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Identification of Factors Influencing Out-of-county Hospitalizations in the New Cooperative Medical Scheme

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Summary: Throughout the duration of the New Cooperative Medical Scheme (NCMS), it was found that an increasing number of rural patients were seeking out-of-county medical treatment, which posed a great burden on the NCMS fund. Our study was conducted to examine the prevalence of out-of-county hospitalizations and its related factors, and to provide a scientific basis for follow-up health insurance policies. A total of 215 counties in central and western China from 2008 to 2016 were selected. The total out-of-county hospitalization rate in nine years was 16.95%, which increased from 12.37% in 2008 to 19.21% in 2016 with an average annual growth rate of 5.66%. Its related expenses and compensations were shown to increase each year, with those in the central region being higher than those in the western region. Stepwise logistic regression reveals that the increase in out-of-county hospitalization rate was associated with region (X1), rural population (X2), per capita per year net income (X3), per capita gross domestic product (GDP) (X4), per capita funding amount of NCMS (X5), compensation ratio of out-of-county hospitalization cost (X6), per time average in-county (X7) and out-of-county hospitalization cost (X8). According to Bayesian network (BN), the marginal probability of high out-of-county hospitalization rate was as high as 81.7%. Out-of-county hospitalizations were directly related to X8, X3, X4 and X6. The probability of high out-of-county hospitalization obtained based on hospitalization expenses factors, economy factors, regional characteristics and NCMS policy factors was 95.7%, 91.1%, 93.0% and 88.8%, respectively. And how these factors affect out-of-county hospitalization and their interrelationships were found out. Our findings suggest that more attention should be paid to the influence mechanism of these factors on out-of-county hospitalizations, and the increase of hospitalizations outside the county should be reasonably supervised and controlled and our results will be used to help guide the formulation of proper intervention policies.

Key words: New Cooperative Medical Scheme (NCMS); out-of-county hospitalization rate; Bayesian network (BN); Max-Min Hill-Climbing algorithm; related factors

The New Cooperative Medical Scheme (NCMS) is a heavily subsidized voluntary health insurance program that was piloted nationwide in 2003 to safeguard the health of 750 million rural populations from high health care expenditures, improve access to health care services and promote the harmonious development of society[1]. After a five-year trial period, the NCMS was fully implemented throughout China in 2008. The NCMS lasted for a total of 14 years until 2016 when the NCMS was combined with the Urban Residents Basic Medical Insurance System (URBMI), and the Urban and the Rural Residents Medical Insurance System (URRMI) was established[2]. Available healthcare data from the implementation of the NCMS until its end could be meaningful in guiding future policies.

The medical burden of rural residents and the impoverishment, as well as "poverty caused by, returning to poverty due to illness" problem, have been relieved since the implementation of the NCMS[3]. As basic medical needs were gradually met, the rural residents gradually enhanced their pursuit of better medical care outside of the county with the growth

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of the economic ability. The rise in the rate of out-of-county visits will aggravate the irrational structure of inpatients and lead to a substantial increase in out-of-county hospitalization expenses. High out-of-county compensation payment caused by rapid increase in out-of-county medical expenses will over-consume medical insurance funds within the county, which poses an increasingly serious threat to the balance of the NCMS fund and increase the operational risk of the fund. The state and local governments of China attach great importance to out-of-county medical treatment, and a series of policies, such as primary diagnosis at grassroots level and the hierarchical diagnosis and treatment system, have been introduced to ensure that the participating patients first choose primary medical institutions; policies intended to result in 90% of diseases being resolved inside the local county[4].

Medical insurance systems in Britain, the United States, Indian and other countries are also implementing its corresponding hierarchical diagnosis and treatment system to solve the problems of uneven distribution of health resources and low utilization rate of primary health care institutions. To find out the root cause of the problem, foreign scholars have conducted some researches on medical visit behavior and its influencing factors[5–9]. Compared with other countries, the existing research on the Chinese NCMS primarily focused on the effect of the NCMS[10–12], the NCMS fund safety[13], the NCMS medical expenses burden[14–16], and the accessibility or fairness of the NCMS[17–19]. There remains a relative paucity of studies on medical visit behavior and its influencing factors in China.

