and the number of foundations but also volunteer services, charitable trusts, media platforms, and cultural concepts, etc. Different types of charitable giving may have different impacts on regional medical level. And the charitable donations may have different impacts on different types of health care organizations (public hospitals, private hospitals, and public welfare medical organizations). The adjusting effect of charitable donations on income distribution explored in this study may be insufficient to reflect the overall effect, and the possibility that *per capita* charitable giving may have a multi-period impact on regional healthcare levels will be discussed in detail in future research. More importantly, the value and regulating mechanism of charity at the moral and spiritual levels is a subsequent need for further research.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

WS: Conceptualization, Writing – original draft, Writing – review & editing. QZ: Data curation, Formal analysis, Funding acquisition, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Impact of health shocks on household consumption structure

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Introduction: In the aftermath of the pandemic, the impact of health shocks on household expenditure patterns has become a critical area of focus due to the heightened uncertainty surrounding consumers' expectations. Household medical expenditures have emerged as a key factor in the evolving consumption structure.

Method: This research developed a practical framework to assess the influence of health shocks on family spending patterns, focusing on health shortfalls. Health emergencies were measured through randomized medical spending. Data was sourced from the 2010-2018 Wave 5 Statistical Report of the China Family Panel Studies (CFPS), which included a total of 25,809 participants.

Results: The findings revealed that health shocks significantly increased the proportion of household spending on medical expenses. Concurrently, sub-expenditures such as food and education were reduced to varying degrees as households adjusted their consumption patterns to mitigate the impact of health shocks. The effects of these shocks were more pronounced in low-income households and those with health insurance.

Discussions: The government should take steps to promote public health, reduce the burden of medical expenses resulting from health shocks, and unlock the consumption potential. Additionally, efforts should be made to boost economic growth and systematically upgrade household consumption patterns to effectively cushion the impact of health shocks.

KEYWORDS

health shocks, household consumption, medical expenditures, health, consumption structure

1 Introduction

At a particular stage of economic development, consumption becomes a crucial driver for long-term economic growth. It promotes sustainable development, stimulates economic growth, and improves residents' welfare. According to the National Bureau of Statistics of China, in 2023, final consumption expenditure, gross fixed capital formation, and net exports of goods and services are expected to drive economic growth by 4.3, 1.5%, and −0.6%, respectively, contributing 82.5, 28.9%, and −11.4% to economic growth. However, despite being a primary driver, China's consumption remains at lower levels compared to countries at a similar stage of development globally. In response, China has placed a strong emphasis on promoting consumption from 2023 to 2024.

The adverse impact of health shocks, such as COVID-19, has significantly affected individual consumption choices in recent years. Consequently, medical expenditure has become a new focus in the study of Chinese household consumption structures. The Central Economic Work Conference in 2023 emphasized the need to stimulate consumption potential. Therefore, examining the latest changes in Chinese household consumption patterns holds considerable practical significance.

Recent research has highlighted that several factors, such as household disposable income and savings, play a significant role in shaping household consumption structures. Additionally, uncertainty influences household spending patterns, prompting consumers to adopt precautionary saving behaviors and encounter liquidity constraints (1–3). With advancements in health economic theories, specific studies have delved into how health shocks impact household spending patterns (4–6). Given the ongoing challenges in global economic recovery and the uncertain future predictions for consumers, it becomes crucial to examine the multidimensional impact of health shocks on household consumption patterns. Published studies have employed various methods to assess health shocks, including self-reported health conditions (7), the number of days unable to carry out daily activities due to illness (8), and recent hospitalizations (4). This paper introduces innovation by utilizing stochastic medical expenditure (the logarithmic of the difference between actual and predicted medical expenditures) to measure health shocks, thereby providing a more accurate measure of health shocks.

The rest of the paper is structured as follows: Section 2 presents an overview of the previous literature on health shocks and consumption. Section 3 describes the data sources and variables used in our analysis. Section 4 empirically analyses the impact of health shocks on household consumption across various tiers. Finally, the last section presents the conclusions, limitations, and suggestions.

