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Coupling coordination between health resource allocation and economic development in Xinjiang, China, 2010–2022

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Abstract

Background: Health resource allocation in remote and sparsely populated areas has structural problems that are completely different from those in densely populated areas. This paper selects data from 2010 to 2022 to explore the chronological evolution of coupling coordination between medical resources and regional economic development in Xinjiang, and screens out the core indicators affecting coordinated development.

Methods: Relying on official yearbook data to build an evaluation system divided into two subsystems: health resource allocation (6 indicators) and economic development (10 indicators), with a total of 16 indicators. The entropy weight method, coupling coordination degree model and grey relational analysis were applied in turn to measure the system's coordinated changes and identify the key influencing factors.

Results: The regional coupling coordination degree (D) increased from 0.116 in 2010 to 0.631 in 2022, and the development status changed from severe imbalance to primary coordination. The whole process is divided into three stages: the imbalance stage of 2010–2013 (D = 0.116–0.387), the transition stage of 2014–2015 (D = 0.433–0.467), and the coordination stage of 2016–2022 (D = 0.502–0.631); the COVID-19 pandemic caused D to fall briefly to 0.597 in 2020. The results of grey relational analysis show that medical manpower indicators have the highest correlation with the economic system: licensed physicians (0.803), health technicians (0.700), and registered nurses (0.695), while the correlation of healthcare institutions is only 0.492. The correlation of consumption indicators in the economic dimension is better than that of income indicators: total retail sales (0.647), urban consumption expenditure (0.644), and rural consumption expenditure (0.644) are all higher than the income indicators (0.631–0.636).

Conclusions: In the coordinated development of local medical care and the economy, the role of health workforce density is far greater than the scale of hardware facilities; the driving effect of residents' consumption capacity on the allocation of medical resources is stronger than the income level. It can be seen that areas with limited resources and geographical dispersion should give priority to the construction of medical talent, and open up channels for the transformation of residents' consumption into medical service utilization, so as to promote high-quality coordination between the two systems.

Keywords: Health resource allocation; Economic development; Coupling coordination; Grey relational analysis; Xinjiang; Resource-limited settings

1. Background

Health resources are the material foundation of the medical service system, and the rationality of their distribution directly determines the accessibility and operational efficiency of services. Against the background of population ageing, a high incidence of chronic diseases and increasing demand for medical treatment, the challenge of matching limited resources with continuously growing medical demand has become a core difficulty in global health governance. The World

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Health Organization (WHO) takes universal health coverage (UHC) as the core path to achieving health equity [1]. Pichon-Riviere and others confirmed that there is no linear relationship between the growth of medical expenditure and life expectancy, and that there are significant differences in resource conversion efficiency between countries [2].

Two complementary theoretical frameworks support the medical-economic correlation analysis in this study. The WHO health system building blocks framework divides the system into six core modules: service delivery, health workforce, information, medical products, financing and governance, which constitute the basis for the operation of the medical system [3]. The framework points to the two-way promotion between medical resources and the economy: economic growth expands medical financial investment, improves national health and optimizes human capital, which in turn boosts labor productivity and supports economic growth [4]. However, this two-way virtuous cycle depends on the system and the capital allocation model, which directly determine the efficiency of converting medical investment into service capacity [5]. Research on low- and middle-income countries (LMICs) adds that economic growth alone cannot automatically increase the medical treatment rate, and income needs to be converted into actual medical consumption through medical insurance coverage, ability to pay, willingness to seek medical treatment and other channels [6]. This article empirically examines the linkage relationship between the two: manpower and infrastructure indicators represent service delivery and health workforce, medical expenditure corresponds to financing, economic indicators reflect the macro development environment, and resident consumption indicators measure the demand-side support baseline.

China exhibits substantial regional variation in economic base, population density, and geographic conditions, and the coordination between health resources and economic systems shows clear spatial differentiation. Since the 2009 healthcare reform, total health resources have increased steadily, yet urban–rural and inter-regional structural mismatches persist. Gong et al. applied the coupling coordination model at the national level [7]; Xu et al. examined coordination in Sichuan Province [8]; Guo et al. explored patterns in the Beijing–Tianjin–Hebei region [9]. Methodologically, combining coupling coordination degree with grey relational analysis enables both the characterization of dynamic evolution and the identification of sensitive contributing indicators. However, most existing studies focus on eastern provinces or national aggregates. For Xinjiang — a vast northwestern border region with a highly dispersed population and large service radii — a detailed long-term analysis of coordinated evolution between health resources and economic development, and its key contributors, remains absent.