Consequently, we applied a Bayesian network (BN) optimization with the Max-Min Hill-Climbing (MMHC) hybrid algorithm to jointly model the status of out-of-county medical treatment and its influencing factors and examine how they interrelate in central and western China during the duration of the NCMS. For China, the current hierarchical diagnosis and treatment system is still in the continuous exploratory stage, and we attempt to provide a scientific basis for both patients and supervision of the flow of funds in the health insurance policy developed in the future. This country-specific study will increase the understanding of China's hierarchical diagnosis and treatment status and provide valuable clues for adjustment and correct planning of international health insurance policies.

1 METHODS

1.1 Data Collection and Study Sampling

The National Health Commission Statistical Information Center (NHCSIC) of China provided all of the data, which had been collected and reported by local health departments. Given regional distribution, economy and other factors, key assessment was performed across 13 representative provinces in the underdeveloped central and western regions of China, and a total of 215 sampled counties included in the current analysis. The data spanned from 2008 to 2016, covering the duration of the NCMS in China. The geographic locations of sampled counties and distribution of out-of-county hospitalization rate were plotted using ArcGIS 10.2 and illustrated in fig. 1.

1.2 Variables and Pre-processing

Data for all variables assumed to be related to the rate of out-of-county visits were collected through a review of the literature and domain knowledge. The annual inflation rate of the Bank of China from 2008 to 2016 was used for monetary conversion and the final results for money related variables were inflated to the year of 2016 based on this factor. Some of the variables were calculated as follows (All of the indicators are within the scope of the NCMS.): (1) Y=OHN/THN×100% (Y: out-of-county hospitalization rate; OHN: out-of-county hospitalization number; THN: total hospitalization number); (2) OHCR=OHCC/OHC×100% (OHCR: compensation ratio of out-of-county hospitalization cost; OHCC: out-of-county hospitalization cost compensation; OHC: out-of-county hospitalization cost); (3) OHCP=OHC/THC×100% (OHCP: the proportion of out-of-county hospitalization cost; THC: total hospitalization cost); (4) OHPP=OHCC/FTP×100% (OHPP: the proportion of out-of-county hospitalization compensation payment; FTP: the total payment of the insurance fund).

Continuous variables were discretized to meet the variable requirements of Bayesian networks. In accordance with the evaluation criterion of the Chinese grading diagnosis and treatment system in which 90% of disease treatments should occur within the county, the out-of-county hospitalization rate was classified into one of two groups, either a non-standard group (>10%) or a standard group (≤10%). The discretization of continuous variables was based on the Chimerge-χ^2 method, which is a general, robust and supervised algorithm that uses the χ^2 statistic to discretize numeric attributes from the bottom to the top, taking all category information into consideration[20]. It is superior to both the equidistance method and the equifrequency method, which are commonly used in BN classification of continuous variables. The variables and the results of the classification are shown in table 1.

1.3 MMHC Hybrid-based BN

A BN consists of a directed acyclic graph (DAG)[21, 22]. The nodes in the graph correspond to the random variables, and the directed edges represent the correlation among the random variables. If a directed edge points from node X to another node Y, then X is specified as the parent node of Y and Y becomes a child node of X. It is worth noting that directed edges

