

How Do Health Insurance and Household Health Financial Risks Jointly Influence Chinese Residents' Health-Seeking Behavior? — Evidence from CFPS and CHARLS

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Abstract

Background

Background: Healthcare-seeking behavior is a key indicator of the efficiency and equity of a healthcare system and is crucial for achieving universal health coverage. Against the backdrop of China's ongoing reforms to its healthcare security system and the integration of its social insurance system, identifying the factors influencing residents' healthcare-seeking behavior is of great significance for accurately evaluating policy outcomes and optimizing resource allocation.

Methods

Using the Anderson model, we integrated data from the China Family Panel Studies (CFPS 2022, all ages, N = 8,610) and the China Health and Retirement Longitudinal Study (CHARLS 2020, middle-aged and elderly, N = 10,354). Binary logistic regression analyzed the interaction effects between insurance type (public, NRCMS, urban resident, urban employee, uninsured) and household financial risk (medical expenditure/household income: low < 0.1, medium 0.1–0.4, high ≥ 0.4), with robustness checks conducted using gender subgroups and complementary log-log models.

Results

The financial risk effect showed population heterogeneity: high-risk individuals in CFPS had a 7.60-fold increased probability of hospitalization, while high-risk individuals in CHARLS had a 2.19-fold increased probability of outpatient visits. Health insurance effects varied by system: In CFPS, urban employee medical insurance users had lower outpatient utilization than the uninsured (OR = 0.79, 0.62–0.99) but higher hospitalization (OR = 1.89, 1.15–3.09); in CHARLS, new rural cooperative medical scheme users had lower hospitalization than the uninsured (OR = 0.48, 0.23–1.00). Interaction effects were significant: In CHARLS, the combination of New Rural Cooperative Medical Scheme (NRCMS) and high financial risk increased inpatient care utilization (OR = 2.20, 1.00–4.86), while in CFPS, the combination of Urban Resident Medical Insurance (URMI) and high financial risk suppressed inpatient care utilization (OR = 0.14, 0.02–0.92). Women were more sensitive to financial risk, exhibiting a more pronounced demand-release effect from health insurance.

Conclusion

Health insurance and household financial risk exhibit synergistic effects on healthcare utilization, with effects varying by system, age, gender, and service type. Efforts are needed to enhance the actual coverage level of rural health insurance, establish dynamic financial risk intervention mechanisms, and guide urban employees toward rational healthcare utilization.

1 Introduction

Healthcare utilization refers to the actions individuals take to obtain medical services for disease prevention, diagnosis, and treatment, representing a crucial dimension reflecting the efficiency and equity of healthcare systems[1]. Globally, research on healthcare utilization is a core topic in health economics and health policy, as it directly impacts the progress and quality of achieving Universal Health Coverage (UHC) goals. The World Health Organization defines UHC as "ensuring that all people, regardless of their financial status, have access to the healthcare services they need without facing financial hardship"[2]. As a key indicator measuring the accessibility, affordability, and actual utilization of healthcare services, healthcare utilization has become a vital metric for assessing a country's progress toward UHC [3]. Internationally, research on healthcare utilization has developed a mature theoretical framework and analytical paradigm, with the widespread application of the Andersen Behavioral Model forming the core theoretical pillar of this field. First proposed in the 1960s and revised multiple times, this model systematically explains three major categories of factors influencing individual healthcare utilization: predisposing characteristics (e.g., age, gender, education level), enabling resources (e.g., health insurance, income), and health service need (e.g., chronic disease status, self-rated health)[4]. Due to its systematic structure, operational variables, and guidance for policy interventions, the model has been applied by numerous scholars globally to study variations in healthcare utilization across different countries and healthcare systems. It has become a vital tool for international comparisons and assessments of healthcare equity and efficiency [5].

Against the backdrop of China's efforts to integrate its medical insurance systems and achieve universal coverage, clarifying the factors influencing residents' healthcare-seeking behavior is crucial for policymakers to accurately assess policy effectiveness, optimize resource allocation, and narrow disparities in healthcare utilization[6]. Over the past two decades, extensive academic research has examined Chinese residents' healthcare utilization patterns. Within the resource empowerment dimension, health insurance emerges as a key determinant of healthcare service utilization. Both domestic and international consensus holds that health insurance significantly boosts overall healthcare utilization by reducing the marginal cost of services[7]. For instance, social insurance systems like the Urban Employee Basic Medical Insurance (UEBMI) for urban workers and the New Rural Cooperative Medical Scheme (NCMS) for rural residents have both been shown to promote healthcare utilization by reducing out-of-pocket expenses[8, 9]. However, in-depth studies examining the effects of different insurance types reveal a more complex picture, with findings subject to some debate. This variability stems precisely from the interaction between insurance and other individual and household contextual factors: Cao et al. found that UEBMI enrollees may actually reduce their utilization of primary outpatient services due to relatively higher time costs; conversely, Han et al. noted that NCMS had no significant impact on inpatient service utilization among rural elderly residents, potentially due to limited reimbursement levels during the early stages of coverage[10]. These conflicting findings indicate that the effects of health insurance are not isolated. Further exploration is needed into how its interactions with specific contextual factors, such as household health financial risks, collectively influence healthcare utilization decisions.

Beyond health insurance, household-level financial constraints also play a crucial role in influencing healthcare decisions[11]. The core consensus in international research on the relationship between household health financial risks and healthcare-seeking behavior is that financial risks primarily inhibit service accessibility through the "price effect," but this impact exhibits significant heterogeneity and may lead to more complex social consequences[12, 13]. In China, catastrophic healthcare expenditures remain a primary challenge for rural and low-income households. Che et al.'s study of critically ill patients in rural Shandong revealed high risks of catastrophic medical expenses among this group, leading to delayed or abandoned healthcare services[14]. Shu et al. further confirmed a positive correlation between household financial risks and hospitalization utilization among chronic disease patients, indicating that severe health issues necessitating hospitalization cannot be avoided despite economic burdens[15]. The apparent contradiction between these two findings reveals the complexity of household financial constraints on healthcare-seeking behavior, primarily stemming from fundamental differences in study populations and disease types: while high costs may inhibit initial treatment for critically ill patients, essential medical needs like acute exacerbations of chronic diseases exhibit inelasticity, making financial pressures insufficient to prevent eventual hospitalization. Existing research predominantly analyzes the effects of health insurance or financial risk in isolation, with limited exploration of the synergistic effects between insurance coverage and household health-related financial risks. This limitation hinders a comprehensive understanding of how health insurance modulates the impact of financial constraints on healthcare utilization.

Beyond the dimension of enabling resources, the influence of demographic and health-related factors has been extensively validated in the dimensions of predisposing characteristics and health service demand. Domestic and international studies confirm that women exhibit higher outpatient utilization rates[16], while older adults and individuals with chronic conditions experience more frequent hospitalizations[17, 18]. Additionally, married individuals typically have higher hospitalization rates[19], whereas those with higher educational attainment tend to make more rational healthcare decisions[20]. However, existing research lacks gender-differentiated analyses of the mechanisms underlying the effects of health insurance and household health financial risk. It also fails to systematically compare how these mechanisms differ across the entire population versus the elderly population.