Xinjiang has a vast territory, and the accessibility of basic medical care at the grass-roots level is insufficient, while the supply of medical resources faces high space costs and development pressures [10]. Existing literature mostly discusses the fairness of local medical resources, and systematic research on long-term timing of coupling and coordination is relatively scarce [11]. Based on this, this paper chooses 2010–2022 as the observation cycle, and uses entropy weighting, coupling coordination, and grey relational analysis to sort out the characteristics of co-evolution, and identify core indicators to provide a basis for the optimization of medical resources and the construction of health systems in border areas.

2. Methods

2.1 Study design and data sources

The research scope is the Xinjiang Uygur Autonomous Region, with a time span from 2010 to 2022. Medical resource data are taken from the China Health Statistics Yearbook, the China Health and Wellness Statistics Yearbook and Xinjiang local statistics; economic data come from the China Statistical Yearbook, the Xinjiang Statistical Yearbook, the National Bureau of

Statistics, and Xinjiang Bureau of Statistics; the policy reference document is the Guiding Opinions on Promoting the Construction of the Tiered Diagnosis and Treatment System. In order to ensure data comparability, priority was given to continuous annual data from the yearbook, and we cross-checked indicators of different calibers from the same source, with all data sorted by October 2025.

There are two reasons for choosing 2010 as the starting year: first, the national medical reform in 2009 opened a period of centralized policy adjustment, and the data after 2010 can intuitively reflect the results of the reform; second, by October 2025, the core indicators of this study had been updated to 2022, forming a complete continuous time series. Based on 2010, the Xinjiang GDP deflator was used to deflate various monetary indicators. All data are public statistics and do not require ethical approval.

2.2 Indicator system construction

Combining existing research results [12–14] and the international medical system evaluation framework [3,6] to build a dual-system comprehensive evaluation index system. The health resource allocation subsystem measures medical supply, talent allocation and capital investment level, with a total of 6 indicators: number of healthcare institutions (X_1), hospital beds per 1,000 population (X_2), health technicians per 1,000 population (X_3), licensed (assistant) physicians per 1,000 population (X_4), registered nurses per 1,000 population (X_5), and total health expenditure (X_6). The economic development subsystem covers the regional economic base, investment and consumption level, industrial structure, urbanization, and resident income, with a total of 10 indicators: per capita GDP (Y_1), total retail sales of consumer goods (Y_2), total fixed asset investment (Y_3), urban per capita consumption expenditure (Y_4), rural per capita consumption expenditure (Y_5), urbanization rate of the permanent population (Y_6), proportion of secondary industry in GDP (Y_7), proportion of tertiary industry in GDP (Y_8), urban per capita disposable income (Y_9), and rural per capita disposable income (Y_{10}).

All indicators are positive indicators, meaning that larger values indicate higher levels of health resource allocation or economic development. Indicator selection followed three principles: representativeness — indicators comprehensively reflect the main dimensions of each subsystem; data availability — all indicators are continuous official statistical data published during 2010–2022; and comparability — indicator definitions and statistical calibers remain consistent across years. Weights are presented in Table 1.

Table 1 Evaluation indicators and subsystem entropy weights for health resource allocation and economic development

Target System	Indicator Code	Indicator Name	Unit	Nature	Weight
Health Resources	X_1	Number of healthcare institutions	Count	Positive	0.036
Health Resources	X_2	Hospital beds per 1,000 population	Beds	Positive	0.050
Health Resources	X_3	Health technicians per 1,000 population	Persons	Positive	0.056
Health Resources	X_4	Licensed (assistant) physicians per 1,000 population	Persons	Positive	0.101
Health Resources	X_5	Registered nurses per 1,000 population	Persons	Positive	0.054