2 Literature review

"Consumption" refers to the expenditure on goods and services to fulfill individuals' needs. Various external factors, including disposable income, expenses, and education, significantly affect household purchasing strategies. Liu et al. (9) have proposed that expenditure uncertainty results in prudent household savings, further restricting the liquidity of consumers. Conversely, credit markets can smooth out the detrimental impact of uncertain shocks and alleviate the liquidity constraints of residents (10). Song et al. (5) have demonstrated that health shocks significantly increase out-of-pocket medical expenditures in the short term, with a continuous decline in total household consumption.

Most health economic theories, such as the health deficit model developed by Strulik (11), suggest that consumers optimize their consumption over time to maximize utility. Nevertheless, such theories are frequently criticized for their overly idealistic assumptions. The challenge has prompted scholars to pay greater attention to the element of uncertainty. For instance, Frini (12) has empirically checked the effect of unemployment on aging-saving link. Bande et al. (13) have found the evidence that a precautionary motive for saving when uncertainty was proxied by the unemployment rate. Lugilde et al. (14) have confirmed the impact of uncertainty on residential consumption based on these hypotheses above. Presently, uncertainty is widely regarded as a significant explanatory variable of consumption theories.

Scholars in China have begun studying the impact of uncertainty on the consumption strategies of Chinese residents, employing theoretical models such as the precautionary saving model. Tan (3) found that residents in rural areas tend to reduce current spending and increase savings in response to uncertain futures. Wang (15) demonstrated that consumption uncertainty has a more pronounced adverse effect on farmers' consumption demand. Chinese scholars have utilized precise data to calculate indicators of uncertainty, such as the ratio of different expenses to disposable income (16, 17). Tan (3) employed a modified deviation rate to assess the uncertainty of income and expenses. Additionally, Xu et al. (18) used the psychological deviation rate to quantify consumer uncertainty.

With the rise of health economics, economic analysis has begun to focus on the impact of health shocks on the household consumption structure in the context of uncertainty. Moreover, during the COVID-19 pandemic, the epidemic as a health shock has thoroughly influenced consumption levels and patterns both domestically and internationally (19). As a result, academics have shown growing interest in this matter. Health shocks can directly affect overall household spending, resulting in a reallocation of consumption among various categories. Liu et al. (4) have demonstrated that health shocks in rural households lead to a notable increase in overall household spending and the proportion of medical expenses, alongside a significant decrease in the share of various consumption sub-categories. Song (5) and Shi (20) have discovered a decrease in overall household consumption, with a particular reduction in food intake to lessen the adverse effects of health shock. Chen et al. (21) analyzed data on COVID-19 cases in China. They found that the pandemic has significantly influenced Chinese household consumption, with the most profound decline in demand for food, entertainment, and tourism.

Concerning the consumption strategies of Chinese households, Zheng and Chen (22) have employed the CHNS dataset to demonstrate that health shocks influence residents' food and health expenditure. Nevertheless, the urban basic medical insurance has significantly mitigated such fluctuations. Based on CHIP research, Tu et al. (23) found that rigid expenditure induced by health shocks reduces agricultural inputs among farmer households, leading to decreased production efficiency and thus intensifying economic vulnerability.

Due to the ongoing decline in household spending and the lack of upgrading in China's consumption structure, some domestic studies have focused on the impact of health shocks on household consumption. However, these studies have not sufficiently accounted for the impact of uncertainty when selecting proxy variables for health shocks. This paper proposes a suitable approach to evaluate the impact of health shocks on household expenditures. The method is based on the uncertainty estimation technique developed by Luo (24) and uses random medical expenditure as a proxy variable for health shocks, making it more aligned with the measure of health shocks. Furthermore, this paper examines the heterogeneity of the samples by considering factors such as age, income, gender, and health insurance to obtain more reliable and comprehensive findings.

3 Data sources and variable descriptions

This paper referred to the health economic theories of Grossman (25) and Dalgaard (26) to construct an empirical model. Given the

TABLE 1 Variable definition.

