RESEARCH ARTICLE

Analysis of user perceptions and access to social medicine and the impact on health management challenges

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Analyzing user perception and access to social medicine reveals important insights into health management challenges, especially when considering factors like accessibility, public trust, and knowledge levels. This study explored the connection between Chinese adult population health insurance coverage and access to primary, tertiary, and preventive social medicine healthcare using the open database of the Chinese Social Survey (CSS). The CSS survey is a health insurance coverage that gathers information on social attitudes, family and social life, labor and employment, and other topics. The study employed the original CSS 2023 dataset to construct important metrics including personal sociodemographic, coverage levels of higher, reasonable, poor, and absent, and access to medical care such as physical examinations, doctor visits, appointments, inpatient treatment, and healthcare satisfaction. After adjusting for personal traits and aggregating across different villages, the odds ratio (OR) and 95% CI of health insurance coverage for the four indicators of access to healthcare were estimated by using an enhanced moth-flame optimization based on multi-linear random forest regression (EMFO-MLRFR) algorithm. The results showed that, by using EMFO-MLRFR algorithm, 3.16% of Chinese adults were uninsured, whereas the majority had some form of health insurance. Nonetheless, the majority (64.83%) had insurance with minimal coverage followed by moderately covered (16.71%) and extensive coverage (15.34%). Access to primary, tertiary, and preventive healthcare was substantially and favorably correlated with health insurance. Additionally, there was a noteworthy gradient relationship between access to healthcare and the insurance coverage levels. Health insurance was important for improving obtaining healthcare, but there was also a strong gradient relationship between coverage of insurance and access with better access being associated with higher coverage.

Keywords: social medicine; health insurance; health management; user perception; multi-linear random forest regression.

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Introduction

China has seen tremendous social and economic advancement, which has raised living standards and lengthened life expectancy [1]. The nation's primary healthcare system has achieved significant strides in the management and prevention of chronic diseases because of significantly increased financial investment and the adoption of new policies. Nonetheless, several obstacles still exist in China's delivery of first-rate primary healthcare. The impact of the 2019 corona virus pandemic and the dawn of the intelligence era have raised awareness of the need for new technology and creative approaches to improve primary healthcare quality [2]. Given the old population and the rising prevalence of chronic illnesses, this understanding is especially crucial. It is necessary to carefully evaluate China's basic healthcare quality, paying particular attention to three major factors that lead to less-than-ideal healthcare outcomes including a significant knowledge and practice gap (know-do gap), inequalities in the distribution of the health workforce, and a lack of knowledge among healthcare providers [3, 4]. An essential component of a nation's citizens' pleasure is its healthcare system [5]. Varied combinations of components make up many health systems that exist throughout the world. China's healthcare system has achieved widely recognized successes in handling public health issues and medical services for the Chinese people. However, as the population ages more severely, the need for public medical care is growing among the elderly. The healthcare system in China is dealing with previously unheard-of difficulties [6].

Social medicine access is essential to address health management issues and influence public health outcomes. Promoting fair access to healthcare and enhancing general well-being are the goals of social medicine, which includes community-based treatments, publicly financed healthcare services, and social determinants of health [7, 8]. However, differences in pricing, accessibility, and public image of socialized healthcare still influence its level of success. The use of social healthcare services is frequently influenced by public trust, awareness, and satisfaction levels, whereas access gaps are caused by structural obstacles such as socioeconomic reasons [9], administrative inefficiencies, and regional inequalities. Different areas or municipalities have varied policies on how to pay for health insurance, which is influenced by the degree of economic development [10]. The cost of health insurance has not grown in tandem with the economy, and premiums for both individuals and businesses are pitiful. The situation is worse because some employees who do not have good long-term planning boost their monthly income by not paying for health insurance. Consequently, there is typically not enough money in the medical insurance fund [11]. In addition, most of China's health insurance systems are coordinated at the county level with inconsistent policy wording and a lack of an exchange mechanism, leading to disagreements and unfair treatment among residents in different regions. Further, there is an uneven distribution of medical resources. Large and medium-sized cities tend to have better medical facilities [12]. The effects of these differences in health insurance benefits and the tiers of healthcare services are particularly vulnerable to older people. In many provinces, basic health institutions typically have greater reimbursement rates than tertiary institutions. As a result, local governments purposefully work to support patients to use the basic level health institutions by implementing medical insurance programs [13]. However, senior patients are more likely to have conditions that need extensive examinations, medical care, and medications from big hospitals, which may not be covered by the healthcare insurance plan they signed up for, so their actual reimbursement rates are low. In tertiary hospitals, the need for in-patient and other services for disability and chronic diseases is growing due to deteriorating circumstances of the body and mind, making them vulnerable to catastrophic health costs [14].