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Health Resources	X_6	Total health expenditure	100 million yuan	Positive	0.056
Economic Development	Y_1	Per capita GDP	Yuan	Positive	0.058
Economic Development	Y_2	Total retail sales of consumer goods	100 million yuan	Positive	0.047
Economic Development	Y_3	Total fixed asset investment	100 million yuan	Positive	0.062
Economic Development	Y_4	Urban per capita consumption expenditure	Yuan	Positive	0.064
Economic Development	Y_5	Rural per capita consumption expenditure	Yuan	Positive	0.096
Economic Development	Y_6	Urbanization rate of permanent population	%	Positive	0.097
Economic Development	Y_7	Proportion of secondary industry in GDP	%	Positive	0.068
Economic Development	Y_8	Proportion of tertiary industry in GDP	%	Positive	0.058
Economic Development	Y_9	Urban per capita disposable income	Yuan	Positive	0.050
Economic Development	Y_{10}	Rural per capita disposable income	Yuan	Positive	0.048

Note: Weights are entropy weights within each subsystem. The health resource allocation system and the economic development system were standardized and weighted separately.

2.3 Data standardization

Due to the different dimensions and scales of the indicators, range standardization was applied for dimensionless processing. Let x_{ij} be the original value of the j-th indicator in the i-th year, and z_{ij} be the standardized value. All indicators are positive, and the calculation formula is:

$$z_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}$$

where $\max(x_j)$ and $\min(x_j)$ represent the maximum and minimum values of the j-th indicator during 2010–2022, respectively. After standardization, all indicator values fall within the [0,1] interval.

2.4 Entropy weight method

The entropy weight method is an objective weighting technique widely used in multi-indicator comprehensive evaluation [15,16]. All 16 indicators across both subsystems were standardized together, and entropy weights were calculated across all indicators jointly, ensuring that the sum of all 16 weights equals 1.000. This approach allows the relative information content of each indicator to be compared on a common basis. The calculation steps are as follows:

Step 1: Calculate the proportion of the j-th indicator in the i-th year:

$$p_{ij} = \frac{z_{ij}}{\sum_{i=1}^{n} z_{ij}}$$

Step 2: Calculate the information entropy of the j-th indicator:

$$e_j = -k \sum_{i=1}^{n} p_{ij} \ln p_{ij}$$

$$k = \frac{1}{\ln n}$$

where k = 1/ln(n), n = 13, representing the 13 years from 2010 to 2022. When $p_{ij} = 0$, $p_{ij} \ln p_{ij} = 0$.

Step 3: Calculate the difference coefficient:

$$d_j = 1 - e_j$$

Step 4: Calculate the entropy weight of each indicator:

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j}$$

where the summation is across all 16 indicators (m = 16), ensuring that the sum of all weights equals 1.

Step 5: Calculate the comprehensive evaluation indices of the two subsystems:

$$U_1 = \sum_{j=1}^{m_1} w_j z_{ij} \ , \qquad U_2 = \sum_{j=1}^{m_2} w_j z_{ij}$$

2.5 Coupling coordination degree model

To analyze the coordination relationship between the two subsystems, a coupling coordination degree model was constructed. Let U_1 be the comprehensive evaluation index of health resource allocation and U_2 be that of economic development. The coupling degree C is calculated as:

$$C = \frac{\sqrt[2]{U_1 U_2}}{U_1 + U_2}$$

where $C \in [0,1]$. A larger C value indicates stronger interaction between the two subsystems. The coupling degree reflects only the strength of association, not the level of coordination. When both subsystems are at low levels, the coupling degree may still be high — a "low-level coupling" that does not represent coordinated development. Therefore, the comprehensive coordination index T and coupling coordination degree D are introduced:

$$T = \lambda U_1 + \mu U_2$$

$$D = \sqrt{C \times T}$$

where λ and μ represent the contribution coefficients of the health resource allocation and economic development subsystems, respectively, with λ + μ = 1. This study considers the two subsystems equally important and takes λ = μ = 0.5. $D \in [0,1]$, with larger values indicating higher coordination levels. Classification standards are presented in Table 2.

Table 2 Classification standards for coupling coordination degree

Coupling Coordination Degree *D*	**Coordination Level**
$0 \le D < 0.1$	Extreme imbalance
$0.1 \le D < 0.2$	Severe imbalance
$0.2 \le D < 0.3$	Moderate imbalance

$0.3 \leq D < 0.4$	Mild imbalance
$0.4 \leq D < 0.5$	On the verge of imbalance
$0.5 \leq D < 0.6$	Barely coordinated
$0.6 \leq D < 0.7$	Primary coordination
$0.7 \leq D < 0.8$	Intermediate coordination
$0.8 \leq D < 0.9$	Good coordination
$0.9 \leq D \leq 1.0$	Excellent coordination

Note: This table classifies coordination levels based on the coupling coordination degree D value.