Based on the aforementioned research gaps, this study focuses on two core variables: basic medical insurance and household health financial risk. This focus is primarily informed by two key considerations. First, medical insurance serves as a central pillar of China's healthcare system reform. Following the integration of the New Rural Cooperative Medical Scheme (NCMS) and the Urban Resident Basic Medical Insurance (URBMI) into the unified Urban-Rural Resident Basic Medical Insurance (URRBMI) in 2016, the medical insurance system has become more consolidated[21]. However, disparities in coverage scope and reimbursement rates persist between the integrated URRBMI and other schemes, such as the Urban Employee Basic Medical Insurance (UEBMI). Clarifying how different types of medical insurance influence healthcare-seeking behavior is therefore crucial for refining insurance policies and enhancing the accessibility of healthcare services. Second, household health financial risk directly reflects the economic burden imposed by healthcare. Currently, out-of-pocket medical expenses still account for over 27% of total health expenditures in China[22]. Even individuals with insurance coverage may forgo necessary medical services due to financial constraints. Examining the interaction between medical insurance and financial risk can help elucidate whether the insurance system effectively mitigates the suppression of healthcare-seeking behavior caused by financial pressure. This is particularly important for evaluating the protective effects of the system on vulnerable groups, such as the rural elderly and low-income families.

In terms of research design, previous studies have primarily measured residents' healthcare-seeking behavior using variables such as two-week outpatient visit rates, four-week outpatient visit rates, hospitalization rates, and healthcare facilities utilized[23, 24]. This study employs outpatient visit rates and hospitalization rates as dependent variables for healthcare utilization, with health insurance type and household health financial risk as core independent variables. Using the Anderson model as the theoretical framework, a binary Logit regression model is constructed. The aim is to analyze the relationship between basic medical insurance type and household health financial risk using two major Chinese longitudinal datasets: the China Family Panel Studies (CFPS 2022) and the China Health and Retirement Longitudinal Study (CHARLS 2020). CFPS 2022 and the China Health and Retirement Longitudinal Study (CHARLS 2020). It examines the impact of basic medical insurance type and household health financial risk on residents' outpatient and inpatient healthcare utilization, tests the interaction effect between medical insurance and household health financial risk, and explores the heterogeneity of this effect across different genders and age groups. This research aims to provide insights for other countries and regions.

2 Methods

2.1 Data Sources

This study utilizes the latest annual cross-sectional data from the 2022 China Family Panel Studies (CFPS) and the 2020 China Health and Retirement Longitudinal Study (CHARLS). Both are longitudinal surveys conducted by Peking University using a multistage probability sampling method proportional to population size. They possess authoritative representativeness and form precise complementarity. Specifically, the complementary strengths of these two databases manifest as follows: CFPS covers the entire age group aged 18 and above across 25 provinces. Its detailed household income and medical expenditure modules directly support the calculation of the core variable "household health financial risk," while its granular classification of medical insurance types aligns with the needs of institutional heterogeneity analysis. CHARLS focuses on middle-aged and older adults aged 45 and above, incorporating in-depth health indicators such as objective physical examination data and chronic disease diagnoses. This enables precise capture of behavioral characteristics among populations with inelastic healthcare demand. Furthermore, its rural sample exceeding 65% supplements analysis scenarios for rural medical insurance coverage effectiveness. Concurrently, the combined use of both databases allows cross-validation of core conclusions through complementary population coverage and variable dimensions. This effectively mitigates biases inherent in single-database studies, enhancing the robustness and generalizability of research findings.

The CFPS 2022 dataset selected adult samples aged 18 and above. Minors were excluded as their healthcare decisions are predominantly made by guardians and the sample lacked sufficient representativeness. The initial adult sample size was 27,001. Focusing on basic medical insurance, supplementary medical insurance samples were excluded, leaving 20,589. After removing samples with "don't know" or "refused to answer" responses for

key variables (e.g., insurance type, healthcare utilization), 10,046 valid samples remained. Further deletion of samples with missing values in other core covariates yielded a final valid sample of 8,610. In CHARLS 2020, all modules were first merged and duplicate samples removed, resulting in 19,395 samples. After excluding supplementary medical insurance samples and removing invalid responses and missing value samples, the final valid sample size was 10,354.

2.2 Variables

Dependent variables

This study utilizes the 2022 CFPS questionnaire and the 2020 CHALS questionnaire design to measure residents' healthcare utilization behavior through the indicators "whether there was an outpatient visit in the past month" and "whether there was an inpatient visit in the past year."

Independent Variables

The core explanatory variables are residents' health insurance coverage status and health financial risk. Health insurance type is measured by the questionnaire item "What type of health insurance do you currently have?" and categorized into five groups: No insurance, Government-funded Medical Insurance (GFM), New Rural Cooperative Medical Scheme (NCMS), Urban Resident Basic Medical Insurance (URBMI), and Urban Employee Basic Medical Insurance (UEBMI). No sample had dual coverage under two basic insurance schemes.

Household health financial risk is measured by the ratio of medical expenditures to household income. Household income is calculated based on per capita annual household income, while total medical expenditures encompass both outpatient and inpatient costs incurred over the past year. A medical expenditure/household income ratio < 0.1 indicates low health financial risk; a ratio ≥ 0.1 and < 0.4 indicates moderate risk; and a ratio ≥ 0.4 indicates high risk. The study references commonly used classification thresholds in existing literature, incorporating the median and quartile classifications from the CFPS and CHARLS databases used in this research. Patients with zero household income are defined as having high health financial risk[25, 26]. Specific definitions are provided in Appendix A.

Controlled Variables

The Andersen model serves as the mainstream framework in healthcare for analyzing factors influencing individual healthcare utilization and accessibility[1]. This study adapted the model (Fig. 1) based on data availability and research objectives, categorizing determinants of healthcare utilization among residents into propensity characteristics, enabling resources, and health service demands. Propensity characteristics include age, gender, and marital status. Enabling resources encompass health insurance type, household health financial risk, place of residence, education level, and total healthcare expenditure. Health service demands comprise whether the individual has a chronic disease and self-rated health status. Chronic disease is defined as "having been diagnosed by a physician with at least one chronic condition (e.g., hypertension, diabetes, coronary heart disease) for more than six months."

2.3 Statistical analysis

Descriptive statistics were employed to examine basic medical insurance and household health financial risks, analyzing the distribution characteristics of insurance types and household health financial risks, as well as the frequency of medical visits across different groups. Chi-square (χ^2) tests were conducted to assess differences in medical visit behaviors among individuals with varying insurance types and health financial risk levels, with a significance level of $\alpha = 0.05$.

Additionally, a binary logistic regression model was employed. The model incorporated control variables including propensity score characteristics, empowerment resources, and healthcare service needs to analyze the impact of medical insurance and household health financial risk on outpatient and inpatient behaviors. An interaction term "Medical Insurance $\times$ Household Health Financial Risk" was introduced to test for synergistic effects. Outpatient visits and hospitalizations represented binary outcome variables (yes or no). The binary logistic regression model is expressed as follows:

$$y_i = \text{logit}(p) = \delta_0 + \delta_1 X_i + \eta_{1i}, \eta_{1i} \sim N(0, 1)$$

Where "y" represents the probability that an individual, i, seeks outpatient or inpatient care; X denotes the explanatory variable, and δ is the parameter estimate for the explanatory variable; η is the residual, (0, 1).