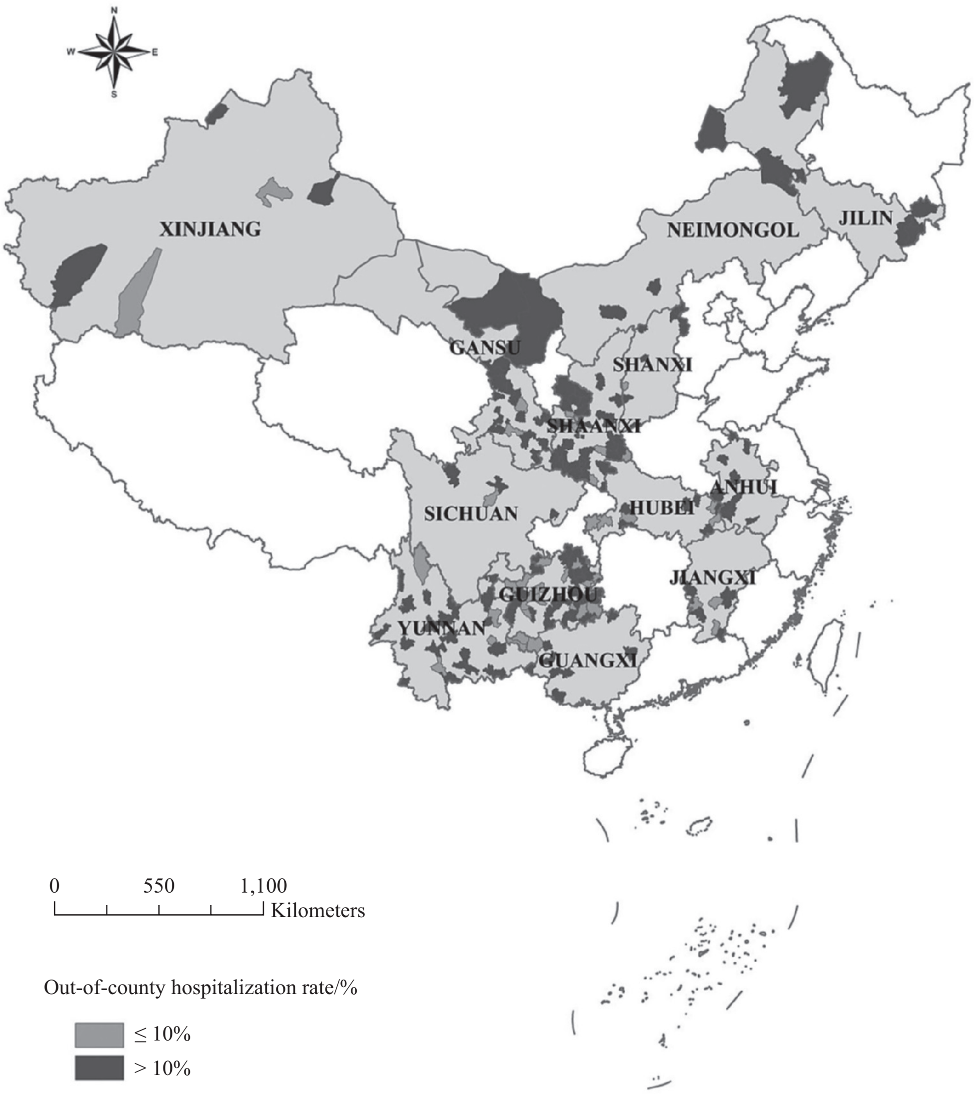

Fig. 1 The geographic locations of sample counties and distribution of out-of-county hospitalization rate

reflect probabilistic dependencies between adjoined nodes rather than the causal relationship between a target variable and explanatory variables[23]. There is a conditional probability distribution table (CPT) at each node, which shows the quantification of the correlation strength between variables[24]. A BN is a mathematical structure that compactly expresses a joint probability distribution P among a set variables X[25, 26]. The joint probability distribution of variable xi can be obtained from the chain rules of probability theory as follows: $P(X)=P(x_1, x_2, \cdots, x_n)=\prod_{i=1}^{n}(x_i|x_1, x_2, \cdots, x_n)=\prod_{i=1}^{n}(x_i|\pi(x_i))$, where $\pi(x_i)$ represents the direct parent node of xi.

BN intuitively reflects the potential interrelationship and the strength of dependency relationship between related factors[27]. Compared with logistic regression, a BN is not limited to independent variables[28] and the estimation of the subsequent probability of any target variable given any set of conditional variables is allowed[29–31].

MMHC is a hybrid algorithm combining ideas from local learning, constraint-based, and search-and-score techniques in an effective and principled mode, which uses the framework reconstructed by Max-Min Parents and Children (MMPC)[32]. First, a conditional independence test is used to reduce the complexity of search space. The framework of the Bayesian network is then reconstructed, and the edges are oriented using a Bayesian-scoring greedy hill-climbing search[25, 33]. The MMHC hybrid algorithm in BN structure learning results in an average performance and various metrics that are superior to several prototypical and advanced algorithms such as Sparse Candidate, phenotypically constrained-optimal inter vention (PC), Optimal Reinsertion, and Greedy Search[25, 34].