2.6 Grey relational analysis

Grey relational analysis is used to distinguish the core driving indicators of the two systems. The method adapts to small sample time-series data, relying on the geometric similarity of the sequence curve to judge the strength of the association, without strict data distribution and sample size constraints.

We took the economic comprehensive index U_2 as the reference sequence, and the standardized data of each medical indicator as the comparative sequence, and measured the correlation between medical indicators and the economic system; we took the medical comprehensive index U_1 as the reference sequence, and the standardized data of each economic indicator as the comparative sequence, and measured the correlation between economic indicators and the medical system. Taking the subsystem comprehensive index as the benchmark is a general research paradigm in the field of coupling coordination, which can accurately screen the single indicators with the highest degree of matching with overall development.

Step 1: Determine the reference sequence and comparison sequences. Let the reference sequence be:

$$X_0 = \{x_0(1), x_0(2), \ldots, x_0(n)\}$$

and the comparison sequence be:

$$X_j = \{x_j(1), x_j(2), \ldots, x_j(n)\}$$

where n = 13 and j denotes the j-th comparison indicator.

Step 2: Calculate absolute differences:

$$\Delta_j(k) = |x_0(k) - x_j(k)|$$

Step 3: Calculate the grey relational coefficient:

$$\xi_j(k) = \frac{\Delta_{min} + \beta\Delta_{max}}{\Delta j(k) + \beta\Delta max}$$

where Δmin and Δmax are the global minimum and maximum values among all absolute differences, and β is the resolution coefficient, taken as 0.5.

Step 4: Calculate the grey relational degree:

$$r_j = \frac{1}{n}\sum_{k=1}^{n} \xi_j(k)$$

where $r_j \in [0,1]$. A larger value indicates greater consistency between the indicator and the reference sequence in terms of change trends.

2.7 Statistical analysis

All data organization, indicator standardization, weight calculation, coupling coordination degree estimation, and grey relational analysis were performed using Microsoft Excel. All figures were drawn using Excel.

3. Results

3.1 Indicator weights

The indicator weights calculated by the entropy weight method are presented in Table 1. In the health resource allocation subsystem, the weight of licensed (assistant) physicians per 1,000 population was the highest (0.101), followed by health technicians per 1,000 population (0.056) and total health expenditure (0.056), while the number of healthcare institutions had the lowest weight (0.036). In the economic development subsystem, the urbanization rate of permanent population had the highest weight (0.097), followed by rural per capita consumption expenditure (0.096) and the proportion of secondary industry in GDP (0.068), while total retail sales of consumer goods had the lowest weight (0.047). The weight distribution indicates that physician density and urbanization level are the indicators with the greatest information entropy variation within the health resource and economic systems, respectively. All subsequent coupling coordination degree calculations were based on these weights.

3.2 Comprehensive indices and coupling coordination characteristics

Table 3 lists the measurement results of the Xinjiang Medical Composite Index U_1, Economic Composite Index U_2 and coupling coordination degree (D) from 2010 to 2022. Figure 1 shows the trend of temporal changes.

At the comprehensive index level, U_1 fluctuated upward from 0.003 in 2010 to 0.285 in 2022; it reached a peak of 0.303 in 2019, and fell back to 0.261 in 2020 under the impact of the COVID-19 pandemic, before gradually recovering in 2021 and 2022 to 0.273 and 0.285. U_2 continued to grow steadily, from 0.063 in 2010 to 0.556 in 2022, and only fell slightly to 0.485 in 2020, with continued growth in the rest of the years. Overall, the local economic growth rate from 2010 to 2022 was higher than the development rate of medical resources, and the momentum of economic growth was stronger.