Next, regression analyses were conducted by gender to explore differences in the impact of health insurance and household health financial risk across gender groups. Finally, the complementary log-log model (cloglog) is employed to validate the reliability of the results, offering greater flexibility in handling potential asymmetry in the probability distribution of healthcare utilization. All statistical analyses were conducted using STATA 17.0. Regression results are presented as odds ratios (OR) with 95% confidence intervals (95% CI), with $p < 0.05$ indicating statistically significant differences.

3 Results

3.1 Descriptive Analysis of Sample Characteristics and Healthcare Utilization

This study examined differences in healthcare utilization patterns (outpatient and inpatient care) across distinct demographic groups using CHARLS 2020 (n = 10,354) and CFPS 2022 (n = 8,610) data. Differences with $p < 0.05$ were considered statistically significant. Results are presented in Tables 1 and 2.

In CHARLS 2020, the sample exhibited a relatively high average age, predominantly aged 45–74 (91.25%). Rural residents constituted 65.66% of the sample, 63.46% had primary school education or below, and 86.71% were married. NCMS enrollees constituted the largest proportion (75.22%), followed by UEBMI

enrollees (14.96%), with the uninsured accounting for 3.96%. High-risk households for health financial risk were the most prevalent (49.82%), followed by medium-risk (33.88%) and low-risk (16.30%) households. The outpatient visit rates for the uninsured, public medical care, NRCMS, urban resident medical insurance, and urban employee medical insurance groups were 22.68%, 17.21%, 22.97%, 22.89%, and 23.76%, respectively. Hospitalization rates were 22.44%, 27.05%, 21.29%, 21.24%, and 24.92%, respectively.

In the CFPS 2022 survey, the sample exhibited a relatively young age distribution, with 41.61% aged 18–44. The urban-rural distribution was fairly balanced (urban: 52.93%, rural: 47.07%). Secondary education was the most common educational attainment (45.83%), and 76.55% of respondents were married. NCMS enrollees constituted 61.35%, UEBMI 21.45%, and the uninsured 7.28%. Regarding household health financial risk, low-risk cases accounted for 79.42%, medium-risk 15.81%, and high-risk 4.77%.

Outpatient visit rates for the uninsured, public medical care, NRCMS, urban resident medical insurance, and urban employee medical insurance groups were 37.86%, 27.66%, 40.30%, 38.53%, and 32.20%, respectively; inpatient visit rates were 9.27%, 21.28%, 16.76%, 13.04%, and 17.05%, respectively.

In both databases, female outpatient visit rates (CHARLS: 57.72%, CFPS: 57.30%) exceeded male rates (CHARLS: 42.28%, CFPS: 42.70%), indicating stronger female utilization of outpatient services. Marital status significantly influenced healthcare utilization ($p < 0.001$). Married individuals exhibited higher hospitalization rates (CHARLS: 82.57%, CFPS: 83.32%) than unmarried individuals (CHARLS: 17.43%, CFPS: 16.68%), while widowed individuals had higher outpatient rates (CHARLS: 15.62%, CFPS: 21.57%) was higher than that of unmarried individuals. Higher total medical expenditures, poorer self-rated health status, and chronic disease prevalence were all associated with significantly increased outpatient and inpatient visit rates ($p < 0.001$). For instance, in CFPS, the outpatient visit rate among chronic disease patients (36.56%) was 1.47 times that of those without chronic diseases (63.44%), and the hospitalization rate (46.06%) was 1.73 times that of those without chronic diseases (53.94%).

Table 1

Basic Characteristics and Correlation Analysis of Outpatient Medical Care Seeking Among Chinese Residents in the CHARLS and CFPS Samples

Outpatient visits (last month)										
	CHARLS					CFPS				
	NO	YES	Total	χ^2	P	NO	YES	Total	χ^2	P
Medical insurance				2.8382	0.585				46.8532	< 0.001
No insurance	317(3.98)	93(3.90)	410(3.96)			389(7.28)	237(7.25)	626(7.27)		
GFMI	101(1.27)	21(0.88)	122(1.18)			136(2.55)	52(1.59)	188(2.18)		
NCMS	5999(75.25)	1789(75.10)	7788(75.22)			3153(59.03)	2128(65.10)	5281(61.34)		
URBMI	374(4.69)	111(4.66)	485(4.68)			410(7.68)	257(7.86)	667(7.75)		
UEBMI	1181(14.81)	368(15.45)	1549(14.96)			1253(23.46)	595(18.20)	1848(21.46)		
Family health financial risk				116.9073	< 0.001				316.2318	< 0.001
Health expenditure/family income < 0.1	1426(17.89)	262(11.00)	1688(16.30)			4563(85.43)	2276(69.62)	6839(79.43)		
Health expenditure/family income $\geq$ 0.1 and < 0.4	2790(35.00)	718(30.14)	3508(33.88)			619(11.59)	742(22.70)	1361(15.81)		
Health expenditure/family income $\geq$ 0.4	3756(47.11)	1402(58.86)	5158(49.82)			159(2.98)	251(7.68)	410(4.76)		
Gender				28.3599	< 0.001				49.6042	< 0.001
Male	3865(48.48)	1007(42.28)	4872(47.05)			2698(50.51)	1396(42.70)	4094(47.55)		
Female	4107(51.52)	1375(57.72)	5482(52.95)			2643(49.49)	1873(57.30)	4516(52.45)		
Age(years)				8.7199	0.013				231.2062	< 0.001
18–44						2559(47.91)	1024(31.32)	3583(41.61)		
45–59	3588(45.01)	991(41.60)	4579(44.22)			1488(27.86)	1163(35.58)	2651(30.79)		
60–74	3700(46.41)	1169(49.08)	4869(47.03)			1083(20.28)	910(27.84)	1993(23.15)		
$\geq$ 75	684(8.58)	222(9.32)	906(8.75)			211(3.95)	172(5.26)	383(4.45)		
Education				12.1060	0.002				133.5709	< 0.001
Primary school and below	4996(62.97)	1575(66.12)	6571(63.46)			1880(35.20)	1544(47.23)	3424(39.77)		
Secondary school	2796(35.07)	745(31.28)	3541(34.20)			2584(48.38)	1362(41.66)	3946(45.83)		
College and above	180(2.26)	62(2.60)	242(2.34)			877(16.42)	363(11.10)	1240(14.40)		
Residence				0.6252	0.429				17.5556	< 0.001
Urban	2754(34.55)	802(33.67)	3556(34.34)			2921(54.69)	1636(50.05)	4557(52.93)		
Rural	5218(65.45)	1580(66.33)	6798(65.66)			2420(45.31)	1633(49.95)	4053(47.07)		
Marital status				14.5449	< 0.001				10.4119	< 0.001
Unmarried	1004(12.59)	372(15.62)	1376(13.29)			1314(24.60)	705(21.57)	2019(23.45)		
Married	6968(87.41)	2010(84.38)	8978(86.71)			4027(75.40)	2564(78.43)	6591(76.55)		
Health expenditure(CNY)				143.5650	< 0.001				440.0604	< 0.001
< 1000	1637(20.53)	281(11.80)	1918(18.52)			2765(51.77)	955(29.21)	3720(43.21)		
1000–3500	3112(39.04)	849(35.64)	3961(38.26)			1506(28.20)	1211(37.04)	2717(31.56)		

