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Spatial differences, dynamic evolution and influencing factors of the coupling and coordination relationship between health resources allocation and health service utilization in China

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Abstract

Background With the progress of economic and social development, the demand for healthcare has increased, making the rational allocation of health resources and the efficient utilization of services crucial for public health. However, mismatches between resource allocation and service utilization have led to strain on resources. This study aims to assess the spatiotemporal evolution and influencing factors of the coupling coordination between health resource allocation (HRA) and health service utilization (HSU) in China, contributing to the realization of the "Healthy China" strategy.

Methods Based on the panel data from 2010 to 2022, The entropy method is employed to measure the comprehensive development index of HRA and HSU. The Coupling Coordination Degree Model (CCDM) was used to measure the coupling coordination degree (CCD)of HRA and HSU. The standard deviation ellipse (SDE) and kernel density estimation (KDE) to find the gravity centers movement trends and dynamic evolution of CCD. The XGBoost-SHAP machine learning was used to explore the key factors affecting CCD.

Results (1) The comprehensive development levels of the subsystems of HRA and HSU showed an overall upward trend, but they do not rise simultaneously. (2) CCD exhibited a stable upward trend over time, with higher values in the south and east, and lower values in the north and west. (3) The spatial migration of CCD was centered in Henan Province, with shifts from northwest to southwest to northeast, and after initial fluctuations, the distribution became more concentrated, and polarization diminished. (4) CCD is primarily influenced by healthcare investment and economic development. Additionally, influencing factors exhibit regional heterogeneity: in the eastern region, URRBMI coverage positively impacts CCD; in the central region, traffic network density positively influences CCD; and in the western region, population density negatively affects CCD.

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Conclusions This study investigates the spatiotemporal evolution and influencing factors of CCD, suggesting that governments adopt differentiated strategies to enhance CCD and offering a theoretical foundation for implementing the "Healthy China" strategy.

Keywords Health resource allocation, Health service utilization, Coupling coordination degree, Standard deviation ellipse, Kernel density estimation, Influencing factors

Introduction

Health is a fundamental human right and a core objective for promoting social progress and sustainable development [1]. Health resources, as the essential foundation for the operation of the healthcare system, encompass multiple dimensions including human resources, material resources, financial resources, information, and technology. The rational allocation of these resources not only affects the operational efficiency of the healthcare system but also directly influences the equity and accessibility of healthcare services [2]. Health service utilization(HSU)reflects the extent to which healthcare resources are effectively applied in health interventions and is a key indicator for assessing the effectiveness of resource allocation and the performance of the service system [3]. The two are complementary and mutually reinforcing, and their coordinated development is a key pathway to improving the efficiency of the healthcare system and alleviating structural issues such as the difficulty in accessing healthcare and the high cost of medical services.

Since the reform and opening-up, China's healthcare sector has undergone continuous development, and the overall health level has steadily improved. By 2023, the average life expectancy of residents increased from 35.0 years at the founding of the People's Republic of China to 76.1 years. Maternal mortality decreased from 80.0 per 100,000 in 1991 to 15.1 per 100,000, while the mortality rates for newborns, infants, and children under five years old dropped to 2.8 per 1,000, 4.5 per 1,000, and 6.2 per 1,000, respectively [4]. However, China's healthcare system still faces numerous challenges. On the one hand, the number of doctors and nurses per thousand people is only 3.40 and 4.00 respectively, which is lower than the OECD average. On the other hand, high-quality resources are highly concentrated in major cities and high-level medical institutions, while healthcare capacity in grassroots and rural areas remains weak. This results in a mismatch between supply and demand, as well as low coordination efficiency within the system [5]. More critically, with the continued aging of the population, the demand for healthcare services is growing, becoming more diverse and complex. This exacerbates the uneven distribution of medical resources and service capacities across regions. Therefore, identifying regions with misaligned Health resource allocation (HRA)and HSU, understanding the causes of this misalignment, and clarifying the coupling mechanisms between the two are crucial for promoting the high-quality development of regional healthcare systems.

Rational allocation of health resources is an important issue in the health field, and its relationship with HSU has attracted increasing attention [6–8]. Existing studies have explored the link between HRA and HSU from different perspectives. Some studies introduced the coupling coordination theory to build a two-dimensional dynamic coupling coordination degree (CCD) model of"time and space", and analyzed the coupling coordination level of HRA and HSU in different regions and periods, revealing significant regional differences and spatial aggregation of HRA and HSU in China [9–11]. Other studies focused on the impact of different influencing factors such as economic development, policy support and infrastructure construction on the coupling relationship between HRA and HSU [12–14]. Additionally, existing research generally employs spatial econometric models, barrier models, and Pearson correlation coefficient analysis methods [15–17]. However, these traditional methods often rely on linear assumptions or predefined functional forms, making it challenging to comprehensively characterize the complex synergies and nonlinear mechanisms among multiple factors. Machine learning, with its advantage in high-dimensional data modeling, combined with interaction models and explanation methods, can further reveal the key factors affecting the coupling coordination level and effectively avoid overfitting issues [18, 19].

This study focuses on China and constructs an index system for HRA and HSU, the entropy method is employed to measure the comprehensive development index of HRA and HSU. Subsequently, the CCDM is utilized to quantify the CCD between HRA and HSU. The standard deviation ellipse (SDE) and kernel density estimation (KDE) to find the gravity centers movement trends and dynamic evolution of CCD. Finally, the XGBoost-SHAP machine learning model is applied to identify the key factors influencing CCD and to provide differentiated policy recommendations., contributing to the realization of the"Healthy China"strategy. The research framework is depicted in Fig. 1.

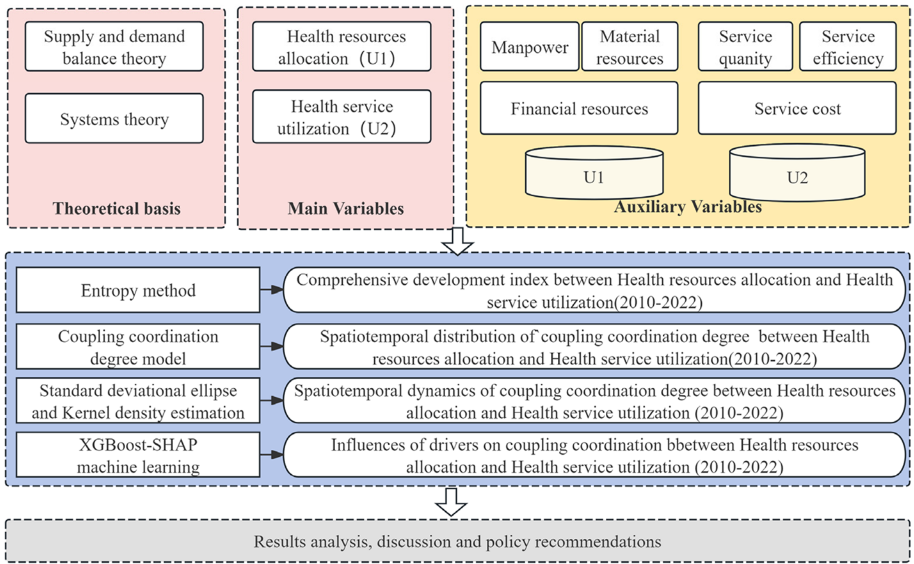

Fig. 1 Theoretical framework of this paper. Source: Author's own drawing

Study region

China has a land area of approximately 9.6 million square kilometers and is divided into 34 provincial-level administrative regions. Due to inconsistencies in statistical standards and data collection, this study selects 31 provinces on the Chinese mainland, excluding the Hong Kong Special Administrative Region, the Macau Special Administrative Region, and Taiwan. Based on geographical location, economic development levels, and the standards referenced in the"China Health Statistics Yearbook,"the 31 provinces, autonomous regions, and municipalities on the mainland are categorized into three regions: Eastern, Central, and Western China. The Eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan (11 provinces and municipalities). The Central region includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan (8 provinces). The Western region includes Inner Mongolia, Chongqing, Guangxi, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang (12 provinces, autonomous regions, and municipalities). The geographical locations of these three administrative regions are shown in Fig. 2.