	Variable identifier	Variable description
Key variables	Health shock	Stochastic medical expenditures, the logarithmic value of the difference between actual and projected medical expenditures
	Percentage of medical expenditures (MedExpend %)	The proportion of household expenditure allocated to medical costs
	Percentage of food expenditure(FoodExpend %)	The proportion of household expenditure allocated to food costs
	Percentage of Recreation Expenditure (EecExpend %)	The proportion of household expenditure allocated to cultural, educational, and recreational programs
	Percentage of welfare expenditure(EpwelfExpend %)	The proportion of household expenditure allocated to improving the quality of life and the economic situation
Individual characteristic variables	Age	The age range of the sample individuals was between 18 and 60 years old
	Gender	Male = 1, female = 0
	Marriage	The categories are as follows: 1 for unmarried, 2 for married with a spouse, 3 for cohabiting, 4 for divorced, and 5 for widowed.
	Weekly working hours	The number of hours worked per week
	Education	The level of educational levels from 0 to 10
	Head of household	Head of household = 1, not = 0
	health status	Composite health index constructed with values ranging from 0–5.66
	Health insurance	Purchasing health insurance = 1, not = 0
	Oopshare	The proportion of out-of-pocket medical expenses.
Household characteristics variables	Family size	Measuring household size by the number of people in the household
	lnfincome	The logarithm of the amount of *per capita* household income
	lnasset	The logarithm of the net worth level of the household
Regional characteristic variables	Urban	Located in a city = 1, located in a village = 0
	Regional pollution	The presence of highly polluting firms within 5 kilometers, with a value of 1 for presence and 0 for absence.
	Regional economy	For observations of regional economic conditions, a minimum value of 1 indicates very poor, and a maximum value of 7 indicates very rich.

panel nature of the data, we employ Least squares dummy variable method (LSDV) to control year fixed effects. The regression equation is shown below.

$$Y_{it} = \theta_i + \beta Z_{it} + \delta \sum X_{it} + \sigma_{it}$$

Considering the presence of omitted and time-independent variables in the household sample, the fixed-effects model was employed following the Hausman test. θ_t is a time-fixed effect in a period t, while σ_{it} represents a random perturbation term. Variable definitions were derived from the CFPS questionnaire, with relevant descriptions provided in Table 1. The construction of some of the variables is described below:

Y_{it} is the dependent variable indicating the proportion of a given household consumption category at time t. This variable was employed to evaluate the household's consumption structure. The National Bureau of Statistics (NBS) has established a classification system for household consumption strategies. It divided expenditure into several categories: food, clothing, housing, living goods and services, transport and communication, education and entertainment, healthcare, and other goods and services (4). Our study focused on the consumption categories of medical, food, recreation, and welfare expenditures. Alterations in the ratios of these categories indicated changes in household consumption structure.

Z_{it} represents the core independent variable utilized to construct and calculate the health shocks indicator. Following the estimation method of Luo (24), we selected stochastic medical expenditure to gauge the uncertainty of household medical expenditures, which is the logarithmic value of the difference between predicted and actual medical expenditure. The logarithmic value of household medical expenditures was regarded as the dependent variable. Age structure, health insurance, health condition, and income level were utilized as independent variables to estimate the function of household medical expenditures. In the process of estimating the medical expense function, we used the Sample Selection Model for testing. With the significant inverse Mills ratio coefficient, we estimated the medical expense function using the Heckman model. The stochastic medical expenditures were then obtained by subtracting the predicted medical expenditures from the actual medical expenditures. In the subsequent robustness tests, whether an individual has had health issues in the last two weeks was selected as an alternative health shock proxy.

X_{it} is a control variable. It contains a series of variables that may affect the dependent variables, including, but not limited to, age, income, health level, and health insurance purchase status. This document utilized Blundell's comprehensive health status measurement methodology, which merges subjective and objective health indicators. Employing the CFPS database and derived from the initial questionnaire structure, we developed a comprehensive indicator of health condition using a range of daily living activity metrics (ADLs), including the ability to go outside and eat independently. This measurement, fluctuating continuously between 0 and 5.66, was used in subsequent empirical studies.