From 2010 to 2022, the D value rose steadily from 0.116 to 0.631, and the coordination level was upgraded from severe imbalance to primary coordination. In stages: 2010–2013 was the imbalance stage (D = 0.116–0.387), when the overall development level of the two systems was low; 2014–2015 was the transition stage (D = 0.433–0.467), when the coordination trend initially appeared; in 2016, D broke through 0.5 to 0.502 for the first time, entering the barely coordinated stage and continuing until 2018 (D = 0.534–0.558); in 2019, D reached 0.619, entering the primary coordination stage; it fell to 0.597 in 2020 due to the impact of the epidemic, and quickly recovered to 0.622 and 0.631 in 2021 and 2022. Except for 2010, the coupling degree C over the years was higher than 0.915, proving the long-term high-intensity interaction between the two systems; the comprehensive coordination index T increased from 0.033 in 2010 to 0.421 in 2022, reflecting the synchronous development of medical care and the economy.

Table 3 Comprehensive indices and coupling coordination degree of health resource allocation and economic development in Xinjiang, 2010–2022

Year	U_1	U_2	C	T	D	Coordination Level
2010	0.003	0.063	0.407	0.033	0.116	Severe imbalance
2011	0.045	0.106	0.915	0.075	0.263	Moderate imbalance
2012	0.075	0.149	0.944	0.112	0.325	Mild imbalance
2013	0.113	0.2	0.961	0.156	0.387	Mild imbalance
2014	0.138	0.255	0.955	0.197	0.433	On the verge of imbalance
2015	0.159	0.299	0.952	0.229	0.467	On the verge of imbalance
2016	0.193	0.328	0.966	0.261	0.502	Barely coordinated
2017	0.212	0.384	0.957	0.298	0.534	Barely coordinated
2018	0.221	0.437	0.945	0.329	0.558	Barely coordinated
2019	0.303	0.486	0.973	0.394	0.619	Primary coordination
2020	0.261	0.485	0.954	0.373	0.597	Barely coordinated
2021	0.273	0.547	0.943	0.41	0.622	Primary coordination
2022	0.285	0.556	0.946	0.421	0.631	Primary coordination

Note: U_1 represents the comprehensive evaluation index of health resource allocation,U_2represents the comprehensive evaluation index of economic development, C represents the coupling degree, T represents the comprehensive coordination index, and D epresents the coupling coordination degree. C、T、and D were calculated according to the coupling coordination degree model in this study, all based on unrounded data, with values rounded to three decimal places.