Outpatient visits (last month)								
	CHARLS				CFPS			
> 3500	3223(40.43)	1252(52.56)	4475(43.22)		1070(20.03)	1103(33.74)	2173(25.24)	
self-rated health				488.7203	< 0.001			1100.0000 < 0.001
Poor	1849(23.19)	1064(44.67)	2913(28.13)		489(9.16)	1192(36.46)	1681(19.52)	
Fair	4156(52.13)	1064(44.67)	5220(50.42)		449(8.41)	394(12.05)	843(9.79)	
Good	1967(24.67)	254(10.66)	2221(21.45)		4403(82.44)	1683(51.48)	6086(70.69)	
chronic				206.9663	< 0.001			419.1434 < 0.001
No	1486(18.64)	152(6.38)	1638(15.82)		4432(82.98)	2074(63.44)	6506(75.56)	
Yes	6486(81.36)	2230(93.62)	8716(84.18)		909(17.02)	1195(36.56)	2104(24.44)	

Table 2
Basic Characteristics and Correlation Analysis of Outpatient Seeking Behavior Among Chinese Residents in the CHARLS and CFPS Samples

	Impatient visits (last year)									
	CHARLS					CFPS				
	NO	YES	Total	χ^2	P	NO	YES	Total	χ^2	P
Medical insurance				12.0121	0.017				32.9304	< 0.001
No insurance	318(3.93)	92(4.05)	410(3.96)			568(7.86)	58(4.19)	626(7.27)		
GFMI	89(1.10)	33(1.45)	122(1.18)			148(2.05)	40(2.89)	188(2.18)		
NCMS	6130(75.85)	1658(72.98)	7788(75.22)			4396(60.84)	885(63.90)	5281(61.34)		
URBMI	382(4.73)	103(4.53)	485(4.68)			580(8.03)	87(6.28)	667(7.75)		
UEBMI	1163(14.39)	386(16.99)	1549(14.96)			1533(21.22)	315(22.74)	1848(21.46)		
Family health financial risk				427.1937	< 0.001				1900.0000	< 0.001
Health expenditure/family income < 0.1	1520(18.81)	168(7.39)	1688(16.30)			6318(87.45)	521(37.62)	6839(79.43)		
Health expenditure/family income $\geq$ 0.1 and < 0.4	2960(36.62)	548(24.12)	3508(33.88)			762(10.55)	599(43.25)	1361(15.81)		
Health expenditure/family income $\geq$ 0.4	3602(44.57)	1556(68.49)	5158(49.82)			145(2.01)	266(19.13)	410(4.76)		
Gender				0.3782	0.539				1.0495	0.306
Male	3790(46.89)	1082(47.62)	4872(47.05)			3418(47.31)	676(48.81)	4094(47.55)		
Female	4292(53.11)	1190(52.38)	5482(52.95)			3807(52.69)	709(51.19)	4516(52.45)		
Age(years)				199.6736	< 0.001				241.2661	< 0.001
18–44						3245(44.91)	338(24.40)	3583(41.61)		
45–59	3837(47.48)	742(32.66)	4579(44.22)			2178(30.15)	473(34.15)	2651(30.79)		
60–74	3653(45.20)	1216(53.52)	4869(47.03)			1523(21.08)	470(33.94)	1993(23.15)		
$\geq$ 75	592(7.32)	314(13.82)	906(8.75)			279(3.86)	104(7.51)	383(4.45)		
Education				10.8808	0.004				36.8509	< 0.001
Primary school and below	5063(62.65)	1508(66.37)	6571(63.46)			2776(38.42)	648(46.79)	3424(39.77)		
Secondary school	2829(35.00)	712(31.34)	3541(34.20)			3366(46.59)	580(41.88)	3946(45.83)		
College and above	190(2.35)	52(2.29)	242(2.34)			1083(14.99)	157(11.34)	1240(14.40)		
Residence				0.8375	0.36				0.2775	0.599
Urban	2794(34.57)	762(33.54)	3556(34.34)			3815(52.80)	742(53.57)	4557(52.93)		
Rural	5288(65.43)	1510(66.46)	6798(65.66)			3410(47.20)	643(46.43)	4053(47.07)		
Marital status				43.2935	< 0.001				42.1513	< 0.001
Unmarried	980(12.13)	396(17.43)	1376(13.29)			1788(24.75)	231(16.68)	2019(23.45)		
Married	7102(87.87)	1876(82.57)	8978(86.71)			5437(75.25)	1154(83.32)	6591(76.55)		
Health expenditure(CNY)				514.3316	< 0.001				2900.0000	< 0.001
< 1000	1726(21.36)	192(8.45)	1918(18.52)			3689(51.06)	31(2.24)	3720(43.21)		

(Note: Although the National Rural Cooperative Medical Scheme (NCMS) and the Urban Resident Basic Medical Insurance (URBMI) were integrated into a unified URBMI system beginning in 2016, this study maintains the original classification from the questionnaire in its empirical analysis. This approach treat NCMS and URBMI as two distinct categories due to variations in local implementation progress, requirements for data comparability, and the potential persistence of differences in capturing the original insured populations.)

	Impatient visits (last year)					
	CHARLS			CFPS		
1000–3500	3323(41.12)	638(28.08)	3961(38.26)	2500(34.60)	217(15.67)	2717(31.56)
> 3500	3033(37.53)	1442(63.47)	4475(43.22)	1036(14.34)	1137(82.09)	2173(25.24)
self-rated health			652.3612			330.0227
			< 0.001			< 0.001
Poor	1808(22.37)	1105(48.64)	2913(28.13)	1182(16.36)	499(36.03)	1681(19.52)
Fair	4289(53.07)	931(40.98)	5220(50.42)	669(9.26)	174(12.56)	843(9.79)
Good	1985(24.56)	236(10.39)	2221(21.45)	5374(74.38)	712(51.41)	6086(70.69)
chronic			220.9386			418.1245
			< 0.001			< 0.001
No	1507(18.65)	131(5.77)	1638(15.82)	5759(79.71)	747(53.94)	6506(75.56)
Yes	6575(81.35)	2141(94.23)	8716(84.18)	1466(20.29)	638(46.06)	2104(24.44)

(Note: Although the National Rural Cooperative Medical Scheme (NCMS) and the Urban Resident Basic Medical Insurance (URBMI) were integrated into a unified URBMI system beginning in 2016, this study maintains the original classification from the questionnaire in its empirical analysis. This approach treats NCMS and URBMI as two distinct categories due to variations in local implementation progress, requirements for data comparability, and the potential persistence of differences in capturing the original insured populations.)

3.2 Regression Analysis of Health Insurance and Household Health Financial Risk on Healthcare-Seeking Behavior

3.2.1 Impact of Health Insurance and Household Health Financial Risk on Outpatient Care-Seeking Behavior

Results indicate (Table 3) that health insurance and household health financial risk are statistically significant factors influencing outpatient treatment, with differing effects across the two datasets. In CHARLS 2020, high-risk individuals exhibited a 2.19-fold higher probability of outpatient visits compared to low-risk individuals ($OR = 2.188, p < 0.1$), indicating that moderate-to-high risk levels stimulate outpatient demand among middle-aged and elderly populations. This may stem from the rigid demand for chronic disease management, as high-risk individuals are more inclined to control their conditions through outpatient care. The type of health insurance had no significant effect ($p > 0.05$). Gender, education level, total healthcare expenditure, chronic disease status, and self-rated health also influenced outpatient behavior. Women, individuals with college education or higher, those with high total healthcare expenditure, chronic disease sufferers, and residents with poorer self-rated health exhibited significantly higher outpatient visit probabilities.