Public satisfaction research is one of the most active fields of study examining how the public views the healthcare system. Public satisfaction is a broad subjective evaluation of the medical care system for everyone including those who do not use healthcare services [15]. Rather than the system's actual performance, contentment with the medical-care system may be more influenced by economic and cultural factors [16]. Ruelens studied people’s opinion across 61 nations and discovered that sentiments of the healthcare system were significantly influenced by people's perceptions of accessibility and affordability [17]. Overcrowding in hospitals in major cities was a consequence of the primary care system's absence of a patient referral network before

2015. The nationwide implementation of a general practitioner referral system in 2015 aimed at increasing accessibility and decreasing the unnecessary utilization of top-tier hospital treatment. The purpose of setting a higher reimbursement rate for conventional medical facilities is to encourage their use and discourage patients from using mega hospitals. Patients still prefer to get treatment at hospitals, even for minor illnesses, therefore the referral system has not seen heavy usage [18]. To combat the inferior quality of treatment offered by low-level clinics, hospitals are also leading medical alliance networks. The latest model, the "Modern Hospital Administration System", aims for a more evidence-based approach by evaluating hospital performance using clearly defined measures such as patient volume, patient's satisfaction, and expenditure level [19]. There is a severe absence of integrity management and disciplinary procedures for dishonesty in China, which impacts both insured persons and medical professionals. Weird medical occurrences and insurance company payouts have been commonplace in the last 19 years. A few people who are already insured apply for health insurance using fraudulent documents. Some patients purposefully delay the discharge to undergo more tests and treatments. In addition, some medical facilities collude with patients by submitting false requests for in-patient procedures to scam consumers out of their insurance money. Furthermore, certain medical institutions or doctors create medical records, charge fees, and execute fake medical treatments to make a profit from health insurance payments.

The medical insurance information system in China is inadequate, especially considering that 90% of regions have their own systems. The absence of information sharing and unique identifiers for medical services leads to issues with reimbursement. The essential national platform for supervising health insurance has become less effective due to the COVID-19 pandemic. Neither improper medical practice nor the misuse of health insurance payments can be effectively monitored at this time. Regular medical insurance rounds and fee checks are essential to prevent infractions of rules during routine medical diagnosis and treatment. Establishing a blacklist system for illicit medical facilities and those involved in intentional disruptions is crucial for insurance integrity. The Chinese government has improved healthcare access and reduced burden, but insufficient medical insurance funds and risk management remain issues. Establishing rules and regulations is crucial for a secure and efficient system.

This study combined surveys, statistical modelling, and AI-driven analysis to address public concerns, optimize service delivery, and utilize technology breakthroughs to overcome healthcare inequities, which would contribute to policy conversations on strengthening healthcare systems. In addition, this study highlighted the need for digital health technologies and adaptable health policies by illuminating the relationship between user perceptions and access to social medicine. The results of this study would help academics, politicians, and healthcare professionals create inclusive plans for long-term health management systems.

Materials and methods

Data collection

The open database of the Chinese Social Survey (CSS) (http://css.cssn.cn/css_sy/xmjs/) was employed for this research, which is a health insurance coverage that gathers information on social attitudes, family and social life, labor and employment, and other topics. A representative sample that mirrored the characteristics of households throughout China was chosen and interviewed using a multi-stage stratified probability sampling technique. The original CSS 2023 dataset was used with a total of 110,136 people living in 582 villages/communities and 150 counties/districts in 62 Chinese provinces/cities/autonomous regions. The selection criteria were restricted to respondents who were 60 years old and above. A final sample size of 2,179 data records was obtained after the variables were meticulously vetted, matched, and processed.