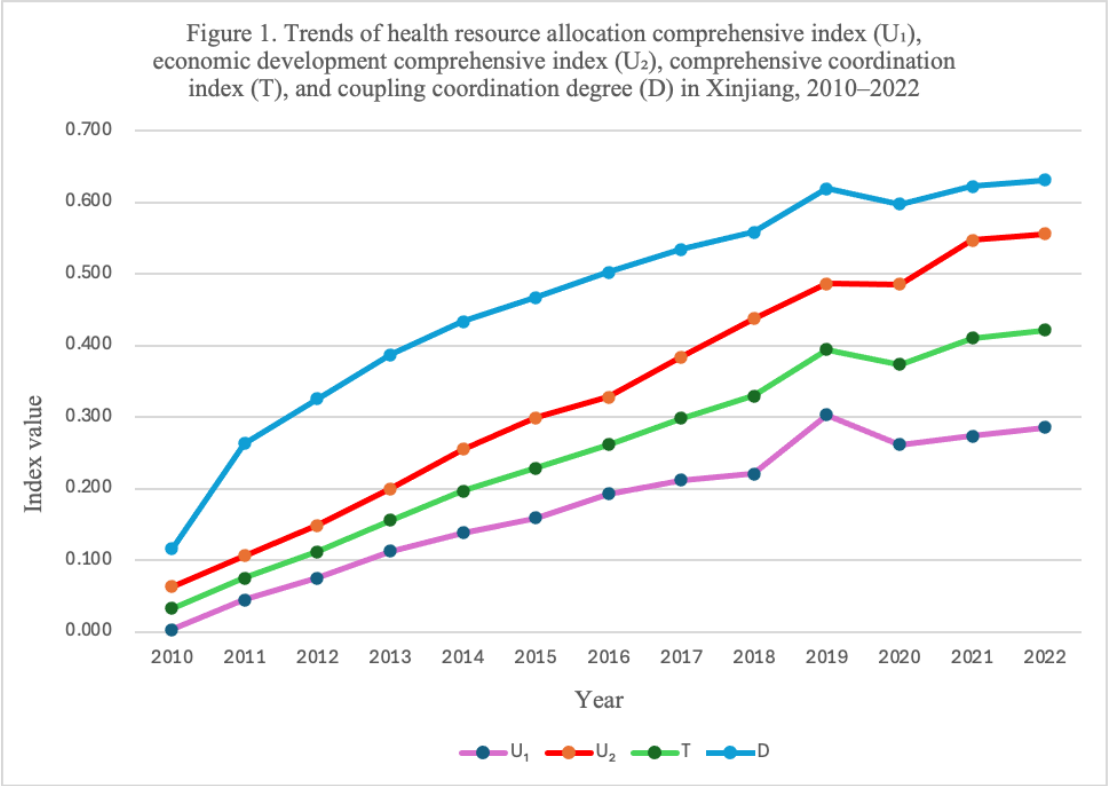


Figure 1. Trends of health resource allocation comprehensive index(U_1),economic development comprehensive index(U_2),comprehensive coordination index(T),and coupling

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coordination degree(D) in Xinjiang,2010-2022

3.3 Grey relational analysis

As shown in Table 4, the grey relational degrees between health resource indicators and the economic development system ranged from 0.492 to 0.803. The ranking was: licensed (assistant) physicians per 1,000 population (0.803) > health technicians per 1,000 population (0.700) > registered nurses per 1,000 population (0.695) > total health expenditure (0.684) > hospital beds per 1,000 population (0.637) > number of healthcare institutions (0.492). The relational degree of licensed physicians was the highest and the only indicator exceeding 0.8, indicating that workforce-related indicators track most closely with economic development.

As shown in Table 5, the grey relational degrees between economic indicators and the health resource system ranged from 0.547 to 0.647. The ranking was: total retail sales of consumer goods (0.647) > urban per capita consumption expenditure (0.644) = rural per capita consumption expenditure (0.644) > per capita GDP (0.641) > proportion of tertiary industry in GDP (0.640) > total fixed asset investment (0.638) > urban per capita disposable income (0.636) > rural per capita disposable income (0.631) > urbanization rate (0.629) > proportion of secondary industry in GDP (0.547). Consumption-related indicators (urban 0.644, rural 0.644) consistently exceeded income-related indicators (urban 0.636, rural 0.631).

Table 4 Grey correlation degrees between health resource allocation indicators and the economic development system

Indicator Code	Indicator Name	Grey Correlation Degree	Rank
X_4	Licensed (assistant) physicians per 1,000 population	0.803	1
X_3	Health technicians per 1,000 population	0.700	2
X_5	Registered nurses per 1,000 population	0.695	3
X_6	Total health expenditure	0.684	4
X_2	Hospital beds per 1,000 population	0.637	5
X_1	Number of healthcare institutions	0.492	6

Note: Resolution coefficient β=0.5; grey correlation degrees are the means of the correlation coefficients for each year from 2010 to 2022; rankings are determined by correlation degree from highest to lowest.

Table 5 Grey correlation degrees between economic development indicators and the health resource allocation system

Indicator Code	Indicator Name	Grey Correlation Degree	Rank
Y_2	Total retail sales of consumer goods	0.647	1
Y_4	Urban per capita consumption expenditure	0.644	2
Y_5	Rural per capita consumption expenditure	0.644	2
Y_1	Per capita GDP	0.641	4
Y_8	Proportion of tertiary industry in GDP	0.640	5

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Y3	Total fixed asset investment	0.638	6
Y_9	Urban per capita disposable income	0.636	7
Y_{10}	Rural per capita disposable income	0.631	8
Y_6	Urbanization rate of permanent population	0.629	9
Y_7	Proportion of secondary industry in GDP	0.547	10

Note: Resolution coefficient β=0.5; grey correlation degrees are the means of the correlation coefficients for each year from 2010 to 2022; rankings are determined by correlation degree from highest to lowest.