1.4 Statistical Analysis

Stepwise logistic regression was carried out for the most relevant variables and identifying nodes in the BNs. MMHC hybrid-based BNs were performed

Table 1 Variable assignment of the possible influence factors of out-of-county hospitalization rate

Variables	Factors	Abbreviation	Assignments*	Control group
Dependent variables	Out-of-county hospitalization rate	Y	<10% = Low; >0% = High	Low
Independent variables	Region	X1	0 = Central region; 1 = Western region	Central region
	Rural population	X2	<160 thousand people = Low; >160 thousand people = High	Low
	Rural per capita net income	X3	<4859.71¥ = Low; >4859.71¥ = High	Low
	Per capita GDP	X4	<24573.84 ¥ = Low; >24573.84 ¥ = High	Low
	Per capita funding amount of NCMS	X5	<131.54 ¥ = Low; >131.54 ¥ = High	Low
	Compensation ratio of out-of-county hospitalization cost	X6	<37.47% = Low; >37.47% = High	Low
	Per-time average in-county hospitalization cost	X7	<1403.71¥ = Low; 1403.71–2456.27¥ = Medium; >2456.27¥ = High	Low
	Per-time average out-of-county hospitalization cost	X8	<7741.43¥ = Low; 7741.43–10829.57¥ = Medium; > 10829.57¥ = High	Low
	County population density	X9	<78 people per km^2 = Low; >78 people per km^2 = High	Low
	Per capita fund expenditure	X10	<216.42¥ = Low; >316.42¥ = High	Low
	National poverty county or not	X11	0 = No; 1 = Yes	No

*The Chimerge-χ^2 method was used to discretize continuous variables.

in order to explore the factors related to out-of-county hospitalization. The parameter learning and the CPT were based on the maximum likelihood estimation (MLE) method. The following three indicators were used to evaluate the BN model: a) Accuracy (the proportion of correctly predicted samples among all predictions); b) AUC (the area under the ROC curve, which reflects the discrimination of the BN model); c) Bayesian Information Criterion (BIC) score (represents the goodness of model fit)[32, 35, 36]. Stepwise logistic regression analysis was carried out using the 9.4 version of the SAS statistical analysis package. R software was used for: a) Chimerge-χ^2 method (package discretization); b) performing MMHC hybrid-based BN structure learning (package pROC and package bnlearn). The BN model plotting and CPT computing were performed using the Netica software.

2 RESULTS

2.1 Out-of-county Hospitalizations in Central and Western China

Fig. 1 clearly showed a high incidence of out-of-county hospitalization rate greater than 10%. It can be seen from table 2 that the inpatient number and the out-of-county hospitalization rate in sampled regions (n=215) increased each year, with an average annual growth rate (AAGR) of 19.29% and 5.66%, respectively. The total out-of-county hospitalization rate in 9 years was 16.95%, which increased from

Table 2 Out-of-county hospitalization status of NSCM sample county, 2008-2016

Year	△OHNc	Y (%)	#OHCc (million yuan)	**OHCCc (million yuan)	OHCR (%)	OHCP (%)	OHPP (%)	X8/X7 (%)
2008	1665	12.37	12.76	4.27	33.83	40.57	30.11	4.84
2009	2172	12.14	18.25	6.65	36.03	41.65	31.28	5.17
2010	2736	14.11	23.84	8.74	37.03	42.31	32.47	4.47
2011	3709	16.81	35.50	15.31	41.96	48.12	38.98	4.59
2012	4648	16.93	46.07	23.79	49.13	46.26	39.16	4.22
2013	5522	17.05	57.55	29.57	50.16	47.21	39.79	4.35
2014	5858	18.69	68.25	32.37	47.80	49.28	41.56	4.23
2015	6245	19.27	73.72	33.32	44.88	49.47	40.66	4.10
2016	6826	19.21	76.59	35.69	45.84	48.14	39.54	3.90
*AAGR (%)	19.29	5.66	25.11	30.36	3.87	2.16	3.46	-0.3