Data source

The study period of this research spans from 2010 to 2022. The data for various indicators, such as HRA and HSU, were sourced from the"China Statistical Yearbook,""China Health Statistics Yearbook,""China Health and Family Planning Statistics Yearbook,"and"China Health and Wellness Statistics Yearbook,"published between 2011 and 2023 by the National Health Commission and the National Bureau of Statistics. For missing data points in certain years, linear interpolation was applied to fill the gaps, ensuring data completeness and the continuity of the time series analysis.

Indicators

Based on an extensive literature review and in-depth theoretical analysis, and adhering to the principles of data availability, scientific rigor, operability, and systematics, a comprehensive evaluation indicator system for HRA and HSU subsystems was developed. This system adopts a hierarchical structure, with each subsystem consisting of several specific indicators. The influence of each indicator on the subsystem is classified into two types: positive (+) and negative (-). Positive influence indicators suggest that higher values lead to better subsystem performance, while negative influence indicators imply that higher values result in poorer performance. In the dimension of HRA, three primary indicators are included: material resources, manpower and financial resources. Material resources are represented by the number of healthcare institutions and the number of hospital beds in healthcare institutions. Manpower is represented by the number of healthcare personnel, including doctors, nurses, clinical staff, administrative staff, and other non-clinical personnel. Financial resources are represented by government fiscal subsidies. In the dimension of HSU, three primary indicators are also included: service quantity, service efficiency, and service costs. Service quantity includes inpatient and

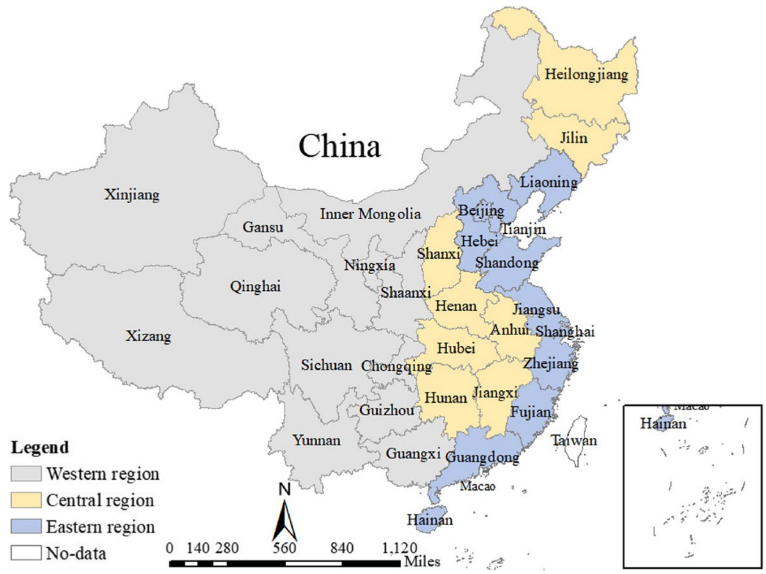

Fig. 2 The distribution of 3 administrative regions in China

Table 1 Evaluation indicators and weights of health resource allocation and health service utilization

System	Subsystems	Variables & direction	Unit	Weight	References
Health resource allocation (HRA)	Material resources	The number of medical institutions (+)	ten thousand	0.239	[20, 21]
		The number of beds (+)	ten thousand	0.177	[22, 23]
	Manpower	The number of health workers (+)	ten thousand people	0.169	
	Financial resources	Government financial subsidy (+)	ten thousand CNY	0.415	[24, 25]
Health service utilization (HSU)	Service quantity	Inpatient visits (+)	ten thousand people	0.252	[26, 27]
		Outpatient visits (+)	ten thousand people	0.295	
	Service efficiency	Bed utilization rate (+)	%	0.046	[28, 29]
		Average length of stay (-)	Days	0.018	
		Average number of visits per day for doctors (+)	Person/day	0.140	
	Service cost	Total health expenditure per capita (+)	CNY	0.248	[17, 30]

outpatient visits. Service efficiency is measured by bed occupancy rate, average length of stay, and the average number of patients treated per doctor per day. Service costs are represented by per capita total health expenditure. The evaluation indicators within each subsystem are interconnected, forming an interactive and interrelated framework (Table 1).

Influencing factor variable selection

In view of the limited in-depth studies on the influencing factors of the coupling relationship between HRA and HSU, this study focuses on the independent influencing factors of both, aiming to verify their joint impact on the CCD. These factors include economic development, population structure and distribution, education level, healthcare investment, infrastructure and information technology, and medical security coverage (Table 2). Economic development is measured by gross domestic product (GDP), per capita GDP, and the urban–rural income gap ratio. Population structure and distribution are assessed through population density, urbanization rate, child dependency ratio, and elderly dependency ratio. Education level is represented by the illiteracy rate and the ratio of the population with higher education (RHEP). Healthcare investment is measured by total health expenditure and government health expenditure. Medical security coverage is assessed through the coverage rate of urban and rural residents'basic medical insurance (URRBMI coverage rate) and the coverage rate of basic medical insurance for employees (Employee BMI coverage rate). Infrastructure and information technology are reflected in traffic network density and internet penetration rate (Table 2).

Table 2 Explanatory variables in the study

Factor	Specific indicator	Unit	Reference
Level of economic development	GDP	CNY	[31–33]
	Per capita GDP	CNY	
	income gap between urban and rural residents	times	
Population structure and distribution	Population density	person	[34–37]
	Urbanization rate	%	
	Child dependency ratio	%	
	Old-age dependency ratio	%	
Level of education	Illiteracy rate	%	[38, 39]
	RHEP	%	
Health care investment	Total health expenditure	CNY	[21, 40]
	Government health expenditure	CNY	
Medical insurance coverage	URRBMI Coverage Rate	%	[41, 42]
	Employee BMI Coverage Rate	%	
Infrastructure and Informatization technology	Traffic Network Density	km/km^2	[43, 44]
	Internet Penetration Rate	%	

Research methods

Entropy method

The entropy method was applied to determine the index weights of the HRA and HSU subsystems. As an objective weighting approach, the entropy method minimizes the influence of subjective bias that may arise in manual weighting procedures, reduces information redundancy among indicators, and corrects selection bias caused by minimal variation between indicators [45]. Before applying the entropy method, the range normalization method was used to standardize the original data, ensuring that differences in units and scales among indicators do not affect the analysis results. The calculation formula is as follows:

$$Y_{ij} = \frac{X_{ij}-X_{ijmin}}{X_{ijmax}-X_{ijmin}}\left(i = 1,2,\cdots,n; j = 1,2\cdots,m\right)(positive\ index) \quad (1)$$

$$Y_{ij} = \frac{X_{ijmax}-X_{ij}}{X_{ijmax}-X_{ijmin}}\left(i = 1,2,\cdots,n; j = 1,2\cdots,m\right)(negative\ index) \quad (2)$$

where X_{ij} is the original value of the indicator, X_{ijmin} is the minimum value of the j indicator of the i the evaluation object, and X_{ijmax} is the maximum value of the j indicator of the i the evaluation object.

$$P_{ij} = \frac{Y_{ij}+1}{\sum_{i=1}^{m}(Y_{ij}+1)}\left(i = 1,2,\cdots,n; j = 1,2\cdots,m\right) \quad (3)$$

$$e_j = \frac{-1}{\ln m\sum_{i=1}^{n}P_{ij}\times \ln P_{ij}}\left(i = 1,2,\cdots,n; j = 1,2\cdots,m\right) \quad (4)$$

$$w_j = \left(1-e_j\right)\sum_{i=1}^{n}\left(1-e_j\right), j = 1,2,\cdots\cdots,n \quad (5)$$

where p_{ij} is the proportion of index values of i provinces in the j indicator, e_i is j the information entropy of j indicator, and w_j is the weight of each indicator.