4. Discussion

4.1 Temporal evolution and policy context

From 2010 to 2022, Xinjiang coupling coordination (D) improved greatly, completing the transformation from severe imbalance to primary coordination. The evolution process is divided into three stages. The regional medical supply in the 2010–2013 imbalance stage was weak, and economic support for health undertakings was insufficient; the 2014–2015 transition stage initially formed a coordinated trend; after 2016 it entered the coordination stage, and the time node coincides with the comprehensive implementation of the national tiered diagnosis and treatment system. In September 2015, the State Council issued the Guiding Opinions on Promoting the Construction of the Tiered Diagnosis and Treatment System, and Xinjiang issued supporting implementation documents the following year. Existing research confirms that the tiered diagnosis and treatment system can optimize the layout of resources and release grass-roots medical demand [17,18], and county hospitals cooperating with reform can open up the barriers to resource circulation [19]. The D value reached a high level in 2019, and the epidemic in 2020 briefly depressed the index, which then rebounded rapidly, consistent with research conclusions related to health system resilience [20].

Except for 2010, the coupling degree (C) remained high in previous years, and the medical-economic interaction was close and stable; the comprehensive coordination index (T) continued to rise, and the quality of the two major fields improved simultaneously. On the one hand, the continuous improvement in the level of coordination comes from the improvement in financial medical investment capacity brought about by economic growth, and on the other hand, it relies on medical system reform to promote the sinking of resources.

4.2 Health workforce as the strongest supply-side correlate

Grey relational analysis shows that the correlation between health workforce indicators and the economic system is significantly higher than that of other supply indicators: licensed physicians (0.803), health technicians (0.700) and registered nurses (0.695) are much higher than healthcare institutions (0.492) and the bed index (0.637), which is consistent with international research. The GBD 2019 analysis confirms that the scale of the health workforce is significantly positively correlated with UHC, and talent density is the core predictive variable of effective medical coverage [20]. In resource-limited settings, talent shortage, unbalanced distribution, and skill mismatch are the core constraints: funds can quickly expand hardware, but the talent training cycle for professionals is long and it is difficult to retain them [21]. Domestic research also supports that the imbalance in manpower allocation widens the regional medical efficiency gap [22]. Public health talents are concentrated in economically developed areas, and the reserves of western provinces are insufficient [23].

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The role of medical capital investment cannot be ignored, but its effectiveness depends on the efficiency of transformation. The correlation of total health expenditure (0.684) falls between human resources and infrastructure indicators, indicating that funds are the foundation of development, but if they cannot be transformed into talents and service capabilities, the investment benefits will be limited. International studies have pointed out that a large amount of medical funds in developing countries are lost due to inefficient allocation [24]. Chen and Ding proposed that the structure of capital investment directly affects medical-economic synergy [25]. If funds are only used to expand beds and medical institutions, it is difficult to improve the level of coordination without supporting talent construction. Therefore, the expansion of medical funds must simultaneously promote the cultivation of talents.

4.3 Household consumption as a demand-side factor

The economic indicators with the highest correlation with the medical system are all measures of residents' consumption: total retail sales (0.647), urban consumption expenditure (0.644), and rural consumption expenditure (0.644). The correlation of consumption indicators is consistently higher than that of income indicators (urban 0.636, rural 0.631), indicating that the impact of actual consumption behavior on the allocation of medical resources exceeds that of potential income purchasing power.

This result can be explained by the Grossman health demand model [26]. The theory proposes that health is a long-term capital product, and medical demand is a derivative demand for health. Income affects the medical treatment rate in two ways: directly improving the ability to pay and increasing the willingness to invest in preventive health [27]. The higher correlation of consumption indicators reflects a lag in income transmission, meaning that income growth needs to be transformed into consumption and medical behavior in order to in turn promote the optimization of medical resources.

The conversion of income to medical service utilization cannot be automatically realized. China's basic medical insurance covers more than 95% of the population, but unexpected diseases can still increase family medical expenditure and squeeze daily consumption [28]. Out-of-pocket (OOP) expenditure in global LMICs accounts for a high proportion of routine medical expenditure, and high out-of-pocket costs are among the main reasons that people delay or give up seeking medical care [29]. Merely increasing residents' income is not enough to optimize medical supply. It is necessary to improve medical insurance coverage at the same time, improve the accessibility of grass-roots medical care, and promote health literacy.

5. Policy implications and transferability

The research findings provide a number of policy references. First, the strong correlation of the health workforce shows that the priority of talent investment in resource-constrained areas is higher than that of infrastructure expansion. The follow-up health plan can set annual growth targets for licensed physicians, with supporting special training, remuneration incentives, and promotion channels to improve the talent system. Second, the D value was quickly restored after the impact of the epidemic, which proved the importance of diversified capital channels and flexible service models to building health system resilience. Third, the core role of consumption indicators shows that demand-side policies can work in conjunction with supply-side construction to activate medical demand by expanding medical insurance coverage and reducing OOP expenditure.