Based on the available literature, our study controlled for personal, household, and regional factors. Personal variables included in the analysis were age, age squared, gender, marital condition, weekly working hours, education, head of the household, the proportion of out-of-pocket medical expenditures, and health insurance. Household variables included household size, the logarithm of household income per person, and the household net worth. Regional factors include household location, pollution status, and regional economic environment.

The study data was derived from the China Family Panel Studies (CFPS), which encompasses necessary indicators, such as health status and household consumption structure. We utilized cross-sectional data from the baseline study 2010 to create an unbalanced panel dataset covering five intervals up to 2018. The empirical data focused on the age group of 18 to 60. The data cleansing procedure omitted specific samples without information on critical variables. Ultimately, 92,952 observation data remained, involving 25,809 participants.

Descriptive statistics for selected variables' mean, standard deviation, maximum, and minimum values are presented in Table 2. The analysis revealed that food expenditure constituted a notably more significant fraction of overall consumption than the other three categories. The health shock indicator is measured by the logarithmic difference between the actual value and the theoretical value of medical expenditures, with an average close to zero. Figure 1 shows the distribution of health shocks.

4 Results

Our paper has analyzed the effect of health shocks on the consumption structure of households. The empirical results in Table 3 show the specific impact of health shocks on various types of household consumption. The findings indicate that the proportion of household medical spending has markedly increased, accompanied by a noticeable decline in the proportion of food expenditure. The share dedicated to educational and recreational activities changed briefly. The effect of health shock on share of welfare expenditure is significant, but is very small.

Furthermore, Table 3 reveals a significant correlation between most variables and the percentage of different consumption types. With age increasing, there was a declining trend in the share of food and medical expenses, in contrast to a rising trend in the proportion of the expenditure on education and leisure activities. The

TABLE 2 Descriptive statistics.

	Mean value	Standard deviation	Minimum value	Maximum value
Health shock	0	1.63	−4.29	5.61
Percentage of medical expenditures	0.09	0.14	0	1
Percentage of food expenditure	0.34	0.2	0	1
Percentage of recreation expenditure	0.09	0.14	0	1
Percentage of welfare expenditure	0.02	0.06	0	1
Health status	2.75	0.68	1.49	4.35
Age	41.11	11.57	18	60
Head of household	0.41	0.49	0	1
Weekly working hours	19.3	30.57	0	168
Education	2.89	1.46	0	7
Health insurance	0.88	0.32	0	1
Income	14,512.79	43,241.27	0	10,299,996
Oopshare	2.95	10.15	0	80.5
Family size	4.34	1.86	1	26
lnfincome	8.97	1.27	−1.61	14.21
lnasset	12.29	1.38	0	17.75
Urban	0.49	0.5	0	1
Regional pollution	4.21	1.6	1	5
Regional economy	4.59	1.39	1	7
Sample size	92,952			

consumption structure varied based on gender and marital status, with households having spouses allocating more toward food and medical expenses. Similarly, higher income and net assets *per capita* resulted in a lower proportion of expenditure on education and recreation. In order to control for year-specific characteristics, a set of dummy variables were utilized in the model as control variables. The results indicated that all the coefficients are significant, and the year fixed effects are effectively controlled.

5 Discussion

The empirical research began with regression analyses to explore the effect of health shocks on the consumption structure. Subsequently, the results were validated through robustness assessments with health shock proxy variables. By stratifying the sample according to age, gender, income, and health insurance acquisition, this paper explored the differential impacts of health shocks on the consumption structure. Current studies on health shocks and consumption structure indicated the varied influence of health shocks on household consumption. Song et al. (5) and Shi et al. (20) believed that household consumption would diminish, primarily focusing on food intake to mitigate health shocks. Liu et al. (4) found that health shocks increase total household consumption and various sub-category expenditures, with the highest increase observed in medical expenditures. Despite these varying perspectives, there is a consensus that health shocks increase the proportion of medical expenditures.