*AAGR: average annual growth rate; △OHNc: out-of-county hospitalization number/county. #OHCc: out-of-county hospitalization cost/county; **OHCCc: out-of-county hospitalization cost compensation/county

12.37% in 2008 to 19.21% in 2016. At the same time, there was a sharp growth in the out-of-county hospitalization expenses and compensation amount over the 9 years; their share in the total amount of hospitalization expenses and the total payment of the insurance fund was also shown to have a general upward trend. When compared with the prevalence of out-of-county hospitalizations in central and western China, the central region appeared to have a higher prevalence than the western region from 2008 to 2016, as shown in fig. 1 and fig. 2. The out-of-county hospitalization rates in central region and western region were 18.63% and 16.32%, respectively.

2.2 Factor Selection Using Stepwise Logistic Regression Analysis

The variables to be used for the BN model were selected using the stepwise regression methodology (α_{in}=0.10, α_{out}=0.15). All available variables which might influence the out-of-county hospitalization rate were included as independent variables and the variables for the high and low out-of-county hospitalization rate were included as dependent variables in the Logistic regression model (table 3). The result revealed that the out-of-county hospitalization rate (Y) was significantly associated with the following variables: region (X1), rural population (X2), per capita per year net income (X3), per capita GDP (X4), per capita funding amount of NCMS (X5), compensation ratio of out-of-county hospitalization cost (X6), per time average in-county hospitalization cost (X7), and per time average out-of-county hospitalization cost (X8).

2.3 BN Model

A marginal probabilistic BN model with 9 nodes and 15 directed edges was built according to the variables that showed significant differences in the stepwise logistic regression analysis, as shown in fig. 3. The values for accuracy, the AUC area, and the BIC score of the BN model were 88.06%, 81.70% and –9846.25, respectively, which demonstrates that the BN model has good predictive accuracy, discrimination and goodness of fit. The data presented in fig. 3 indicate that there is a direct connection between X3, X4, X6, X8 and the out-of-county hospitalization rate, and an indirect connection between X1, X2, X5, X7 and the out-of-county hospitalization rate in the network structure. The marginal probability of the high out-of-county hospitalization rate was 81.7%.

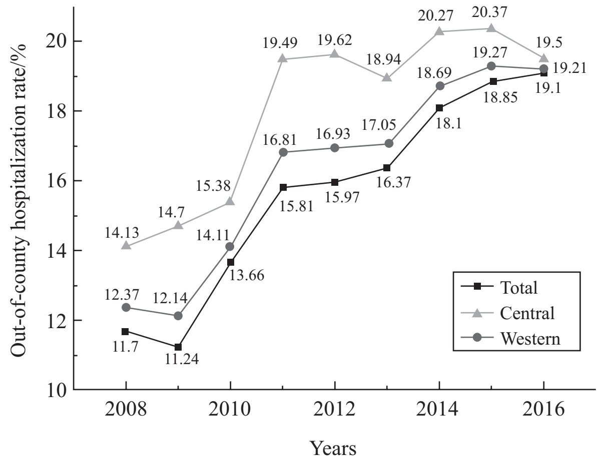

Fig. 2 Prevalence of out-of-county hospitalization in central and western China, 2008-2016