Optimal feature extraction

Principal component analysis (PCA), a data processing technique for unlabeled extraction of features, was performed to extract key features from the dataset. Features were displayed in a newly created feature space with the most essential data as the new features after PCA extraction findings. By optimizing data variance, the primary constituents were acquired. Data visualization was possible in a low-dimensional principal component space since the number of additional dimensions (features) was less than the number of initial attributes. The dataset was then calculated based on each attribute as follows.

$$\overline{w}_i = \frac{1}{s}\sum_{j=1}^{s} w_{ij},\ \ i = 1,2,\ldots\ldots,s \quad j = 1,2,\ldots\ldots,s \tag{1}$$

where *j* was the number of features. w_{ij} was j-sample with i-feature. s was the number of samples. $\overline{w}_i$ was i-feature. The Φ was calculated using equation (2).

$$\Phi = [\Phi_{ji}] = [w_{ji} - \overline{w}_i] \tag{2}$$

where Φ was the matrix size $m \times n$. A Φ matrix was a rectangular array of numbers with *m* rows and *n* columns with *m* representing the number of samples, observations, or data points, *n* representing the number of features, variables, or attributes. The covariance matrix was calculated as below.

$$D = \frac{1}{m-1}\Phi^S\Phi \tag{3}$$

where D was the matrix size $n \times n$.

The features of the D matrix could be calculated as follows.

$$Det\ (\lambda J - D) = 0 \tag{4}$$

where D was covariance matrix. J was identity matrix. The subsequent equation was then used to determine the eigenvectors w that corresponded to the features of the record λ.

$$(\lambda . J - D)w = 0 \tag{5}$$

Form matrix w' used the associated features after sorting the eigenvectors according to the eigenvalues, starting with the greatest. The principal component was calculated as follows.

$$PC = \Phi w' \tag{6}$$

Enhanced moth-flame optimization based on multi-linear random forest regression (EMFO-MLRFR) algorithm

The EMFO-MLRFR algorithm constituted with five parts including healthcare system components part that covered the information of hospitals, clinics, pharmacies, medical imaging and diagnostics, and digital health records; data collection and processing part included collection of data from healthcare institutions, patient records, insurance status, and medical assessments, digitalization and preprocessing of data; feature extraction part using PCA to reduce dimensionality for improved computational efficiency, identifying key healthcare features that impact accessibility and insurance; application of EMFO-MLRFR algorithm part for machine learning model applied for predictive analysis, multilayer feature selection for robust performance, and evaluation of patient access to care, health insurance coverage, and quality perception; results and insights part to improve understanding of healthcare accessibility, data-driven policy recommendations, and enhance patient experience and medical resource allocation. The EMFO-MLRFR computation process was as follows. A M-dimensional solution space was thought to contain each Moth. The list of disease diagnoses could be expressed as follows.

$$K = \begin{matrix} k_1 \\ k_2 \\ k_m \end{matrix} \begin{bmatrix} M_{1,1} & M_{1,2} & M_{1,3} & \cdots & M_{1,n} \\ M_{2,1} & M_{2,2} & M_{2,3} & \cdots & M_{2,n} \\ M_{3,1} & M_{3,2} & M_{3,3} & \cdots & M_{3,n} \\ M_{4,1} & M_{4,2} & M_{4,3} & \cdots & M_{4,n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ M_{m,1} & M_{m,2} & M_{m,3} & \cdots & M_{m,n} \end{bmatrix} \tag{7}$$

$$k_i = [k_{i1,}k_{i^2} \cdot \cdots k_{im}], i \in \{1,2,\dots m\} \tag{8}$$

The problem's dimension was represented by *m*, and the count of moths was denoted by *M.* A single chronic symptom was diagnosed by the vector below.

$$diag[k] = \begin{bmatrix} diag[K_1] \\ diag[K_2] \\ \vdots \\ diag[K_m] \end{bmatrix} \tag{9}$$