In CFPS 2022, household health financial risk showed no significant effect on outpatient behavior ($p > 0.05$). Health insurance type significantly influenced outpatient behavior: participants enrolled in GFMI and UEBMI had significantly lower outpatient visit probabilities than the uninsured ($OR = 0.575, p < 0.05$; $OR = 0.785, p < 0.05$). Probability of outpatient visits was significantly higher among females, older individuals, illiterate residents, those with chronic diseases, and those reporting poorer self-rated health.

3.2.2 Impact of Health Insurance and Household Health Financial Risk on Hospitalization Behavior

Results indicate (Table 3) that household health financial risk exhibits a significant positive correlation with hospitalization behavior, while the effect of health insurance type varies across databases: In CHARLS 2020, household financial risk showed no significant difference in hospitalization probability ($p > 0.05$); NCMS enrollees had a lower hospitalization probability than the uninsured ($OR = 0.484, p < 0.1$). The probability of hospitalization increased significantly with age, was lower for females than males, and was higher for those with higher total medical expenditures, chronic diseases, and self-reported poor health.

In CFPS 2022, household health financial risk positively correlates with hospitalization behavior, with medium-risk individuals showing a 3.34-fold increase in hospitalization probability ($OR = 3.335, p < 0.01$), while high-risk individuals had a 7.6-fold higher probability ($OR = 7.596, p < 0.01$). This finding may reflect how severe health issues simultaneously drive up medical expenditures (leading to high risk) and increase hospitalization demand. NCMS and UEBMI enrollees exhibited significantly higher hospitalization probabilities than the uninsured ($p < 0.05$). Women exhibited lower hospitalization rates than men. Higher total medical expenditures, chronic diseases, and self-reported poor health were associated with increased hospitalization probability. Individuals with primary, junior high, senior high, college, or higher education levels all demonstrated lower hospitalization probability than illiterate individuals ($p < 0.01$).

3.2.3 Interactive Effects of Medical Insurance and Household Financial Risk

Results indicate that in CHARLS 2020, the NCMS $\times$ high-risk interaction term significantly increased the probability of hospitalization ($OR = 2.202, p < 0.05$), suggesting that rural residents with high financial risk under NCMS coverage are more inclined to obtain medical services through hospitalization. The UEBMI $\times$ medium-risk interaction term significantly increased the probability of hospitalization ($OR = 3.274, p < 0.05$), suggesting that UEBMI participants with medium financial risk are more likely to utilize hospitalization services, potentially indicating a tendency toward overmedicalization. In CFPS 2022, the GFMI $\times$ high-risk interaction term significantly reduced the probability of hospitalization ($OR = 0.024, p < 0.05$), and the UREMI $\times$ high-risk interaction term significantly reduced the probability of hospitalization ($OR = 0.136, p < 0.05$).

Table 3
Logistic Regression Results for Healthcare Utilization Behavior by Health Insurance and Household Financial Risk

	Outpatient visits		Inpatient visits	
	CHARLS	CFPS	CHARLS	CFPS
Medical insurance (Ref: no insurance)				
GFMI	0.793	0.575**	0.758	1.431
	[0.188,3.340]	[0.369,0.897]	[0.207,2.778]	[0.650,3.150]
NCMS	1.213	0.869	0.484*	1.824**
	[0.559,2.632]	[0.708,1.067]	[0.234,1.004]	[1.147,2.899]
URBMI	1.488	1.007	0.966	1.351
	[0.579,3.821]	[0.773,1.311]	[0.385,2.421]	[0.766,2.383]
UEBMI	1.408	0.785**	0.574	1.886**
	[0.618,3.207]	[0.622,0.991]	[0.257,1.283]	[1.151,3.090]
Health financial risk (Ref: low)				
Medium [0.1–0.4]	0.924	0.952	0.619	3.335***
	[0.370,2.304]	[0.565,1.605]	[0.260,1.477]	[1.606,6.924]
High (≥ 0.4)	2.188*	2.471*	1.194	7.596***
	[0.969,4.940]	[0.852,7.164]	[0.556,2.566]	[2.191,26.343]
Age(years)				
18–44		1.000		1.000
		[1.000,1.000]		[1.000,1.000]
45–59	1.000	1.288***	1.000	1.152
	[1.000,1.000]	[1.133,1.464]	[1.000,1.000]	[0.940,1.412]
60–74	0.945	1.097	1.335***	1.187
	[0.851,1.050]	[0.951,1.267]	[1.193,1.494]	[0.956,1.474]
≥75	0.862	0.958	1.855***	1.250
	[0.716,1.038]	[0.748,1.227]	[1.550,2.219]	[0.895,1.746]
Gender (Ref: male)	1.183***	1.272***	0.898**	0.900
	[1.070,1.307]	[1.156,1.400]	[0.809,0.997]	[0.778,1.042]
Marital status (Ref: unmarried)				
Married	0.854**	0.861**	0.786***	1.103
	[0.741,0.983]	[0.761,0.974]	[0.681,0.908]	[0.905,1.345]
Residence (Ref: urban)	0.994	1.077	1.006	1.047
	[0.881,1.121]	[0.969,1.197]	[0.886,1.142]	[0.889,1.233]
Education level (Ref: primary school and below)				
Secondary school	0.988	0.932	1.034	0.910
	[0.880,1.109]	[0.833,1.043]	[0.916,1.167]	[0.767,1.080]
College and above	1.416**	0.953	1.067	0.804
* p < 0.1, ** p < 0.05, *** p < 0.01				
(Note: CHARLS age reference group is 45–59 years old, CFPS is 18–44 years old; No insurance; Government-funded medical insurance (GFMI); New Rural Cooperative Medical Scheme (NCMS); Urban Resident Basic Medical Insurance (URBMI); Urban Employee Basic Medical Insurance (UEBMI))				

	Outpatient visits		Inpatient visits	
	CHARLS	CFPS	CHARLS	CFPS
	[1.011,1.984]	[0.789,1.152]	[0.739,1.539]	[0.592,1.091]
Health expenditure	1.002*	1.000	1.007***	1.192***
	[1.000,1.004]	[0.993,1.007]	[1.005,1.010]	[1.173,1.212]
Chronic(Ref:no)	2.322***	1.731***	2.202***	1.638***
	[1.939,2.781]	[1.541,1.945]	[1.813,2.674]	[1.395,1.924]
self-rated health (Ref:poor)				
Fair	0.505***	0.432***	0.421***	1.013
	[0.455,0.560]	[0.362,0.515]	[0.378,0.470]	[0.787,1.304]
Good	0.289***	0.221***	0.266***	0.966
	[0.247,0.339]	[0.194,0.252]	[0.226,0.313]	[0.804,1.160]
Medical insurance* health economic risk(Ref:no insurance*low risk)				
GFMI*Medium risk	1.799	1.465	3.323	0.792
	[0.332,9.750]	[0.523,4.101]	[0.716,15.427]	[0.209,3.005]
GFMI*High risk	0.757	1.206	1.375	0.024**
	[0.147,3.910]	[0.212,6.877]	[0.316,5.991]	[0.001,0.597]
NCMS*Medium risk	1.315	1.559	2.221*	0.732
	[0.517,3.343]	[0.908,2.676]	[0.904,5.457]	[0.345,1.552]
NCMS*High risk	0.679	0.634	2.202*	0.369
	[0.295,1.560]	[0.213,1.886]	[0.997,4.864]	[0.103,1.324]
URBMI*Medium	0.984	1.175	0.917	0.665
	[0.313,3.097]	[0.553,2.496]	[0.287,2.935]	[0.249,1.775]
URBMI*High risk	0.594	0.540	1.178	0.136**
	[0.212,1.661]	[0.127,2.285]	[0.430,3.228]	[0.020,0.916]
UEBMI*Medium risk	1.389	1.535	3.274**	0.581
	[0.520,3.714]	[0.841,2.801]	[1.242,8.632]	[0.257,1.316]
UEBMI*High risk	0.699	1.428	2.498**	0.071***
	[0.288,1.699]	[0.402,5.071]	[1.045,5.970]	[0.014,0.356]
N	10354	8610	10354	8610
* p < 0.1, ** p < 0.05, *** p < 0.01				
(Note: CHARLS age reference group is 45–59 years old, CFPS is 18–44 years old; No insurance; Government-funded medical insurance (GFMI); New Rural Cooperative Medical Scheme (NCMS); Urban Resident Basic Medical Insurance (URBMI); Urban Employee Basic Medical Insurance (UEBMI))				