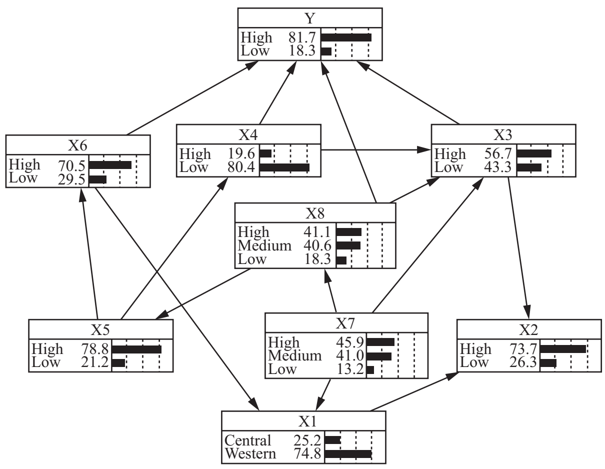

Fig. 3 Marginal probabilities as estimated using the BN model

Table 3 Stepwise logistic regression on out-of-county hospitalization rate

Variables	β	SE	OR	95 % CI	*P*
Intercept	–2.0031	0.4029			<0.0001
Region	–0.4840	0.2025	0.616	(0.414–0.917)	0.0169
Rural population	–0.5985	0.2251	0.550	(0.354–0.854)	0.0078
Rural per capita net income	2.7737	0.2262	16.017	(10.282–24.952)	<0.0001
Per capita GDP	0.9017	0.3514	2.464	(1.237–4.906)	0.0103
Per capita funding amount of NCMS	0.4834	0.2060	1.622	(1.083–2.428)	0.0190
Compensation ratio of out-of-county hospitalization cost	0.7985	0.1834	2.222	(1.551–3.183)	<0.0001
Per-time average in-county hospitalization cost					
Medium	0.5903	0.2327	1.805	(1.144–2.847)	0.0112
High	0.8023	0.3382	2.231	(1.150–4.328)	0.0177
Per-time average out-of-county hospitalization cost					
Medium	2.2768	0.2505	9.745	(5.964–15.924)	<0.0001
High	3.4896	0.3732	32.774	(15.770–68.115)	<0.0001

The correlation, as well as its intensity, between the out-of-county hospitalization rate and its influencing factors was quantitatively analyzed using the resulting BN probabilistic model, in which the conditional probabilities P(y|xi) was computed. The scenarios for a few different observations (Grey color nodes, displayed in fig. 4) were used to update the probabilities of the rest of variables in the process of BN propagation. Four aspects factors including hospitalization expenses, economy, regional characteristics, and NCMS policy were considered. The observations for two variables (X7 and X8) are shown in fig. 4A. In summary, if a county has a high X7 and X8 then the detection of a high out-of-county hospitalization rate increases from 81.7% to P (high out-of-county hospitalization rate | high X7, high X8) = 95.7%. If a county has a high X3 and X4, it has a 91.1% probability of having a high out-of-county hospitalization rate (fig. 4B). The probability increases to 93.0% when the county has a low X2 and belongs to central X1 (fig. 4C). If a county has a high X5 and X6, the probability of having a high out-of-county hospitalization rate is estimated to be 88.8% (fig. 4D).

Similarly, the BN allowed for abductive reasoning; according to a determined probability to have a high out-of-county rate, we can infer the function of the different factors causing it. In addition, we can also compute the interrelationship between the related factors (X) of the out-of-county hospitalization rate from the BN model. For example, if a county has a high X3 and X4, the probability of having a high X5 and a high X7 reaches 99.8% and 59.6%, respectively (fig. 4B), revealing the impact of the economic level on hospitalization expenses and the NCMS funds.

3 DISCUSSION

The increasing rates of out-of-county hospitalizations jeopardize the funding of the NCMS and represent a serious problem for the current medical insurance system. Our results showed that the total out-of-county hospitalization rate in nine years was 16.95%, which increased from 12.37% in 2008 to 19.21% in 2016 with an average annual growth rate of 5.66%. The marginal probability of having a high out-of-county hospitalization rate was 81.7% from 2008 to 2016 in the central and western regions of China, which highlights that 81.7% of counties failed to meet