The prediction matrix was shown below. Given that all of the predictions revolved around chronic disease, the size needed to match the moth matrix that was previously created.

$$FM = \begin{matrix} FM_1 \\ FM_2 \\ FM_m \end{matrix} \begin{bmatrix} FM_{1,1} & FM_{1,2} & FM_{1,3} & \cdots & FM_{1,n} \\ FM_{2,1} & FM_{2,2} & FM_{2,3} & \cdots & FM_{2,n} \\ FM_{3,1} & FM_{3,2} & FM_{3,3} & \cdots & FM_{3,n} \\ FM_{4,1} & FM_{4,2} & FM_{4,3} & \cdots & FM_{4,n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ FM_{m,1} & FM_{m,2} & FM_{m,3} & \cdots & FM_{m,n} \end{bmatrix} \tag{10}$$

The diagnostic matrix for referencing health insurance was provided below.

$$diag[FM] = \begin{bmatrix} diag[FM_1] \\ diag[FM_2] \\ \vdots \\ diag[FM_m] \end{bmatrix} \tag{11}$$

where the distance between a fund transfer at location X_i and its corresponding features of variable (F_{mi}) was shown by $\delta_{\mathrm{i}}= |\ k_i^{x+1} - FM_{\mathrm{i}}\ |$). *b* and *t* determined the spiral fight search, which were random numbers between -1 and 1. The mathematical representation of *t* and the subsequent classifier of the insurance details of the personalized dataset were as follows.

$$x = -1 + current_{iter}\left(\frac{1}{max_{iter}}\right) \tag{12}$$

$$t = (r-1)X\ k + 1 \tag{13}$$

where k was a random number between 0 and 1. *r* was the constant that guaranteed convergence, and its value declined from -1 to -2 linearly, ensuring exploration and exploitation. max_{iter} was the maximum number of iterations. Every global and local search feature values were used to compile and arrange the fame position for the most recent and current iterations. The best and worst footnotes were both first and final fames. The moths then arrived to seize the fames one by one, relying on the same sequence. Over the course of the number of iterations, the same- and lower-ordered moths would always win the last fame. The prediction classification was eventually obtained after *n* samples were extracted using replacement. *m* decision trees were trained using these *n* samples, and so on. Random forest exhibited a robust over fitting characteristic and could be concurrently employed for the advantages of classification and regression tasks. However, because random forests were better at handling high-dimensional and unbalanced data sets, their predictive power would be diminished for low-dimensional data sets. The model would perform worse when it came to learning if the minimal insurance coverage economy error was high. When considering external factors, the primary ones were the size of training samples, the amount and kind of insurance categories, and the imbalance of sample data. The sample doctor prediction scenario yielded the algorithm's overall performance on the test set. The coefficient was 1 if the actual circumstance was entirely consistent with the anticipated outcome. The personalized patient information of index *i*was computed in equation (14).

$$d_{i=}1\text{-}e_i \tag{14}$$

The insurance coverage predictions regression *i* was calculated in equation (15).

$$p_i = \frac{d_i}{\sum_{i=1}^{m} d_i} \tag{15}$$

Lastly, equation (16) computed the degree of multi linear regression development for every province for every year.

$$MLRFR_{jt}=\sum_{i=1}^{M}\sum_{j=1}^{m}\sum_{t=1}^{m} z_{ijt}\ \mathrm{X}\ w_i \tag{16}$$

Both equations 14 and 15 were based on the social medicine regression p_i and the standardised indicators z_{ijt} . The value of $EMFO\_MLRFR_{jt}$, which ranged from 0 to 1, represented the province j multi linear regression level in year t . To validate the research hypotheses, the regression model was built to show how the diagnosing affected sufficient development in social medicine. Equation 17 gave the model's shape as below.

$$EMFO\_MLRFR_{nt} = \beta Digital_{nt} + \gamma X_{nt} + C_n + \alpha_t + V_{nt} \quad (17)$$