3.3 Subgroup Analysis

Regression results stratified by gender (Tables 4 and 5) indicate that significant gender differences exist in the impact of health insurance and household financial risk on healthcare utilization: In CHARLS 2020, among males, those at moderate risk exhibited a 1.35-fold increase in outpatient visit probability (OR = 1.354, $p < 0.05$), while those at high risk showed a 1.66-fold increase in hospitalization probability (OR = 1.657, $p < 0.01$); For women, high-risk individuals had a 1.42-fold higher probability of outpatient visits (OR = 1.422, $p < 0.01$), while UEBMI enrollees exhibited a significantly higher probability of hospitalization compared to the uninsured (OR = 1.820, $p < 0.01$). This indicates women place greater emphasis on health, and the reimbursement advantages of UEBMI more readily stimulate their demand for hospitalization.

In CFPS 2022, male moderate-risk individuals exhibited a 1.42-fold increase in outpatient probability (OR = 1.416, $p < 0.01$), while NCMS enrollees had a higher hospitalization probability than the uninsured (OR = 1.845, $p < 0.05$). High-risk females exhibited a 1.55-fold increase in outpatient probability (OR = 1.550, $p < 0.05$), while their hospitalization probability reached 2.88-fold (OR = 2.881, $p < 0.01$). This indicates greater financial risk sensitivity among women, who are more inclined to address health issues through outpatient and inpatient care during high-risk periods.

Table 4
Logistic Regression Results for Outpatient Care Behavior by Gender

	Male		Female	
	CHARLS	CFPS	CHARLS	CFPS
Medical insurance (Ref: no insurance)				
GFMI	0.727	0.732	1.145	0.466**
	[0.349,1.517]	[0.439,1.220]	[0.451,2.911]	[0.251,0.864]
NCMS	1.169	0.801	0.943	1.021
	[0.759,1.801]	[0.607,1.057]	[0.697,1.277]	[0.789,1.321]
URBMI	1.578	0.926	0.863	1.114
	[0.898,2.775]	[0.644,1.331]	[0.568,1.309]	[0.797,1.557]
UEBMI	1.294	0.745*	1.269	0.949
	[0.810,2.067]	[0.546,1.018]	[0.878,1.836]	[0.705,1.277]
Health financial risk (Ref: low)				
Medium [0.1–0.4)	1.354**	1.416***	1.104	1.404***
	[1.057,1.735]	[1.146,1.748]	[0.894,1.362]	[1.149,1.717]
High (≥ 0.4)	1.657***	2.000***	1.422***	1.550**
	[1.301,2.112]	[1.361,2.938]	[1.157,1.748]	[1.077,2.231]
Age				
18–44		1.000		1.000
		[1.000,1.000]		[1.000,1.000]
45–59	1.000	1.291***	1.000	1.258**
	[1.000,1.000]	[1.068,1.561]	[1.000,1.000]	[1.056,1.499]
60–74	1.150*	1.122	0.805***	1.049
	[0.979,1.350]	[0.909,1.384]	[0.699,0.927]	[0.859,1.281]
≥75	1.006	0.999	0.762**	0.923
	[0.766,1.320]	[0.711,1.403]	[0.590,0.984]	[0.641,1.330]
Marital status (Ref: unmarried)				
Married	0.882	0.866	0.824**	0.879
	[0.685,1.137]	[0.720,1.042]	[0.693,0.980]	[0.742,1.041]
Residence (Ref:urban)	1.059	1.178**	0.941	0.998
	[0.884,1.268]	[1.010,1.373]	[0.800,1.107]	[0.861,1.156]
Education level (Ref:primary school and below)				
Secondary school	1.056	0.995	0.907	0.875
	[0.901,1.237]	[0.848,1.169]	[0.765,1.076]	[0.747,1.027]
College and above	1.769***	0.925	1.046	0.961
	[1.157,2.706]	[0.707,1.209]	[0.599,1.827]	[0.735,1.256]
Health expenditure	1.003**	0.998	1.000	1.004
	[1.000,1.006]	[0.988,1.007]	[0.997,1.004]	[0.994,1.014]
* p < 0.1, ** p < 0.05, *** p < 0.01				

	Male		Female	
	CHARLS	CFPS	CHARLS	CFPS
Chronic(Ref:no)	2.522***	1.626***	2.188***	1.831***
	[1.917,3.318]	[1.374,1.926]	[1.721,2.780]	[1.559,2.152]
self-rated health (Ref:poor)				
Fair	0.504***	0.407***	0.505***	0.458***
	[0.429,0.592]	[0.313,0.529]	[0.440,0.580]	[0.360,0.584]
Good	0.303***	0.266***	0.281***	0.191***
	[0.240,0.383]	[0.219,0.322]	[0.227,0.349]	[0.160,0.228]
N	4872	4094	5482	4516
* p < 0.1, ** p < 0.05, *** p < 0.01				