CCDM (Coupling Coordination Degree Model)

CCDM is an evolution model used to assess the interaction and coordination between subsystems. It has been widely applied in various fields such as digital finance assessment [46], ecological impact assessment [47], economic development evaluation [48]. In this study, the CCDM is used to explore the coupling coordination relationship between HRA and HSU. It measures the degree of interaction and coupling level between two or more systems, thereby determining their development trend [49]. The calculation formula is as follows:

$$CD = \frac{2\sqrt{U1U2}}{U1+U2} \quad (6)$$

$$T = \alpha U_1 + \beta U_2 \quad (7)$$

$$CCD = \sqrt{CD \times T} \quad (8)$$

In this context, CD represents interaction and correlation between HRA and HSU, with a value range of [0,1]. The larger the CD, the higher the degree of correlation. A CD value of 1 indicates the optimal coupling state. U_1 and U_2 represent the comprehensive development level indices of HRA and HSU, respectively. T denotes the coupling coordination development index. However, when each system is at a lower level, the phenomenon of"false high coupling"may occur, and this method cannot eliminate such situations [50]. Therefore, the introduction of the CCD allows for effective analysis of the coordinated development level of the two subsystems and their respective levels of coordination [51]. This study assumes that HRA and HSU are equally important, hence$\alpha = \beta = 0.5$, with CCD ranging from 0 to1.The higher the CCD value, the stronger the coordination relationship. Specific CCD is categorized as listed in Table 3 [52].

Spatial distribution analysis methods

SDE (Standard deviation ellipse)

The SDE is a spatial statistical method used to describe the overall spatial and temporal distribution characteristics of geographic elements [53]. The parameters of the SDE include the center of gravity of the ellipse, the azimuth Angle, and the standard deviation of the x-and y-axes. In this study, SDE was applied to analyze the migration trajectory of the barycenter and the dispersion pattern of the CCD between HRA and HSU across China during the study period. The calculation formulas are as follows:

$$\overline{X}_w = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \tag{9}$$

$$\overline{Y}_w = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \tag{10}$$

$$\theta = \mathrm{arcta\ n}\left[\left(\sum_{i=1}^{n} x_i'^2 - \sum_{i=1}^{n} y_i'^2\right) + \sqrt{\left(\sum_{i=1}^{n} x_i'^2 - \sum_{i=1}^{n} y_i'^2\right)^2 + 4\left(\sum_{i=1}^{n} x_i' y_i'\right)^2}\right] / 2\sum_{i=1}^{n} x_i' y_i' \tag{11}$$

$$\sigma_x = \sqrt{\frac{\sum_{i=1}^{n} \left(w_i \tilde{x}_i \cos\alpha - w_i \tilde{y}_i \sin\alpha\right)^2}{\sum_{i=1}^{n} w_i^2}} \tag{12}$$

$$\sigma_y = \sqrt{\frac{\sum_{i=1}^{n} \left(w_i \tilde{x}_i \sin\alpha - w_i \tilde{y}_i \cos\alpha\right)^2}{\sum_{i=1}^{n} w_i^2}} \tag{13}$$

where $(\overline{X}_w, \overline{Y}_w)$ is the average center; (x_i, y_i) are the coordinates of the geometric centers of the elements and the orientation angle of the ellipse; x_i' and y_i' are coordinate deviations from the factor center to the average center; σ_x and σ_y are the standard deviations along the axis and the axis, respectively [54].

KDE (Kernel Density Estimation)

KDE is a non-parametric statistical method that estimates the probability density of a dataset without assuming any specific distribution, thereby making full use of the sample's characteristics. This study use KDE estimate the dynamic evolution of the spatial distribution of the coupling coordination levels between HRA and HSU.KDE identifies key features of the data, such as central tendency (reflected by the peak position of the density curve), shape and modality (indicated by the number of peaks), regional differences (represented by variations in peak height), and dispersion (reflected by the width of the curve) [55]. The formula is as follows:

$$f(x) = \frac{1}{N_h} \sum_{i=1}^{n} k\left(\frac{x_i - x}{h}\right) \tag{14}$$

$$K(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) \tag{15}$$

where n is the sample size,h is the bandwidth of the kernel function,x_i is the independent and equally distributed observed value, and $k_{(x)}$ is the Gaussian kernel density function.

XGBoost (Extreme Gradient Boosting)

This study uses XGBoost to explain the key factors influencing CCD. Compared to traditional linear regression models, machine learning algorithms can effectively mine valuable information from the complex and uncertain relationships between CCD and its influencing factors. XGBoost is an ensemble learning algorithm based on gradient boosting, which improves model prediction accuracy by constructing multiple weak learners (such as decision trees) [56–58]. In this study, the influencing factors and CCD for each region from 2011 to 2022 were first integrated, followed by missing value imputation and normalization to ensure consistent variable scales. 80% of the data was used for the training set, and the remaining 20% for the test set. To optimize model performance, parameter tuning was performed based on the training set, with key hyperparameters including the maximum depth of the trees, learning rate, subsample ratio, and regularization terms. Grid search combined with fivefold cross-validation was used for optimization, ensuring the model's generalization ability and stability while preventing overfitting.

The performance of the model was evaluated using the coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE). The value of R^2 ranges from 0 to 1, with 1 indicating perfect fit and 0 meaning the model explains no variability. RMSE measures the average deviation between the model's predicted values and the actual values, with smaller values indicating higher prediction accuracy. MAE represents the average absolute difference between predicted and actual values, with smaller values indicating greater model precision.

SHAP (Shapley Additive Explanations)

With the advancement of computational capabilities in machine learning, models have become increasingly complex, making it more challenging to understand their internal mechanisms and decision-making processes. Enhancing model interpretability is a key approach to improving the generalization ability and credibility of machine learning algorithms. In 2017, Lundberg and Lee [59] introduced SHAP, a widely used method based on cooperative game theory (CGT). The core idea of SHAP is to explain the prediction results of various models (including classification and regression) by quantifying the contribution of each feature to the model's predictions [60].

Results

Comprehensive development index analysis of HRA and HSU

From 2010 to 2022, the comprehensive development index of HRA and HSU presented divergent trends. the comprehensive development index of health resource allocation (U_1) increased from 0.152 to 0.266, peaking at 0.325 in 2016 before a slight decline. he comprehensive development index of health resource allocation (U_2) rose from 0.216 to a peak of 0.349 in 2019, then decreased significantly to 0.306 in 2020, rebounded to 0.339 in 2021, and fell again to 0.289 in 2022 (Fig. 3a). At the regional level, the U_1 and U_2 indicators showed varied trends from 2010 to 2022. In the eastern region, U_1

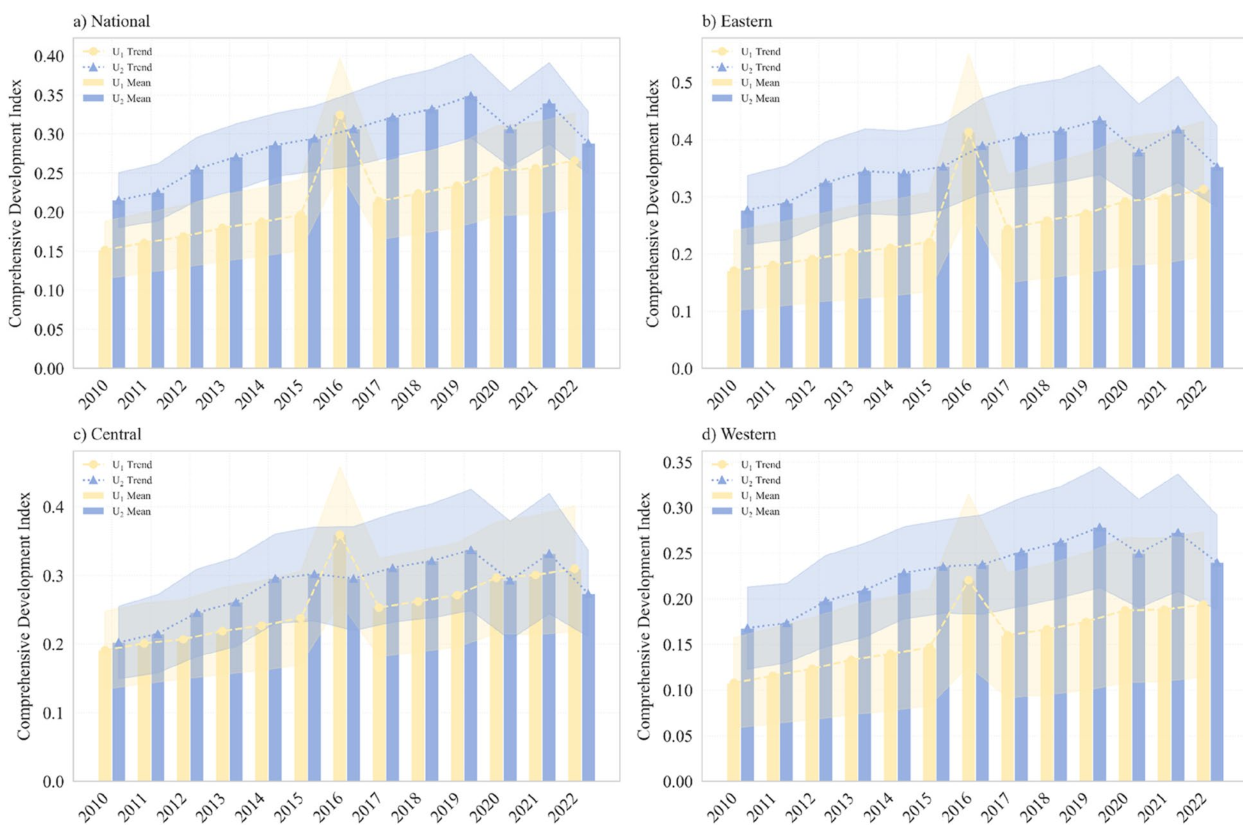

Fig. 3 Dynamic changes of comprehensive development index of health resource allocation and health