The variables $EMFO\_MLRFR_{nt}$ and $Digital_{nt}$ _nt represented the level of multi linear based random forest regression and enough growth of province n in year t , respectively. The impact of the digital economy on the multi linear based random forest regression sufficient development was indicated by the regression coefficient β. Several factors under control were represented by X_{nt}, while C_n and α_t indicated time- and individual-fixed effects, respectively, and V_{nt} was random disturbance. Whether the intermediary variable was total factor productivity was investigated to better understand the potential trend of the impact of the social population on EMFO_MLRFR and sufficient development. A regression model of the insurance impacting overall productivity of factor on the basis of model was constructed as shown in equation (18), as well as a multi linear regression model of the user perception and overall productivity of factor jointly affecting balanced and sufficient development.

$$TFP_{nt} = \beta Digital_{nt} + \gamma X_{nt} + C_n + \alpha_t + V_{nt} \quad (18)$$

Then, whether an intermediary impact existed was determined by evaluating the significant judgment and matching regression coefficient as below.

$$EMFO\_MLRFR_{nt} = \beta_1 Digital_{nt} + \beta_2 TFP_{nt} + \gamma X_{nt} + C_n + \alpha_t + V_{nt} \quad (19)$$

The level of overall productivity of factors in province n in year t was represented by TFP_{nt}, and the remaining variables' meanings were in line with model. The variables as an input were simpler to control than the output variables. Therefore, to increase the overall productivity of factor metric, the input-driven EMFO-MLRFR algorithm based on the variable returns was selected. Equation 20 represented the input-oriented EMFO- MLRFR model.

$$min\left[\theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r + \right)\right] \quad (20)$$

In 20 equations, the efficiency value was denoted by δ . The non-Archimedean infinitesimal was represented by ε. The input and output variables were denoted by x and y, respectively. The weight was represented by λ.

Efficacy of EMFO-MLRFR algorithm

A comparative analysis was carried out between the proposed EMFO-MLRFR and other well-known machine learning techniques including Naïve bayes (NB) [20], support vector machines (SVM) [21], and Logitic Regression (LR) [22]. The model accuracy, one of the most crucial performance indicators for categorization, was determined for each tested model to verify the efficacy of proposed algorithm. In the case of machine learning-based approaches, *P* value reported using bootstrap resampling was used to generate confidence intervals and evaluate statistical significance. Given the structured presentation of odds ratios and confidence intervals, logistic regression with Wald tests was performed in Python's statsmodels.

Results

The results of classifiers' accuracy rate of each approach showed that the EMFO-MLRFR model demonstrated the higher accuracy rate of 99.2% than that of the other currently used methods with NB as 87.8%, SVM as 92.3%, and LR as 94.6% (Table 1), which significantly improved accuracy usage of health insurance rate among people. The access to care and health insurance results showed that individuals with health insurance

Table 1. Classifiers with the accuracy rate.

Algorithm	Accuracy rate (%)
Naïve Bayes (NB)	87.8
Support vector machine (SVM)	92.3
Logistic regression (LR)	94.6
EMFO-MLRFR	99.2

Table 2. EMFO-MLRFR of access to care and health insurance status.