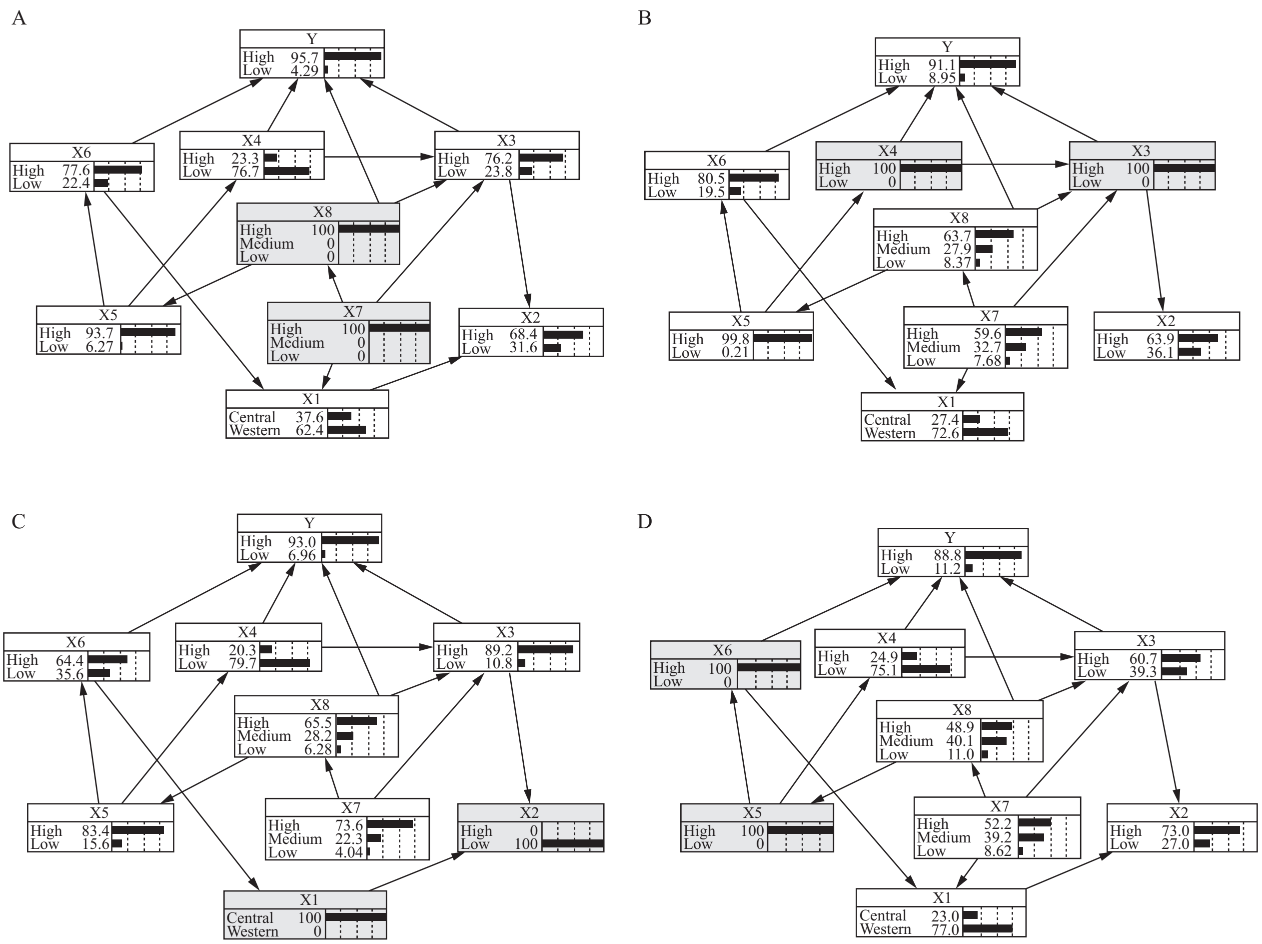

Fig. 4 The final BN with parameters (scenarios for different observations)

A: hospitalization expenses factors; B: economy factors; C: regional characteristics; D: NCMS policy factors the policy standard, which states that 90% of disease treatment should occur within the local county. The phenomenon indicated that the level of medical service inside the county cannot meet the increasing medical needs and expectation of its rural residents, resulting in an irrational structure of hospitalized patients, which is in direct opposition to the goal of strengthening grass-roots as proposed in the New Medical Reform of China.

Consistent with the increasing trend for the out-of-county hospitalization rate, its related expenses and compensation also showed a sharp upward trend. 12%–20% of inpatient expenses outside of the county accounted for almost 30%–40% of the NCMS fund payment, resulting in a large outflow of medical insurance funds, which is not conducive to the stability and sustainability of the NCMS fund. Determining the root cause of out-of-county hospitalizations is of great significance in the creation of scientific fund risk control mechanisms.