increased steadily from 0.171 in 2010 to 0.313 in 2022, peaking at 0.413 in 2016. U_2 rose to 0.434 in 2019 but declined to 0.353 in 2022. In the central region, U_1 grew from 0.191 in 2010 to 0.310 in 2022, with a peak of 0.359 in 2016, while U_2 reached 0.337 in 2019 and fell to 0.273 in 2022. The western region saw a smaller increase in U_1 from 0.108 in 2010 to 0.194 in 2022, peaking at 0.221 in 2016. U_2 in the west rose to 0.279 in 2019 but dropped to 0.240 in 2022(Fig. 3b-d). Overall, the eastern region demonstrated the strongest performance in both U_1 and U_2 indicators. The central region exhibited relatively stable growth, while the western region, despite its slower pace, showed an upward trend and retained significant potential for further improvement.

The temporal trend of the CCD

Based on the CCDM, this study calculated the CCD of HRA and HSU for 31 provinces in China from 2010 to 2022. The results are shown in Fig. 4.The national CCD exhibited a three-stage change pattern:"steady—fluctuating—slow growth."From 2010 to 2015, the CCD showed a steady upward trend, increasing from 0.398 to 0.450. From 2015 to 2017, the CCD fluctuated, presenting an"inverted V"shape. After a brief decline in 2016, it rebounded. From 2018 to 2022, the CCD slowly grew from 0.450 to 0.501, with an average annual growth rate of 2.14%. At the regional level, the Eastern region (0.518) > Central region (0.507) > Western region (0.408). At the provincial level, the top four provinces were Guangdong (0.719), Shandong (0.713), Sichuan (0.691), and Henan (0.688). The bottom four provinces were Hainan (0.245), Qinghai (0.230), Ningxia (0.225), and Tibet (0.199). Notably, the provinces with the highest growth rates were Tibet (6.78%), Ningxia (3.37%), Hainan (3.35%), and Qinghai (3.21%) (Table.S1).

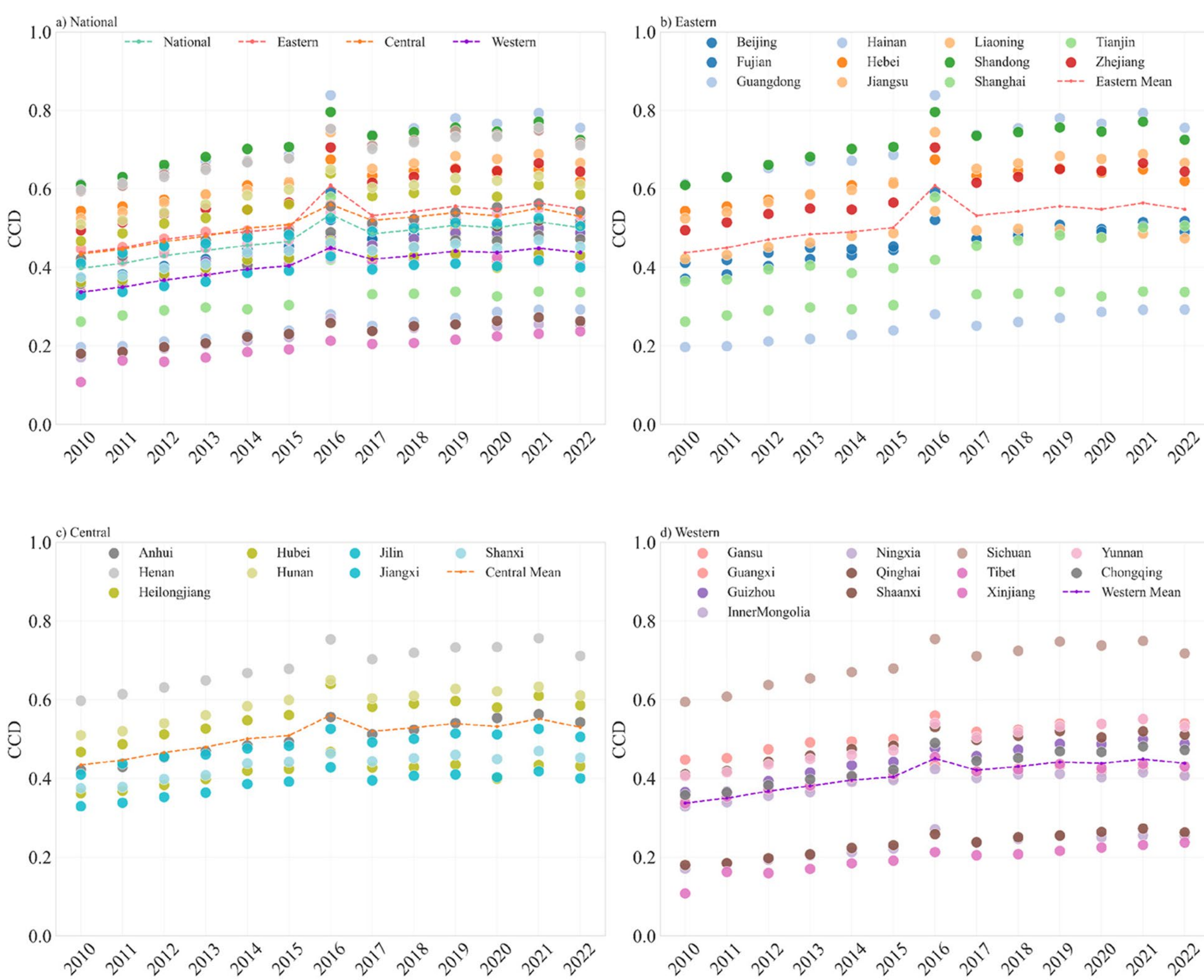

Fig. 4 Temporal changes in coupling coordination degree in China. **a** Dynamic changes in the coupling coordination degree across different regions. **b-d** Dynamic changes of the coupling coordination degree in the provinces of the eastern, central, and western regions, respectively

Spatial pattern of CCD

Further analysis of the spatial evolution of the coupling coordination types of HRA and HSU at the provincial level in China was conducted. The years 2010, 2015, 2020, and 2022 were selected as cross-sectional years during the study period to classify and visualize the CCD at the provincial level in China.

As shown in Fig. 5, the CCD of HRA and HSU at the provincial level in China was relatively low in 2010, with most provinces falling into the"Low serious"category or below. Among them, Tibet, Ningxia, Qinghai, Hainan, and other provinces had CCDs below 0.20, falling into the"Severe imbalance"category. Over time, the CCDs in these provinces improved, moving from the"Severe imbalance"category to the"Low serious"category. At the same time, some economically developed provinces, such as Guangdong, Shandong, Zhejiang, Jiangsu, and Henan, were already in the"Basic coordination"or"Good coordination"categories in 2010 and continued to maintain high levels in subsequent years.

Overall, from 2010 to 2022, the number of provinces in the"Severe imbalance"category decreased from 4 to 0, indicating that this category has essentially been eliminated. The number of provinces in the"Low serious"category decreased from 11 to 5, a reduction of approximately 54.55%. The number of provinces in the"Basic coordination"category increased from 14 to 18, an increase of about 28.57%. The number of provinces in the"Good coordination"category increased from 2 to 8, a remarkable growth of 300%. This indicates that, overall, the CCD of HRA and HSU at the provincial level in China showed a positive trend during the study period. However, the level of coordinated development remains unbalanced across regions, with some areas still facing significant challenges (Fig.S1).