		OR (95% CI)			
		Physical assessment	Visit to the office	Inpatient care	Content with quality
Insurance (*vs.* inadequate coverage)	Highest coverage	5.463 (4.371–6.830)*	1.497 (1.124–1.991)*	2.571 (1.861–3.551)*	1.268 (0.982–1.638)
	Moderate coverage	2.461 (1.982–3.056)*	1.397 (1.055–1.851)*	2.064 (1.497–2.845)*	1.236 (0.962–1.588)
	Lowest coverage	1.818 (1.484–2.228)*	1.343 (1.031–1.751)*	2.067 (1.521–2.811)*	1.262 (1.001–1.591)*
Age	< 63 vs. ≥66	0.995 (0.927–1.068)	1.026 (0.938–1.123)	1.052 (0.962–1.150)	1.086 (0.990–1.190)
Gender	Male vs. female	0.968 (0.904–1.036)	0.992 (0.911–1.083)	0.974 (0.893–1.062)	1.002 (0.915–1.093)
Living environment (*vs.* rural)	Urban	1.004 (0.893–1.131)	0.927 (0.807–1.061)	0.928 (0.813–1.061)	0.918 (0.801–1.053)
	Suburban	0.934 (0.811–1.078)	0.988 (0.832–1.174)	1.010 (0.853–1.195)	0.970 (0.813–1.158)
Occupation (*vs.* unemployed)	Non-agriculture	1.060 (0.915–1.227)	0.678 (0.546–0.842)*	1.011 (0.837–1.217)	0.961 (0.792–1.163)
	Agriculture	1.028 (0.903–1.171)	1.081 (0.918–1.272)	1.003 (0.850–1.183)	1.031 (0.868–1.225)
Education level (*vs.* illiterate)	Elementary school	1.201 (0.921–1.565)	1.072 (0.781–1.476)	1.090 (0.801–1.487)	0.823 (0.596–1.136)
	Middle school	1.178 (1.026–1.354)	0.986 (0.826–1.177)	1.055 (0.888–1.250)	0.856 (0.716–1.024)
	High school	1.051 (0.941–1.174)	0.965 (0.838–1.112)	0.987 (0.860–1.134)	0.902 (0.780–1.042)
	College	0.990 (0.905–1.083)	1.027 (0.916–1.151)	0.966 (0.862–1.081)	0.914 (0.811–1.031)
Health status	Good vs. not good	0.996 (0.926–1.073)	0.891 (0.806–0.983)*	0.854 (0.774–0.941)*	1.081 (0.979–1.194)

Note: * indicated $P < 0.05$.

were more likely to have had a checkup with the odds ratio (OR) and 95% CI as OR = 5.463, 95% CI: 4.371 – 6.830 for highest coverage, OR = 2.461, 95% CI: 1.982 – 3.056 for moderate coverage, and OR = 1.818, 95% CI: 1.484 – 2.228 for lowest coverage, respectively, compared to inadequate coverage (Table 2). The physician office visit showed OR = 1.497, 95% CI: 1.124 – 1.991 for highest coverage, OR = 1.397, 95% CI: 1.055 – 1.851 for moderate coverage, and OR = 1.343, 95% CI: 1.031 – 1.751 for lowest coverage, respectively. Further, received in-patient care demonstrated OR = 2.571, 95% CI: 1.861 – 3.551 for highest coverage, OR = 2.064, 95% CI: 1.497 – 2.845 for moderate coverage, OR = 2.067, 95% CI: 1.521 – 2.811 for lowest coverage, respectively, after adjusting for individual characteristics in the proposed model. However, only those with minimal insurance were more likely to be satisfied with the quality of care than those without insurance with OR = 1.264, 95%CI: 1.001 – 1.591. The relationship between patient experience and satisfaction with medical care showed that patient experience was affected, and fair healthcare was perceived (Figure 1). The year of the previous medical visit, facility level, facility type, province GDP per capita, the proportion of the population over 64 years old, and government spending per capita were also considered.

Discussion

China's multi-level social health insurance system consists of the new cooperative medical scheme (NCMS) for the rural population, urban employee basic medical insurance (UEBMI) for the urban employed and pensioners, and urban resident basic medical insurance (URBMI) for the urban unemployed. UEBMI is regarded as the most generous and covers roughly 80% of the cost of medical treatment when combined with government medical insurance for government employees and private medical insurance that is either purchased by individuals or by employers.