Table 5
Logistic Regression Results for Hospitalization Behavior by Gender

	Male		Female	
	CHARLS	CFPS	CHARLS	CFPS
Medical insurance (Ref: no insurance)				
GFMI	1.626	1.056	0.561	1.320
	[0.866,3.053]	[0.418,2.665]	[0.157,2.007]	[0.555,3.140]
NCMS	0.923	1.845**	1.052	1.344
	[0.614,1.388]	[1.076,3.165]	[0.759,1.459]	[0.864,2.092]
URBMI	1.032	1.067	1.140	1.074
	[0.586,1.816]	[0.530,2.151]	[0.731,1.779]	[0.607,1.899]
UEBMI	1.203	1.739*	1.820***	1.272
	[0.770,1.879]	[0.972,3.113]	[1.225,2.703]	[0.769,2.105]
Health financial risk (Ref: low)				
Medium [0.1–0.4)	1.401**	2.714***	1.357**	2.201***
	[1.063,1.846]	[2.058,3.579]	[1.047,1.760]	[1.708,2.837]
High (≥ 0.4)	2.780***	2.235***	2.280***	2.881***
	[2.136,3.619]	[1.388,3.600]	[1.777,2.925]	[1.899,4.372]
Age				
18–44		1.000		1.000
		[1.000,1.000]		[1.000,1.000]
45–59	1.000	1.034	1.000	1.275*
	[1.000,1.000]	[0.763,1.400]	[1.000,1.000]	[0.966,1.682]
60–74	1.247***	1.254	1.380***	1.143
	[1.057,1.471]	[0.914,1.719]	[1.183,1.609]	[0.844,1.549]
≥75	1.854***	1.071	1.736***	1.447
	[1.436,2.394]	[0.663,1.730]	[1.346,2.239]	[0.898,2.330]
Marital status (Ref: unmarried)				
Married	0.967	1.085	0.713***	1.119
	[0.749,1.249]	[0.802,1.468]	[0.597,0.851]	[0.857,1.459]
Residence (Ref:urban)	1.041	0.989	0.976	1.087
	[0.867,1.249]	[0.779,1.254]	[0.817,1.166]	[0.868,1.362]
Education level (Ref:primary school and below)				
Secondary school	1.114	0.978	0.912	0.858
	[0.949,1.307]	[0.766,1.248]	[0.754,1.102]	[0.673,1.094]
College and above	1.343	0.819	0.751	0.863
	[0.856,2.106]	[0.530,1.264]	[0.385,1.463]	[0.559,1.332]
Health expenditure	1.006***	1.205***	1.008***	1.170***
	[1.003,1.010]	[1.177,1.234]	[1.005,1.011]	[1.145,1.195]
* p < 0.1, ** p < 0.05, *** p < 0.01				

	Male		Female	
	CHARLS	CFPS	CHARLS	CFPS
Chronic(Ref:no)	1.987***	1.498***	2.456***	1.768***
	[1.523,2.592]	[1.180,1.902]	[1.845,3.270]	[1.421,2.198]
self-rated health (Ref:poor)				
Fair	0.396***	1.095	0.441***	0.932
	[0.337,0.464]	[0.750,1.598]	[0.381,0.512]	[0.664,1.309]
Good	0.215***	1.003	0.317***	0.929
	[0.169,0.274]	[0.760,1.324]	[0.253,0.397]	[0.728,1.186]
N	4872	4094	5482	4516
* p < 0.1, ** p < 0.05, *** p < 0.01				

3.4 Robustness Testing

Robustness testing was conducted using the complementary log-log model (cloglog), yielding results consistent with logistic regression (Table 6), indicating reliable conclusions. Both cloglog and logit belong to binary discrete choice models but operate under different distribution assumptions. Comparing their results verifies whether core conclusions change with model specification. Additionally, cloglog better accommodates the distribution characteristics of low-probability events like hospitalization within healthcare-seeking behavior. It also addresses the assumption limitations of the Logit model, enhancing the reliability of research conclusions.

In CHARLS 2020, the interaction term between UEBMI and moderate risk was significant (OR = 2.804, $p < 0.05$), consistent in direction with the Logistic results (OR = 3.274, $p < 0.05$) but with a slightly different coefficient; the impact trend of health insurance type remained unchanged. In CFPS 2022, the hospitalization probability for individuals with high health financial risk remained significantly elevated (OR = 11.892, $p < 0.01$), with a higher coefficient than the Logistic model, indicating that cloglog better fits low-probability events.

Table 6
Robustness Test Results for Healthcare Utilization Across Two Large Databases

	Outpatient visits		Inpatient visits	
	CHARLS	CFPS	CHARLS	CFPS
Medical insurance (Ref: no insurance)				
GFMI	0.812	0.661**	0.841	1.805*
	[0.218,3.028]	[0.459,0.951]	[0.268,2.641]	[0.899,3.623]
NCMS	1.181	0.911	0.536*	1.820***
	[0.583,2.395]	[0.776,1.071]	[0.274,1.047]	[1.170,2.830]
URBMI	1.407	1.021	1.005	1.466
	[0.600,3.297]	[0.830,1.255]	[0.438,2.302]	[0.859,2.503]
UEBMI	1.368	0.841*	0.621	1.955***
	[0.649,2.880]	[0.700,1.010]	[0.296,1.302]	[1.226,3.118]
Health financial risk (Ref: low)				
Medium [0.1–0.4)	0.929	0.915	0.685	5.091***
	[0.404,2.138]	[0.618,1.356]	[0.310,1.515]	[2.695,9.616]
High (≥ 0.4)	1.968*	1.866*	1.227	11.892***
	[0.945,4.098]	[0.993,3.507]	[0.615,2.448]	[5.411,26.133]
Age(years)				
18–44		1.000		1.000
		[1.000,1.000]		[1.000,1.000]
45–59	1.000	1.226***	1.000	1.126
	[1.000,1.000]	[1.110,1.355]	[1.000,1.000]	[0.953,1.330]
60–74	0.950	1.096*	1.287***	1.117
	[0.868,1.039]	[0.983,1.223]	[1.168,1.418]	[0.926,1.347]
≥ 75	0.878	0.991	1.619***	1.096
	[0.750,1.029]	[0.824,1.192]	[1.394,1.880]	[0.837,1.436]
Gender (Ref: male)	1.154***	1.219***	0.920*	0.916
	[1.060,1.257]	[1.134,1.311]	[0.843,1.004]	[0.807,1.041]
Marital status (Ref: unmarried)				
Married	0.878**	0.904**	0.834***	1.172*
	[0.781,0.988]	[0.822,0.994]	[0.741,0.938]	[0.988,1.390]
Residence (Ref: urban)	0.992	1.064	0.997	0.973
	[0.896,1.099]	[0.982,1.152]	[0.897,1.109]	[0.846,1.120]
Education level (Ref: primary school and below)				
Secondary school	0.994	0.955	1.033	1.023
	[0.899,1.098]	[0.878,1.039]	[0.934,1.143]	[0.882,1.186]
College and above	1.330**	0.956	1.078	1.066
	[1.003,1.763]	[0.824,1.109]	[0.795,1.460]	[0.829,1.371]
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$				

	Outpatient visits		Inpatient visits	
	CHARLS	CFPS	CHARLS	CFPS
Health expenditure	1.002**	1.000	1.004***	1.044***
	[1.000,1.003]	[0.995,1.004]	[1.002,1.005]	[1.032,1.055]
Chronic(Ref:no)	2.168***	1.436***	2.069***	1.640***
	[1.831,2.567]	[1.319,1.563]	[1.726,2.481]	[1.423,1.890]
self-rated health (Ref:poor)				
Fair	0.562***	0.587***	0.484***	0.993
	[0.514,0.613]	[0.521,0.663]	[0.442,0.530]	[0.793,1.245]
Good	0.338***	0.344***	0.321***	0.900
	[0.293,0.390]	[0.314,0.377]	[0.277,0.372]	[0.769,1.053]
Medical insurance* health economic risk(Ref:no insurance*low risk)				
GFMI*Medium risk	1.718	1.543	2.675	1.032
	[0.369,8.004]	[0.728,3.270]	[0.705,10.143]	[0.389,2.737]
GFMI*High risk	0.772	1.030	1.251	0.203**
	[0.172,3.454]	[0.283,3.745]	[0.350,4.467]	[0.044,0.923]
NCMS*Medium risk	1.291	1.408*	1.978	0.791
	[0.552,3.018]	[0.940,2.108]	[0.870,4.498]	[0.419,1.496]
NCMS*High risk	0.721	0.723	1.983*	0.389**
	[0.341,1.525]	[0.378,1.380]	[0.968,4.064]	[0.174,0.871]
URBMI*Medium	0.990	1.137	0.881	0.888
	[0.351,2.793]	[0.665,1.944]	[0.307,2.526]	[0.401,1.964]
URBMI*High risk	0.645	0.729	1.098	0.394
	[0.258,1.613]	[0.313,1.695]	[0.447,2.692]	[0.120,1.289]
UEBMI*Medium risk	1.318	1.422	2.804**	0.783
	[0.540,3.216]	[0.908,2.228]	[1.156,6.802]	[0.394,1.554]
UEBMI*High risk	0.733	1.240	2.192*	0.298**
	[0.331,1.624]	[0.576,2.670]	[0.996,4.826]	[0.115,0.776]
N	10354	8610	10354	8610
* p < 0.1, ** p < 0.05, *** p < 0.01				