To delve deeper into the spatiotemporal dynamics of CCD, this study employed the SDE method to track spatial shifts in CCD from 2010 to 2022. The results show that the spatial center of gravity of CCD remained located in Henan Province throughout the study period. However, noticeable migration patterns were observed over time. From 2010 to 2015, the center of gravity shifted northwest by approximately 20.5 km. Between 2015 and 2020, the trajectory moved southwest by 23.7 km. From 2020 to 2022, the center of gravity shifted northeast by 5.3 km. Overall, the migration trajectory of the spatial center of gravity reflects distinct stage-based changes in the development of HRA and HSU at different stages (Fig. 6).

Results of dynamic evolution analysis

KDE estimation

To visually illustrate the distribution evolution of the CCD between HRA and HSU across 31 provinces from 2010 to 2022, KDE was applied to analyze the distribution patterns and disparities of CCD. The results show that nationally the kernel density curve of CCD shifted leftward in the early stage and rightward, indicating an overall improvement in CCD over time. The main peak of the curve increased initially and then declined, while the width of the curve narrowed before widening, suggesting that although CCD improved, the growth rate gradually slowed. The right tail of the curve extended significantly, reflecting a growing disparity in CCD across provinces from 2010 to 2022. The curve also exhibited a transition from unimodal to bimodal and back to unimodal distribution, indicating a weakening of polarization and gradual movement toward greater balance at the national scale (Fig. 7a). Further analysis of the dynamic evolution of CCD in the eastern, central, and western regions revealed distinct patterns. In the eastern and central regions, the kernel density curves shifted steadily rightward each year, with the largest displacement observed in 2016, indicating continuous improvement in CCD. In the western region, the curve shifted leftward initially and then rightward, reflecting an early decline followed by recovery. Regarding the height and width of the curves, the peaks in the eastern and central regions first increased and then stabilized, with the curve widths narrowing before widening. In the western region, the peak height showed an upward trend, and the width gradually expanded, suggesting greater dispersion of CCD values from the perspective of curve extensibility, the right tails of the kernel density curve in the eastern and central regions showed a clear broadening trend, indicating an increasing internal gap in CCD within these regions. In the western region, the kernel density curve shifted leftward in the early stage and rightward, with the distribution changing from concentrated to dispersed. The pattern evolved from a multi-peak to a bimodal structure, suggesting a reduction in internal disparities, although overall imbalance remained evident. In terms of peak distribution, the eastern and central regions maintained a unimodal structure, reflecting relatively balanced development and smaller internal differences. In contrast, the western region exhibited a transition from multiple peaks to two peaks. Overall, from 2010 to 2022, CCD improved nationwide, but significant regional differences remained. The eastern and central regions demonstrated stronger gains in CCD, while the western region continued to lag, although internal disparities narrowed and showed gradual movement toward greater equilibrium (Fig. 7b).

Analysis of influencing factors

To explore the drivers of the CCD, this study XGBoost machine learning algorithm was applied. The model demonstrated strong predictive performance with an R^2

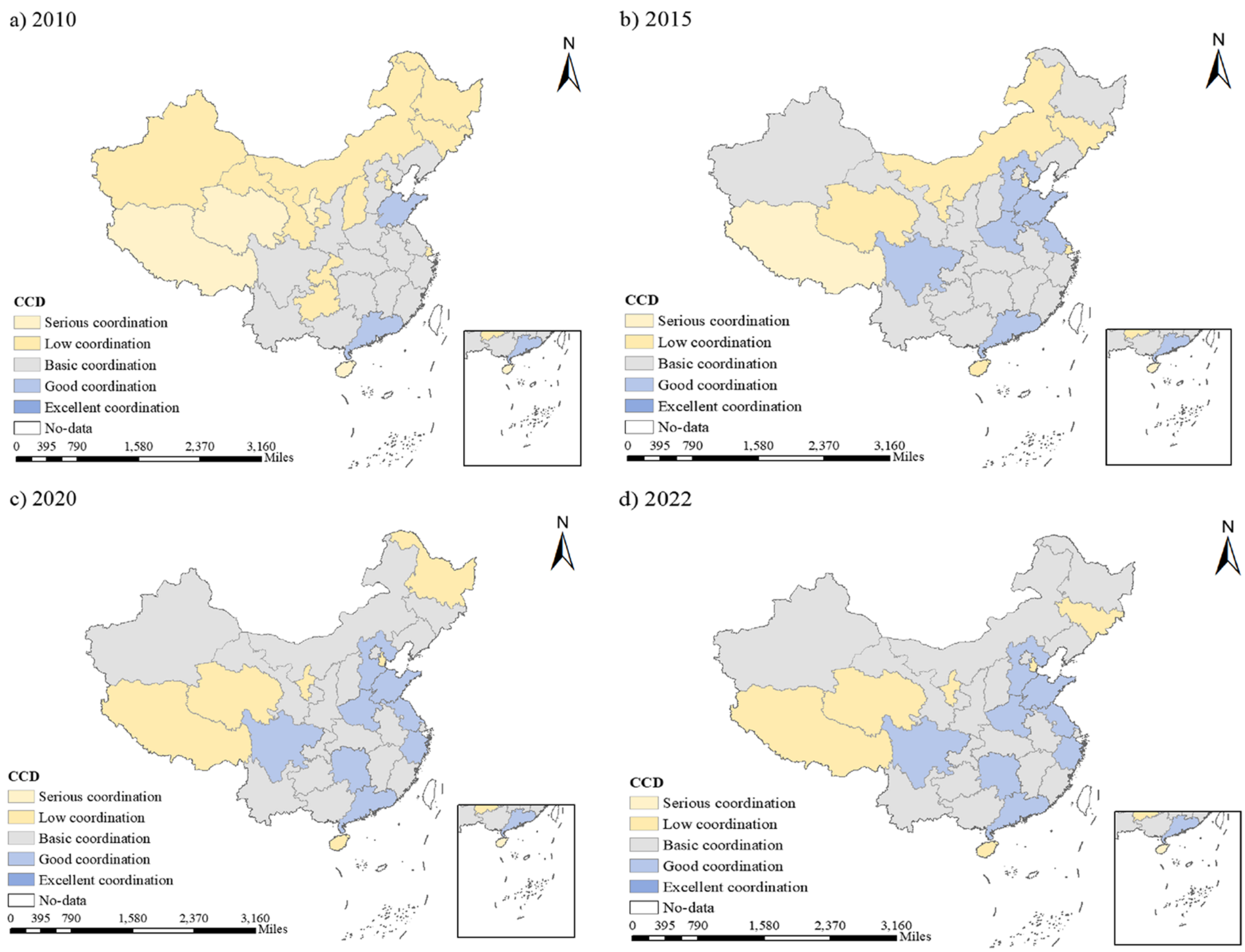

Fig. 5 Spatial distribution of the coupling coordination degree in China in selected years. **a** 2010. **b** 2015. **c** 2020. **d** 2022

of 0.94, RMSE of 0.05, and MAE of 0.04, indicating high accuracy and low error. As shown in Fig. 8a, total health expenditure has the most significant impact on CCD, with a contribution value of 0.441, followed by government health expenditure, with a contribution value of 0.342. The combined contribution of these two factors is 0.783, significantly higher than that of other factors. Figure 8b further emphasizes that healthcare investment emerged as the key factor, accounting for a total of 82.1%. Figure 8c explains the direction of the influencing factors effects, highlights that healthcare investment (total and government expenditure) and economic development level (GDP) exert a positive influence on CCD, suggesting that increases in these factors can effectively improve CCD.

Regional analysis shows that economic development and healthcare investment positively impact CCD across the eastern, central, and western regions. However, influencing factors exhibit regional heterogeneity: in the eastern region, URRBMI coverage positively impacts CCD; in the central region, traffic network density positively influences CCD; and in the western region, population density negatively affects CCD. (Table S2-S4 and Fig S2-S4).