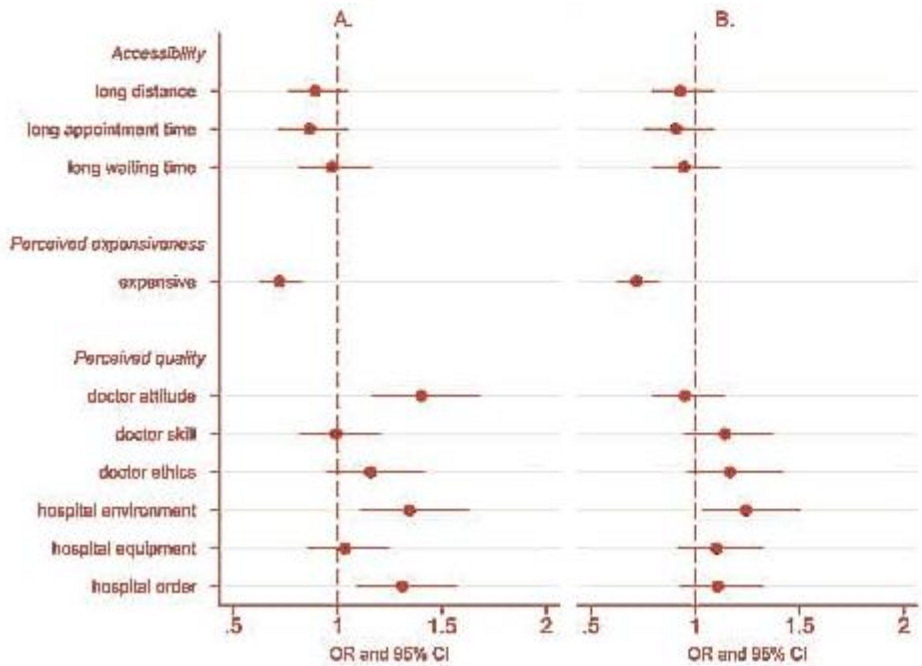

Figure 1. The connection between public opinion and the experience of patients. **A.** The relationship between patient experience and satisfaction with medical care. **B.** Patient experience affected fair healthcare.

URBMI is regarded as a moderate coverage health insurance plan that covers 50 – 80% of medical expenses when combined with medical insurance for both urban and rural residents, which is created in developed towns. This study found that the access to healthcare was substantially and favorably correlated with HI coverage. Specifically, Chinese adults with HI were more likely than those without insurance to undergo physical exams, office visits, and inpatient care. According to a previous study conducted in China, compared with respondents with health insurance, respondents without health insurance were 73% less likely to use outpatient services in the last month, 49% less likely to be hospitalized in the last year, 67% less likely to have a routine physical examination in the last two years, and 84% less likely to receive other treatment in the last month. In contrast to the findings of other studies conducted in Ghana, this study also found that Chinese patients with HI were more satisfied with the quality of care than those without insurance. The findings of this study might have been impacted by different definitions of satisfaction. In a Nigerian study, satisfaction was assessed based on the following areas including hospital bureaucracy, hospital climate, patient waiting time, communication between patients and clinicians, and accessibility. The patients were divided into two groups with patients scored 50% or more in the assessment domains being considered as satisfied, while those scored less than 50% being considered unsatisfied. Therefore, in this study, only "The quality, cost, and convenience of local medical services" was asked to Chinese interviewees. The results were in line with another study conducted in China that older chronic patients in the community who had health insurance were happier with the quality of care (76.28%) and the cost of care (81.01%) compared to those who did not have insurance as 61.11% and 59.30%, respectively. This study identified that the access to care and the degree of insurance coverage were significantly correlated. When compared to those with moderate or low coverage, those with high coverage HI had significantly greater probabilities of getting regular checkups. Similarly, adults with the highest coverage HI were more likely to have inpatient care and physician office visits than adults with moderate or low coverage, which suggested that, although HI was significant overall, sufficient coverage was also necessary to enhance access to treatment, specifically for primary care as doctor visits, tertiary care as inpatient care, and preventive care as checkups in this research. On the other hand, the results also suggested that a significant portion of Chinese people did not have enough insurance, which made healthcare inaccessible and difficult to obtain. The study had some limitations including cross-sectional data, inability to evaluate causality, missing quality and cost metrics, and not considering COVID-19's impact on healthcare access. Future research should explore long-term effects of insurance coverage on healthcare costs, quality, and access, especially during COVID-19. According to the Healthy China 2030 plan, a systematic and coordinated effort is required to improve the standard of primary healthcare in China to raise population-level well-being. Even though this aim has come a long way, there are still some gaps that need to be filled. To close these gaps, more comprehensive policy plans should be created, which should include ways to improve knowledge through computer-aided diagnostic system-based training and education, provide incentives for closing the know-do gap through programs like telemedicine, and balance the distribution of the health workforce through creative methods. The status of China's healthcare system should be considered when implementing these strategies.

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