Stepwise logistic analysis was used to screen 8 variables related to the out-of-county hospitalization rate, among which per time average out-of-county hospitalization cost (OR=32.774, 95%CI: 15.770–68.115) was strongly associated with the out-of-county hospitalization rate, followed by rural per capita net income (OR=16.017, 95%CI: 10.282–24.952). This indicated that the hospitalization expense and economic factors have a significant impact on the out-of-county hospitalization rate. Based on the results of the logistic screening, the BN model was constructed to determine how the factors are influencing the out-of-country hospitalization rate as well as their interrelationships. According to the state of the known nodes, the BN can deduce the probability of unknown nodes[29]. Using the results of the probability for a high or a low out-of-county hospitalization rate obtained based on the known state of the 8 related factors, the out-of-county hospitalization rate was found to be closely related to X8, X3, X4 and X6; the remaining 4 variables are indirectly linked to the out-of-county hospitalization rate through them.

The BN results illustrated that out-of-county hospitalization rate has the strongest correlation with the per time average in-county or out-of-county hospitalization cost. Per time average in-county and out-of-county hospitalization cost are gradually rising. However, the ratio of the two (X8/X7) is constantly decreasing (table 2). This indicates that the gap between the two is narrowing, which promotes an increase in the rate of out-of-county hospitalizations. The economic factors represent the ability of the patients to visit outside of the county; patients in counties with a higher economic status are more likely to be hospitalized outside of the county. Likewise, patients in counties with sufficient funds and a high out-of-county hospitalization compensation are more likely to be hospitalized outside of the county.

In addition, low medical service capabilities and poor accessibility to medical services in sparsely populated areas can easily lead to an increasing rate of out-of-county hospitalizations, which should be taken into consideration. But from the overall perspective, the out-of-county hospitalization rate in western counties was found to be lower than that in the central counties, which showed the impact of regional and economy differences. Compared with the central region, the medical conditions in the western region are poor, but at the same time, the economic and personal medical payment level in the western region is far behind the central region[37, 38]. Such a situation results in some patients who really need to be hospitalized outside the county in the western region unable to get better treatment and aggravates the family's medical burden, and some unnecessary out-of-county hospitalizations in the central region may increase.

Therefore, the factors affecting the increase of out-of-county hospitalization rate should be considered comprehensively. While strengthening the construction of primary medical and health institution and sinking of medical resources, the government of China should implement the system of primary diagnosis at grassroots level to reduce the proportion of out-of-county visits and ensure a reasonable medical structure. In addition, the government should also improve the construction of the hierarchical diagnosis and treatment system and referral system, adjust the compensation ratio of different levels of medical institutions, and control the unreasonable growth of medical expenses. Full play should be given to the control and management ability of medical insurance, so as to achieve the goal of comprehensive regulation and control.

The limitations of the current study include that we failed to determine other possible factors related to target variables such as the nearest clinic distance, disease severity, etc., which may lead to bias in the analysis results. There is a lack of outpatient data for the NCMS, although the vast majority of the patients outside of the county are inpatients. In addition, the Chimerge-χ^2 method requires one to specify discrete interval numbers artificially, which may be difficult to scientifically weight the interval number in order to achieve the best discrete effect due to the limitations of human knowledge.

To the best of our knowledge, this study, for the first time, explored the influencing factors of the out-of-county, using data spanning the entire duration of the NCMS. Using an MMHC-based hybrid BN model can avoid subjective bias by combining prior information with sample information[39] and has no independent constraints on variables, which is superior to logistic regression[40]. The results summarized above are significant to both researchers and policy makers.

The current study highlights that the rising out-of-county hospitalization rate jeopardizes the funding of the NCMS and reveals the underlying factors. While strengthening the medical service capacity in the county, we recommend a comprehensive regulation and control according to local economic and geographical differences in the following policies, which reasonably guides the direction of rural patients seeking medical treatment and promotes the long-term sustainability of the rural health care system.

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Conflict of Interest Statement

The authors of this paper declare they have no conflict of interest.

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