Discussions

Temporal evolution and trend analysis of coupling coordination level

From 2010 to 2022, CCD between HRA and HSU in China exhibited a three-stage change pattern:"steady—fluctuating—slow growth,"with an average annual growth rate of 2.14%. This trend is similar to the findings of Chen et al. [61]. Between 2010 and 2015, the CCD steadily increased from 0.398 to 0.450. This stable growth during this period was primarily driven by the launch of China's New Healthcare Reform in 2009 [62]. The reform marked the comprehensive advancement of China's healthcare system, with key measures including the establishment of a universal health insurance system, improvement of the essential drug system, and promotion of public hospital reforms. These efforts contributed to the improvement in the CCD.

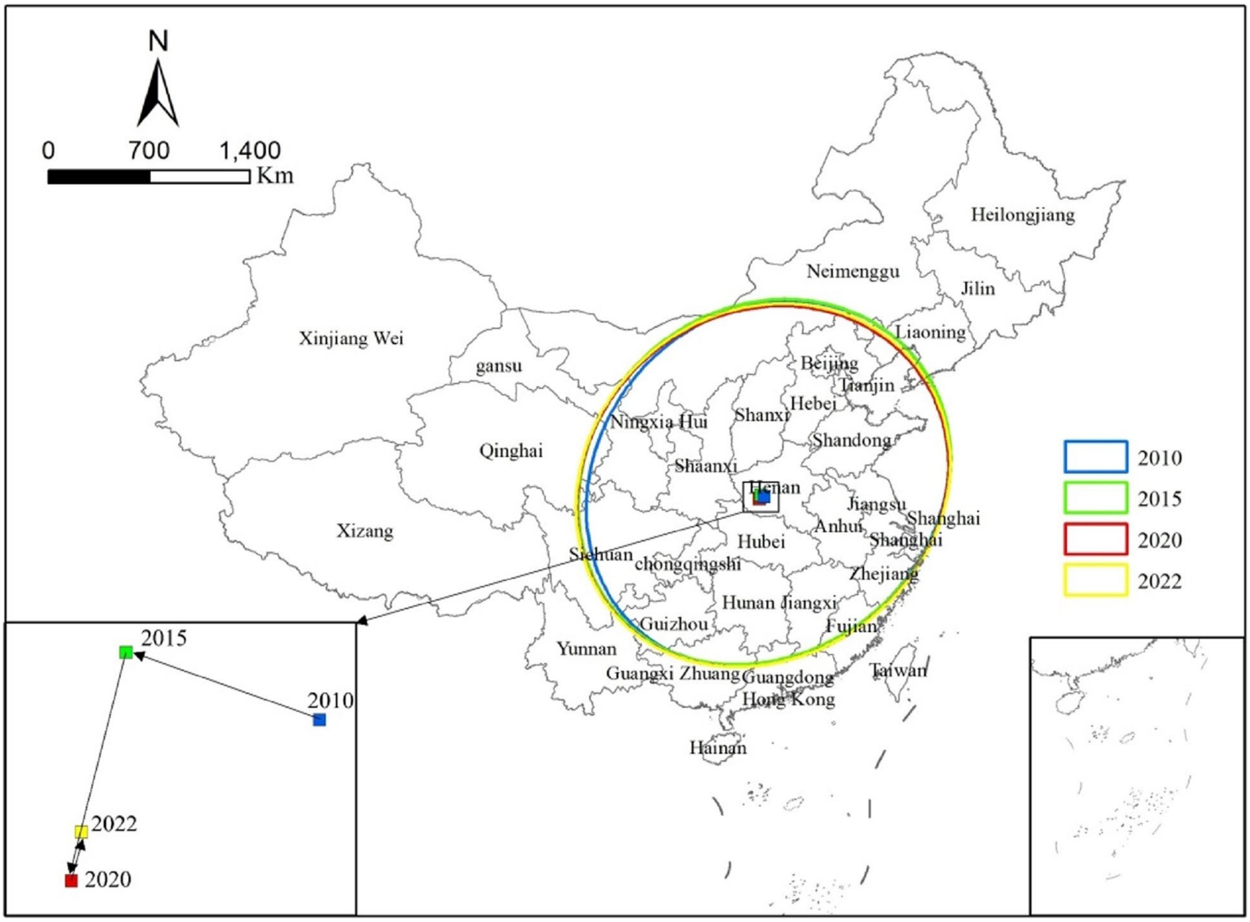

Fig. 6 Spatial distribution in the standard deviation ellipse of coupling coordination degree in China in selected years with a five-year interval

However, from 2015 to 2017, the CCD experienced fluctuations, exhibiting an"inverted V"pattern, with a brief decline in 2016 followed by a rebound. This fluctuation may be related to policy adjustments, the initial adaptation period of reform measures, and regional implementation disparities, especially in some central and western regions as well as rural areas, where the effects of reform required time to materialize. The implementation process of policies is often accompanied by a transition period, which is one of the reasons for the fluctuations in the coordination level between HRA and HSU. Between 2018 and 2022, the CCD slowly grew from 0.450 to 0.501, with an average annual growth rate of 2.14%. This growth was driven by the continuous optimization and deepening of policies, particularly the gradual and comprehensive implementation of medical insurance payment reforms. The DRG/DIP payment reform plan is expected to be completed between 2022 and 2024, and the further advancement of centralized drug procurement policies has reduced the burden of medication costs for patients [63]. These policies have not only optimized the allocation of medical resources but also improved the efficiency and accessibility of healthcare services, driving further development of the healthcare system and providing solid policy support for achieving the"Healthy China"strategic goals.

Regional differences and changes in spatial patterns

At the provincial scale, CCD shows a clear"higher in the south, lower in the north; higher in the east, lower in the west"spatial pattern, reflecting the imbalance in regional coordinated development. This result is consistent with the findings of Chen and other scholars [10, 61]. Provinces in the eastern coastal and central regions, such as Guangdong, Shandong, Zhejiang, Jiangsu, and Henan, generally exhibit higher CCD levels, benefiting from a solid economic foundation and higher per capita income, which provide stable financial support for health resource allocation. At the same time, economic prosperity has improved residents'health awareness, leading to higher levels of active utilization of health services [64]. In contrast, the western regions, such as Tibet, Qinghai, and

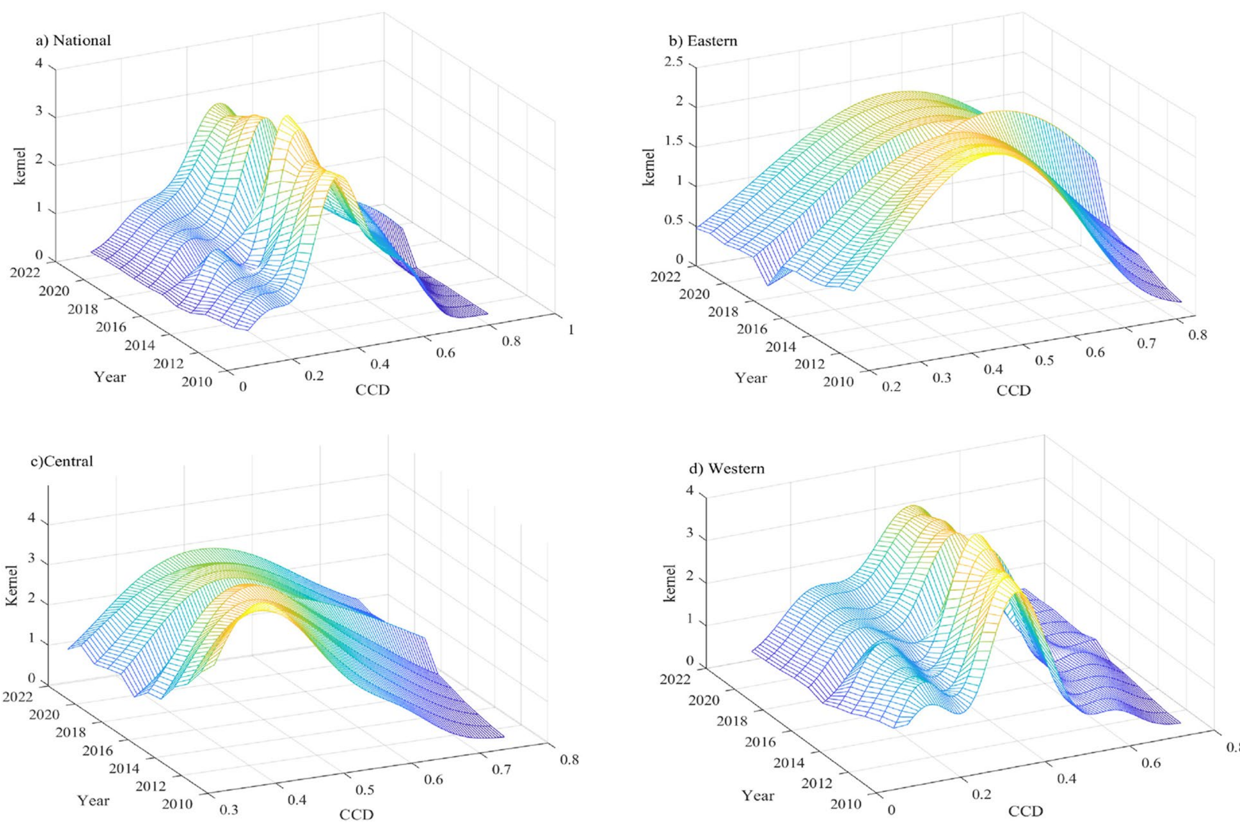

Fig. 7 Kernel density estimation of coupling coordination degree in China from 2010 to 2022. **a** National. **b** Eastern. **c** Central. **d** Western