The Xinjiang research experience has value for popularization in similar regions with vast geography and scattered population. The conclusion that the density of talents determines the level of medical-economic coordination is in line with the global literature [20,21] and adapts to the

development status of areas with tight financial constraints. That consumption indicators have a higher correlation than income indicators indicates that the economic barriers to medical treatment have a significant impact, and reducing out-of-pocket expenses is a necessary measure for infrastructure support [30]. The implementation of the tiered diagnosis and treatment system was synchronized with the time of upgrading in the level of coordination, which proves that areas with limited geographical conditions can promote system coordination by relying on institutional reform to push resources downward and support talent reserves [31]. The generalizability of the conclusion depends on the regional basic medical network, the financial space for talent incentives, and the implementation of reform and other conditions [32].

6. Strengths and limitations

This article has obvious research advantages. The existing literature rarely conducts long-term medical-economic coupling and coordination research in vast border and sparsely populated areas. This article fills the gap in Xinjiang regional research; it integrates entropy weighting, coupling coordination, and grey relational analysis into a unified analysis framework, and at the same time completes the dynamic evolution pattern and core indicator identification, making the research system comprehensive.

There are still several limitations in the research. First, we only analyze the overall characteristics of the whole of Xinjiang, and do not distinguish the internal differences between northern and southern Xinjiang, urban and rural areas, and various prefectures. In the future, regional heterogeneity can be explored in greater depth. Second, coupling coordination and grey relational analysis only verify statistical correlation between variables, and cannot determine causality. In the future, panel regression and quasi-experimental methods can be used to explore the intrinsic mechanisms. Third, taking the U1 and U2 comprehensive indexes as the reference sequence is a common practice in the field, but the results are easily affected by the weight structure. In the future, different indicators can be used to measure and optimize. Fourth, the number of indicators in the two subsystems is unbalanced, with 6 medical items and 10 economic items. The sum of the weights is 0.353 and 0.647 respectively, which may indirectly affect the measurement accuracy of U1, U2 and D values. Fifth, the 13-year observation cycle fits the policy window period, but the sample size for long-term trend analysis is still insufficient. Sixth, the use of provincial-level summary data cannot reflect the details of the equitable allocation of medical resources within the region.

7. Conclusions

This paper measures the coupling coordination relationship between Xinjiang health resource allocation and economic development from 2010 to 2022, and draws three core conclusions. First, the level of coordination has been greatly improved, and the D value has increased from 0.116 to 0.631, achieving the leap from severe imbalance to primary coordination. Second, health workforce indicators (physicians, technicians, nurses) have a much stronger driving effect on coordinated development than all infrastructure indicators. Third, the correlation of consumer economic indicators with medical resource allocation is higher than that of income indicators, highlighting the key value of demand-side factors. In summary, areas with limited resources and geographical dispersion should give priority to building a health workforce team, open up channels for the conversion of residents' consumption capacity into effective utilization of medical services, and promote medical-economic coordination from scale growth to quality improvement.

List of abbreviations

D: Coupling coordination degree; C: Coupling degree; T: Comprehensive coordination index; U_1: Comprehensive evaluation index of health resource allocation; U_2: Comprehensive evaluation

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index of economic development; UHC: Universal health coverage; OOP: Out-of-pocket; LMICs: Low- and middle-income countries; WHO: World Health Organization; GBD: Global Burden of Disease; GDP: Gross domestic product

Authors' contributions

LJ: Conceptualization, Writing — original draft, Writing — review & editing, Visualization, Formal analysis. AT: Data curation, Investigation, Formal analysis, Validation. HX: Supervision, Methodology, Project administration, Writing — review & editing. All authors read and approved the final manuscript.

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Availability of data and materials

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Ethics approval and consent to participate

Not applicable. This study used publicly available statistical data from official yearbooks and government databases. No human participants, patient data, or identifiable personal information were involved.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

Generative AI statement

During the preparation of this manuscript, the authors used DeepSeek (an AI language model) for language polishing and structural editing. All AI-assisted content was reviewed, edited, and verified by the authors, who take full responsibility for the accuracy and integrity of the final manuscript.

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