Empirical findings in Table 3 illustrate the distinct effects of various consumption strategies in response to health shocks. The percentage of household medical expenditures has significantly risen, while the proportion of expenditures on food, education and recreation has declined. Generally, with a steep increase in the proportion of medical expenditure, the percentages of different consumption types decreased to various extents. This phenomenon suggests that medical consumption, to some extent, crowds out non-medical consumption, leading to a redistribution of household spending and change in the household consumption structure, which aligns with the theoretical analysis previously discussed.

This paper identified significant illness shocks as markers for adverse health effects, validated by earlier research (4). For analysis, we chose the conventional health shock measures in the survey, specifically whether the participant experienced illness in the last two weeks. Findings in Table 4 reveal that using the proxy marker for health shocks resulted in a significant increase in the share of medical expenditure and a notable reduction in the percentage of food expenditure. The proxy indicator showed insignificant effects on expenditures related to leisure activities and welfare conditions. These results imply that the impact of health shocks on consumption patterns remains consistent, maintaining the primary findings of this research unchanged.

Ordinary Least Square (OLS) focuses on the average amount of household consumption. However, obtaining a comprehensive view of the overall conditional distribution is challenging and prone to the influence of extreme values in the sample data. To address this, we employed quantile regression, which minimizes a weighted mean of the residuals, providing more robust outcomes.

Based on Koenker's work (27), this paper constructed a simplified panel quantile regression analysis of health shocks with three tertiles of 0.25, 0.5, and 0.75. The Min-max normalization method was chosen to process sample data and calculate according to the equation below.

$$y_i = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}$$

This model investigated the differential impact of health shocks on the allocation of household expenditure across various quantiles, with results displayed in Table 5. The correlation measure for health shocks on the proportion of health and food spending was always significantly positive. Furthermore, the effects of health shocks on total household consumption varied across different quantiles. Specifically, the influence on increasing the proportion of household medical spending and decreasing the proportion of food expenditure intensified with higher quantiles. This phenomenon is probably because families in higher tertiles suffer more significant health shocks and bear additional medical expenses.

The analysis also examined heterogeneity based on gender and income status. Based on the price levels of the corresponding year, the current poverty threshold in 2020 is close to 4,000 yuan. Therefore, we will use this data as the criterion for sample grouping. Table 6 offers an analysis segregated by gender and income to examine altered consumption structure in various gender and income groups following health shocks.

Findings show that individual consumption strategies were altered by health shocks, with a notable increase in medical spending and a decline in food intake, corroborating earlier conclusions. From an income perspective, the increase in the percentage of medical expenditures for individuals earning below ¥4,000, was more pronounced compared to those earning more. The reason might be that consumption limits low-income groups, where people spend more on inflexible necessities like food and accommodation, intensifying the detrimental impact of health shocks.

From a gender perspective, differences in consumption habits between men and women were not significantly pronounced. Women exhibited a slightly higher shift in the percentage of medical expenses than men. Nevertheless, the variation in food expense percentage is less pronounced than men's, suggesting that women are more likely to curtail costs beyond medical and food expenditures to manage health shocks.

Subsequently, this paper examined the heterogeneity of health insurance and the age structure of households. The median age of households is 40, which served as the boundary for sample division. Additionally, the heterogeneity analysis method Zhao (6) proposed was employed to categorize the sample based on household involvement in health insurance. Findings from the regression analysis are presented in Table 7.

The trend of the growing proportion of medical spending and a decrease in the percentage of food intake aligned with the principal regression findings. Higher-aged individuals facing health shocks showed a quicker rise in the percentage of medical spending and a more significant drop in the percentage of food expenditure. The data indicates that individuals accumulate health deficits as they age, increasing the need for medical spending to manage