Ningxia, face challenges due to long-standing geographical conditions, economic underdevelopment, and inadequate infrastructure, making it difficult to achieve scale effects in resource allocation. The accessibility and efficiency of health services in these areas are severely constrained [65]. Development bottlenecks within regions lead to a significant mismatch between resource supply capacity and service demand, thereby inhibiting the overall improvement of the coupling coordination level.

Further analysis at the regional scale using KDE reveals the spatiotemporal evolution dynamics of CCD. From 2010 to 2022, the kernel density curves for the eastern and central regions showed a sustained rightward shift, indicating an overall improvement in regional coordination levels, with slight expansion in distribution differences. In contrast, the western region showed a smaller rightward shift and a slight convergence in differences, indicating some internal coordination improvements, but the overall level remains low. The slowing of the multiploidization trend reflects the early effects of regional coordination mechanisms under policy guidance. The mechanisms behind the evolution of the CCD spatial pattern are multifaceted. First, the Chinese government places great importance on the development of the healthcare sector, with increasing investment each year, supported by various policies that encourage and promote hospitals at all levels, improving the capacity to supply healthcare services and alleviating the growing social demand for health services to some extent. Second, there has been a reasonable guide for social capital to participate in healthcare service provision. For example, the decision made by the Central Committee of the Communist Party of China,"On Further Deepening Reform and Promoting Chinese Modernization,"suggests guiding and standardizing the development of private hospitals, adopting a government-led and market-supplemented model, promoting fair competition in the healthcare market, and attracting more social capital to participate, thereby stimulating the vigorous development of the healthcare sector [66]. At the same time, the construction of urban medical alliances and the development of information platforms have enabled the interconnection of medical resources, enhanced the service capacity of grassroots institutions and improved the regional balance of healthcare services.

It is worth noting that, unlike previous studies that primarily focused on the spatiotemporal evolution of CCD, this study is the first to explore the coupling coordination

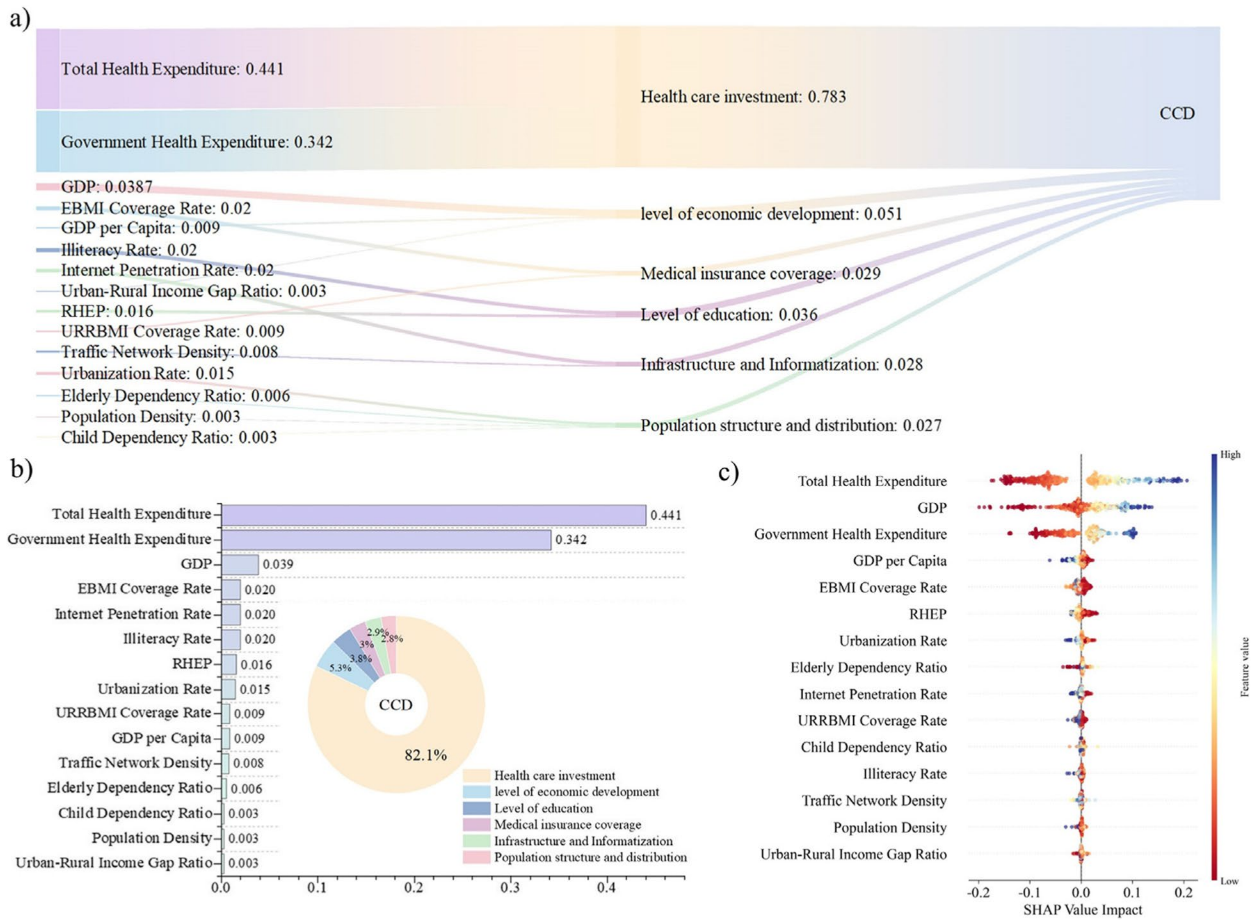

Fig. 8 Analysis of influencing factors of CCD. **a** Influencing factors and their categories. **b** A ring chart illustrates the proportion of each factor's contribution to the CCD. **c** Impact of individual factors on the model output, where each point represents a sample. The color intensity reflects the magnitude of the influencing factor, with red indicating higher values and blue indicating lower values. Samples on the right (SHAP > 0) indicate a positive contribution to CCD, while those on the left (SHAP < 0) indicate a negative contribution

evolution trajectory from the perspective of the spatial centroid shift, thereby filling a research gap in this area. The results show that the spatial centroid of CCD is in Henan Province, and the centroid trajectory exhibits a shift from southwest to northwest to northeast. This shift may be related to the combined effects of national policies, such as the"Belt and Road"initiative for border security, the Rural Revitalization Strategy, and population mobility. As Henan Province strengthens its role as a hub in the central region [67], HRA and HSU in surrounding areas gradually improve, promoting an increase in CCD. Interestingly, this migration trajectory aligns with Wang et al.'s research on the spatial pattern of population aging in China [55]. This finding suggests that policymakers should pay adequate attention to the dual trends of population aging and population mobility when allocating resources, to optimize the layout of healthcare resources and promote regional coordinated development.