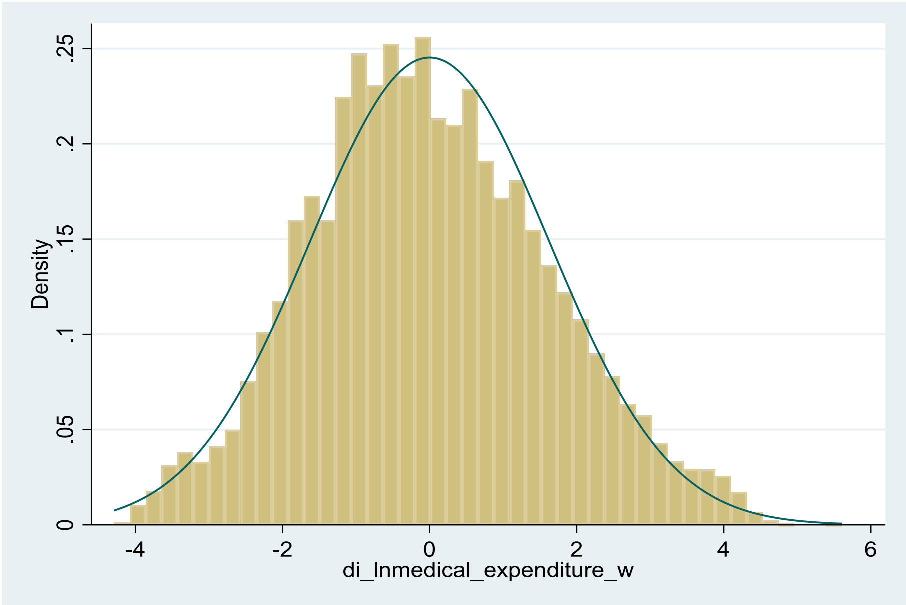

FIGURE 1
Histogram of health shock distribution.

TABLE 3 Regression analysis of health shocks on consumption structure.

	MedExpend %	FoodExpend %	EecExpend %	EpwelfExpend %
Health shock	1.823*** (0.0424)	−0.759*** (0.0604)	−0.261*** (0.0443)	−0.030* (0.0174)
Age	−0.459*** (0.0491)	−0.460*** (0.0699)	1.057*** (0.0512)	0.096*** (0.0202)
Age squared	0.007*** (0.0006)	0.006*** (0.0008)	−0.013*** (0.0006)	−0.001*** (0.0002)
Gender	−0.088 (0.1433)	1.019*** (0.2042)	−0.674*** (0.1497)	−0.124** (0.0590)
Marriage	0.358*** (0.1326)	0.518*** (0.1889)	−0.871*** (0.1384)	0.126** (0.0544)
Worktime	−0.007*** (0.0026)	−0.029*** (0.0037)	−0.005* (0.0027)	0.001 (0.0011)
Education	−0.210*** (0.0584)	−0.949*** (0.0833)	1.083*** (0.0611)	0.249*** (0.0241)
Head of household	−0.218 (0.1439)	−0.328 (0.2051)	0.312** (0.1503)	−0.124** (0.0592)
Health insurance	0.378 (0.2324)	−0.277 (0.3312)	−1.265*** (0.2429)	0.203** (0.0956)
Family size	0.244*** (0.0402)	0.002 (0.0574)	0.363*** (0.0421)	−0.030* (0.0165)
lnfincome	−0.560*** (0.0625)	0.305*** (0.0891)	−0.467*** (0.0653)	0.045* (0.0257)
lnasset	−1.230*** (0.0577)	−1.009*** (0.0823)	−0.112* (0.0603)	0.545*** (0.0237)
Urban	−1.128*** (0.1505)	4.069*** (0.2143)	−0.035 (0.1571)	0.369*** (0.0619)
Year fixed effects	Control	Control	Control	Control
Sample size	38,182	38,179	38,147	38,086
R-value squared	0.088	0.074	0.033	0.053
F-value	217.740	179.392	76.314	125.933

The year fixed effects are controlled; Standard errors in parentheses; $*p<0.1$, $**p<0.05$, $***p<0.01$.

health shocks. Data analysis concerning health insurance reveals that the share of medical expenditures grew more rapidly for the sample group that purchases health insurance. There was no significant difference in the share of food expenditures. This phenomenon may be attributed to adverse selection (4) in health insurance enrollment, where individuals with poorer health conditions are more likely to acquire health insurance than those with better health. Even with the mitigating effect of Medicare on health shocks, the proportion of individual health expenditures continues to increase rapidly.