Identification of driving mechanisms: overall trends and regional heterogeneity

This study found that both the level of economic development and healthcare investment have a significant positive impact on the coupling and coordinated development of overall HRA and HSU, which is consistent with the findings of Liu [68].Regions with better economic development typically have stronger fiscal capacity to invest in healthcare, effectively increasing both the quantity and quality of healthcare resources, thus laying a solid material foundation for the utilization of health services. At the same time, governments are better equipped to implement effective healthcare policies, promote healthcare system reforms, and prioritize support for rural and underdeveloped areas, improve healthcare conditions in these regions and, in turn, boosting overall coupling coordination. This common impact indicates that economic development and healthcare investment are key factors in enhancing CCD, offering general guidance for health policy formulation across different regions.

In terms of regional differences, the influencing factors vary across regions. In the eastern region, URRBMI coverage rate promotes CCD, This finding is like the results of Algazzar and Li et al. [69, 70]. This is mainly due to the high level of economic development, local governments and residents have stronger economic capacity, which can effectively implement the medical insurance policy, increase the insurance coverage, so that more residents can enjoy the medical insurance treatment, and promote the effective allocation and use of medical resources. In the central region, Traffic Network Density has a significant impact on CCD, benefiting from national support, such as the"13 th Five-Year Plan for Promoting the Rise of the Central Region"issued by the National Development and Reform Commission [71]. This policy has provided guidance for improving transportation infrastructure, facilitating the cross-regional flow and rational allocation of healthcare resources, and enhancing emergency response capabilities and resource utilization efficiency. In contrast, in the western region, due to its vast land area, sparse population, and dispersed resources, population density becomes the core factor limiting the improvement of CCD. This is closely related to the region's unique geographic conditions, which make healthcare resource allocation more difficult, result in higher unit service costs, and prevent the scaling of healthcare service provision, in line with the findings of Zhao et al. [21]. These geographical and demographic characteristics limit the coverage of healthcare resources, especially in remote areas where access to medical services is lower, further restricting the improvement of CCD.

Strengths

Compared to previous studies, this research presents two key innovations: First, the methodological innovation. This study is the first to introduce the XGBoost-SHAP machine learning method to explore the factors influencing the coupling coordination relationship between HRA and HSU. It overcomes the obvious limitations of traditional linear regression models when dealing with complex nonlinear relationships and variable interaction effects. Second, perspective innovation. This study adopts a systems theory approach to comprehensively and deeply explore the coupling coordination relationship between HRA and HSU, fully considering the complex relationships among the internal elements of the system and the external environment's impact on the system, providing new theoretical support and empirical evidence.

Limitations

This study has certain limitations. First, the indicator system is not comprehensive enough. China has not yet established a comprehensive evaluation indicator system for HRA and HSU, which limits the comprehensiveness of indicator selection and system construction in this study. Future research should further improve the relevant indicator system. Second, the data granularity is insufficient. Provincial-level panel data may mask intra-provincial differences. Future research should integrate county-level data and individual patient behavior data to more accurately reflect regional disparities. Third, the selection of influencing factors is limited. This study mainly focuses on relatively basic factors and does not comprehensively cover multidimensional factors that may affect CCD, such as population mobility, disease trends, etc. Future research plans will be based on a more complete indicator system and include variables from more dimensions, such as socio-economic factors, policies, and health demands.

Conclusions and policy recommendations

This study investigates the coordination relationship between HRA and HSU from a systems perspective. Using panel data from 31 provincial-level administrative regions in China from 2010 to 2022, the study employs the entropy method and the CCDM to measure the comprehensive development index and the CCD of HRA and HSU. The SDE model and KDE method are applied to explore the spatiotemporal variation characteristics of CCD across regions. Additionally, the XGBoost-SHAP machine learning method is used to analyze the key factors influencing CCD in different regions. The main conclusions are as follows: (1) During the study period, the comprehensive development levels of the subsystems of HRA and HSU showed an overall upward trend, but did not progress synchronously. (2) Over the study period, CCD exhibited a stable upward trend over time, with a spatial distribution pattern of higher values in the south, lower in the north, and higher in the east compared to the west. (3) The center of the CCD spatial migration trajectory for HRA and HSU was in Henan Province, with the overall movement shifting from northwest to southwest to northeast, with displacement distances of 20.5 km, 23.7 km, and 5.3 km, respectively. After initial fluctuations, the distribution became more concentrated, and the polarization phenomenon weakened. (4) CCD is primarily influenced by healthcare investment and economic development. Additionally, influencing factors exhibit regional heterogeneity: in the eastern region, URRBMI coverage positively impacts CCD; in the central region, traffic network density positively influences CCD; and in the western region, population density negatively affects CCD. Based on the conclusions of this study, the following recommendations are proposed:

Optimize healthcare resource allocation to enhance coupling coordination level

To address the"supply-demand mismatch"between HRA and HSU, the focus should be on enhancing CCD. For provinces with high CCD, such as Guangdong, Shandong, Zhejiang, and Jiangsu, existing resources should be fully utilized, promoting the downward flow of high-quality medical resources, reducing the"siphon effect"of large cities and major hospitals, and guiding patients for rational distribution to ease the pressure on large hospitals. At the same time, through the construction of medical alliances and targeted assistance programs, high-quality medical resources should be directed to grassroots healthcare institutions to enhance their capacity to provide services and meet the demand for local medical care. For western provinces with lower CCD, such as Tibet and Ningxia, it is crucial to support and train grassroots healthcare institutions and health personnel, increasing funding for these institutions and improving their infrastructure. Through targeted training programs, talent introduction, and other methods, the workforce of grassroots health professionals should be strengthened, thereby improving the quality of primary healthcare services and ensuring that the public can access nearby healthcare services with confidence.

Regional differentiated policies to promote regional coordinated development

Based on the influencing factors in different regions, differentiated policies should be developed according to the actual conditions of each region to promote coordinated regional development. For the eastern region, the government should increase healthcare insurance fund investment or provide policy incentives to improve insurance coverage, expand the scope of reimbursement, raise reimbursement rates, and reduce the medical burden on residents. At the same time, social capital should be encouraged to participate in the healthcare service industry, increasing the diversity of healthcare service supply. For the central region, optimizing the transportation network between urban and rural areas and increasing investment in transportation infrastructure are essential. Based on factors such as residential patterns and the geographic accessibility of medical services, efforts should be made to promote the rational flow of healthcare resources between urban and rural areas. For the western region, in addition to continued policy and economic support, special attention should be paid to the impact of population density. The number and scale of medical institutions should be scientifically set based on population distribution. Health education and outreach should be enhanced to stimulate the health needs of rural residents, improve their health awareness, and increase their self-care capacity.

Promote digital healthcare and telemedicine services

Some studies suggest that technologies such as virtual artificial intelligence and telemedicine have the potential to help China overcome current limitations in the allocation of healthcare resources [72]. We recommend promoting the development of digital healthcare and telemedicine services. By building digital health platforms and achieving the sharing and interconnection of medical information, healthcare resources can be integrated, and service efficiency can be improved. Additionally, establishing a unified electronic medical record system will facilitate patient access to healthcare and improve doctors'ability to diagnose and treat patients. A remote healthcare collaboration network should be established, connecting major hospitals in large cities with grassroots healthcare institutions in remote areas to enable expert remote consultations and teaching. Finally, strengthening the regulation of telemedicine services is necessary to ensure quality and safety, thus fully utilizing the advantages of digital and remote healthcare services, optimizing resource allocation, and improving the overall efficiency and accessibility of healthcare services.

Abbreviations

HRA	Health Resource Allocation
HSU	Health Service Utilization
CCDM	Coupling Coordination Degree Model
SHAP	Shapley Additive Explanations
CCD	Coupling Coordination Degree
GDP	Gross Domestic Product
RHEP	Ratio of Higher Education Population
SDE	Standard Deviation Ellipse
KDE	Kernel Density Estimation
RMSE	Root Mean Square Error
MAE	Mean Absolute Error

Supplementary Information

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Supplementary Material 1.

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Authors' contributions

XXM collected the data and wrote the first draft. HZL implemented the research and provided technical support. LQ conducted data comparisons and analysis. HMM assisted with data collection. CQL and MZM made key changes to the important content of the paper. FWL, ZSX, and LZC contributed ideas for revising the manuscript. GXY set the overall goal and reviewed the intellectual content of the article. The final draft was read and approved by all authors.

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Data availability
Data is provided within the manuscript or supplementary information files.

Declarations

Ethics approval and consent to participate
This article does not involve human participants or animal research. There is no behavior that does not conform to the ethical standards.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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