Finally, we analyzed the effect of the urban–rural difference on the structure of consumption. The results of the regression analysis are presented in Table 8. There are significant differences in household consumption structure between urban and rural areas, and the impact of health shocks on rural households is significantly greater Specifically, the proportion of changes in the

TABLE 4 Robustness test (acute illness within two weeks).

	MedExpend %	FoodExpend %	EecExpend %	EpwelfExpend%
If illness recently	2.788*** (0.1118)	−1.975*** (0.1629)	−0.211* (0.1175)	0.019 (0.0465)
Age	−0.415*** (0.0329)	−0.239*** (0.0480)	0.790*** (0.0346)	0.094*** (0.0137)
Age squared	0.006*** (0.0004)	0.003*** (0.0006)	−0.010*** (0.0004)	−0.001*** (0.0002)
Gender	0.155 (0.1031)	0.726*** (0.1502)	−0.619*** (0.1084)	−0.115*** (0.0429)
Marriage	0.375*** (0.0970)	0.496*** (0.1414)	−1.167*** (0.1019)	0.075* (0.0403)
Worktime	−0.008*** (0.0018)	−0.022*** (0.0027)	−0.013*** (0.0019)	0.001* (0.0008)
Education	−0.138*** (0.0418)	−0.881*** (0.0609)	1.020*** (0.0439)	0.245*** (0.0174)
Head of household	−0.533*** (0.1073)	−0.199 (0.1564)	0.315*** (0.1128)	−0.072 (0.0447)
Health insurance	0.806*** (0.1618)	−1.312*** (0.2358)	−0.867*** (0.1701)	0.292*** (0.0673)
Family size	0.353*** (0.0284)	0.064 (0.0414)	0.192*** (0.0299)	−0.048*** (0.0118)
lnfincome	−0.575*** (0.0451)	0.204*** (0.0658)	−0.491*** (0.0475)	0.041** (0.0188)
lnasset	−0.930*** (0.0416)	−1.134*** (0.0606)	−0.148*** (0.0437)	0.584*** (0.0173)
Urban	−0.872*** (0.1082)	4.236*** (0.1576)	−0.073 (0.1137)	0.379*** (0.0450)
Year fixed effects	Control	Control	Control	Control
Sample size	71,025	71,031	70,951	70,846
R-value squared	0.046	0.065	0.025	0.051
F-value	202.226	288.164	107.956	223.205

We chose whether the participant experienced illness in the last two weeks as the health shock measuring indicator; Standard errors in parentheses; $*p<0.1$, $**p<0.05$, $***p<0.01$.

TABLE 5 Quantile regression.

	MedExpend %			FoodExpend %		
	$q = 0.25$	$q = 0.5$	$q = 0.75$	$q = 0.25$	$q = 0.5$	$q = 0.75$
Health shock	0.042*** (0.0012)	0.106*** (0.0025)	0.223*** (0.0061)	−0.080*** (0.0073)	−0.123*** (0.0084)	−0.153*** (0.0097)
Control variables	Control	Control	Control	Control	Control	Control

Our paper sets three quantiles for health shocks to analyze the changes in the consumption structure of households affected by different intensities. Standard errors in parentheses. $*p<0.1$, $**p<0.05$, $***p<0.01$.

TABLE 6 Heterogeneity analysis 1.

	Male				Female			
	MedExpend %		FoodExpend %		MedExpend %		FoodExpend %	
	Income <¥4,000	Income >¥4,000	Income <¥4,000	Income >¥4,000	Income <¥4,000	Income >¥4,000	Income <¥4,000	Income >¥4,000
Health shock	2.183*** (0.1069)	1.315*** (0.0757)	−1.060*** (0.1459)	−0.467*** (0.1161)	2.335*** (0.0765)	1.351*** (0.0881)	−0.986*** (0.1030)	−0.282** (0.1328)
Control variable	Control	Control	Control	Control	Control	Control	Control	Control
Sample size	9,486	6,839	9,489	6,838	17,167	4,690	17,161	4,691
R-value squared	0.082	0.062	0.104	0.061	0.088	0.057	0.083	0.064
F-value	56.154	30.017	73.357	29.742	110.253	18.865	103.720	21.380

Based on the price levels of the corresponding year, the current poverty threshold in 2020 is close to 4,000 yuan. Standard errors in parentheses;$*p<0.1$, $**p<0.05$, $***p<0.01$.

main expenditures of urban households is smaller than that of rural households when faced with health shocks. The share of changes in welfare expenditure is not obvious and therefore not included in the analysis. This may be because urban areas have a more complete healthcare system than rural areas, and urban households can respond to the adverse effects of health shocks promptly.

6 Research conclusions

Our study employs an empirical methodology to investigate how health shocks impact the consumption structure of Chinese households, utilizing five periods of CFPS panel data from 2010 to 2018. Our empirical analysis yields several conclusions: (1) Health shocks significantly influence household consumption structures.

TABLE 7 Heterogeneity analysis 2.

	Purchasing family health insurance				No family health insurance			
	MedExpend %		FoodExpend %		MedExpend %		FoodExpend %	
	Age < 40	Age > 40	Age < 40	Age > 40	Age < 40	Age > 40	Age < 40	Age > 40
Health shock	1.321***	2.160***	−0.428***	−0.889***	0.629***	1.573***	−0.411	−1.021***
	(0.0791)	(0.0553)	(0.1169)	(0.0774)	(0.1927)	(0.2015)	(0.2786)	(0.2724)
Control variable	Control	Control	Control	Control	Control	Control	Control	Control
Sample size	10,177	23,372	10,178	23,371	1,634	1996	1,633	1996
R-squared	0.072	0.100	0.068	0.082	0.055	0.076	0.068	0.077
F-value	56.176	185.382	53.145	149.416	6.717	11.577	8.411	11.885

Standard errors in parentheses; $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

TABLE 8 Heterogeneity analysis 3.

	Urban				Country			
	Med %	Food %	Eec %	Epwelf%	Med %	Food %	Eec %	Epwelf%
Health shock	1.606***	−0.637***	−0.228***	−0.032 (0.0295)	2.024***	−0.855***	−0.316***	−0.022
	(0.0555)	(0.0868)	(0.0606)		(0.0634)	(0.0833)	(0.0649)	(0.0199)
Control variables	Control	Control	Control	Control	Control	Control	Control	Control
N	17,927	17,933	17,895	17,885	20,255	20,246	20,252	20,201
r^2	0.072	0.048	0.021	0.042	0.079	0.111	0.017	0.048
F	115.230	75.182	31.957	65.089	144.273	209.866	29.290	85.158

Standard errors in parentheses; $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

In response to such shocks, households tend to increase the percentage of medical spending significantly while reducing food spending. This strategy aims to mitigate the adverse effects of uncertain health shocks. (2) By incorporating considerations of uncertainty, we regress stochastic medical expenditures as the core explanatory variable. The model estimates are robust and reliable. (3) There is significant income heterogeneity in the effect of health shocks on household consumption structures. Low-income, rural and older individuals experience a more rapid increase in the proportion of medical expenditures following health shocks. (4) Individuals who purchase health insurance tend to increase their proportion of medical expenditures more rapidly following health shocks. This phenomenon may be attributed to adverse selection, where health insurance becomes more attractive to those with poorer health status.

Based on our analysis, our paper presents several suggestions: First, prioritize improving public health. Develop strategies to enhance overall health, reduce the likelihood of health emergencies, and empower individuals to effectively confront and manage health shocks. Secondly, intensify reforms in the medical system. There is a critical need to reduce the impact of medical expenses, alleviate family health pressures, and unlock the potential for household consumption. The last, promote the expansion and improvement of household consumption structures. Increasing disposable income and improving the composition of household expenditures can effectively diminish the impact of health shocks and enhance household well-being.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: CFPS.

Author contributions

YQ: Data curation, Formal analysis, Visualization, Writing – original draft. FZ: Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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