4 Discussion

This study, based on Anderson's healthcare utilization model, integrates two major Chinese micro-level databases—CFPS 2022 and CHARLS 2020—to investigate how health insurance and household health financial risk synergistically influence Chinese residents' healthcare-seeking behavior. The core of "synergistic effects" lies in testing whether the effects of these two factors on healthcare-seeking behavior are not independent but interact, meaning the magnitude or direction of one factor's effect depends on the level of the other. In the empirical analysis, this synergistic effect is primarily tested and quantified through "interaction effects." The findings reveal that health insurance, household health financial risk, and their interaction influence residents' healthcare-seeking behavior. Gender, age, education level, chronic disease status, and self-rated health also affect healthcare-seeking behavior. These results not only provide empirical support for understanding patterns in Chinese residents' healthcare-seeking behavior but also offer reference for other regions and countries.

Household health financial risk, as a core indicator reflecting the relationship between household medical expenditures and income, exhibits distinct population heterogeneity in its impact on healthcare-seeking behavior. This is closely related to the age structure characteristics of the data sample. Results from the binomial logistic regression indicate that household financial risk influences healthcare utilization. In the CFPS 2022 sample, household financial risk is highly correlated with hospitalization: residents with moderate household health financial risk have a 3.34 times higher probability of hospitalization than those at low risk, while high-risk residents have a 7.60 times higher probability. However, it has no significant effect on outpatient visits. This association does not represent a unidirectional causal relationship where "high financial risk drives hospitalization." Instead, it reflects a bidirectional dynamic: "severe

illness-increased medical expenditure-heightened household financial risk" and "financial risk constraints-adjustment of healthcare needs." On one hand, severe illness is the core driver of surging household medical expenditures and heightened financial risk. Such conditions create an inelastic demand for hospitalization, as outpatient care can only alleviate symptoms but fails to meet the systemic requirements for disease control. Consequently, even with high out-of-pocket costs for hospitalization, these households tend to choose inpatient care to avoid worsening conditions that would trigger higher medical expenses. This aligns with the findings of Zhan Shu's research[15]. On the other hand, the inhibitory effect of financial constraints on healthcare demand objectively exists, though it is mitigated in the CFPS sample by the rigid demand for treatment. The CFPS sample includes a 41.61% proportion of young adults aged 18–44, who generally enjoy better health and have lower outpatient needs, making the constraining effect of financial risk less apparent. For low-risk households with better health in the sample, increased financial risk does suppress non-essential hospitalization demand. However, since this group has a low hospitalization probability to begin with, it does not alter the overall correlation trend. In contrast, in the CHARLS 2020 elderly sample, household financial risk has no significant impact on hospitalization behavior, with only high-risk individuals showing a 2.19-fold higher probability of outpatient visits compared to low-risk individuals. This divergence stems from the health characteristics and behavioral logic of middle-aged and elderly individuals. With chronic disease prevalence reaching 84.18% in the CHARLS sample, hospitalization demand is rigidly constrained by health status, diminishing the impact of financial risk. The increased utilization of outpatient services represents a rational choice for managing chronic conditions among this demographic. Through regular outpatient monitoring to control disease progression, they avoid uncontrolled conditions leading to hospitalization, thereby reducing overall healthcare burdens. This aligns with the research findings of scholar Zengwen Wang [27].

Different types of health insurance exhibit significant heterogeneity in their impact on healthcare utilization due to variations in funding levels, reimbursement rates, deductibles, and out-of-pocket maximums, and are deeply intertwined with the structural characteristics of the database sample. In the CFPS 2022 sample, both UEMBI and NCMS significantly increased hospitalization rates. Concurrently, a noteworthy finding warrants further exploration: the probability of outpatient utilization among UEMBI and GFMI enrollees was significantly lower than among the uninsured. This seemingly counterintuitive observation may stem from the combined effects of several mechanisms: First, the "substitution effect" of coverage levels: UEMBI and GFMI typically offer high inpatient reimbursement rates (up to 80%-90%), but their outpatient pooling coverage is relatively limited or features high deductibles. This may prompt enrollees, particularly employed workers, to delay or escalate outpatient-manageable health issues to inpatient care to leverage higher inpatient reimbursement rates, statistically manifesting as relatively suppressed outpatient utilization. Second, the health selection effect and healthcare-seeking habits of the insured population. Third, research by Cao et al. also indicates that UEMBI enrollees may reduce utilization of primary care outpatient services due to higher opportunity costs of time[10]. Multiple factors may interact to partially offset the economic subsidy effect. In the CHARLS 2020 sample, health insurance impacts showed divergent trends: NCMS enrollees had a 51.6% lower probability of hospitalization compared to the uninsured. This finding suggests potential "inadequate coverage" in addressing hospitalization needs among rural elderly under the New Rural Cooperative Medical Scheme (NRCMS). Although NCMS provides basic hospitalization reimbursement (approximately 65%), for rural elderly individuals, the hospitalization deductible (typically several hundred yuan) and remaining out-of-pocket costs may still constitute a significant proportion of their household income, creating a substantial economic barrier[8]. Thus, the phenomenon of "having insurance but being afraid to be hospitalized" precisely reflects that the level of coverage fails to fully eliminate economic barriers, leading to suppressed potential hospitalization demand. This finding aligns with studies examining rural healthcare accessibility, underscoring the urgency of enhancing actual reimbursement rates and lowering deductibles to unlock rural elderly healthcare demand. Concurrently, the high prevalence of chronic diseases among older adults in the CHARLS sample indicates that hospitalization needs are primarily driven by health status, diminishing the influence of insurance type. This indirectly highlights the need for further improvements in rural healthcare coverage to better align with the hospitalization requirements of the elderly.

The interactive effects between medical insurance and household financial risk further reveal their synergistic mechanism in influencing healthcare-seeking behavior. In the CHARLS 2020 sample, the interaction term between NCMS and high financial risk significantly increased the probability of hospitalization, while the interaction term between UEBMI and medium financial risk significantly increased the probability of hospitalization. This suggests that when health insurance provides adequate coverage, suppressed rigid hospitalization demand among high-financial-risk populations may be released. Meanwhile, UEBMI participants at medium risk predominantly belong to the urban middle-income group. Reduced out-of-pocket costs due to insurance reimbursement may foster a tendency toward "overmedicalization," such as converting outpatient-treatable conditions into inpatient care. This aligns with the perspectives of scholars like Fengsai Bie and Chuanchuan Zhang[28, 29]. In the CFPS 2022 sample, the interaction effect exhibited a suppression trend: the interaction term between GFMI/URBMI and high financial risk significantly reduced the probability of hospitalization. This may indicate that for specific insured groups (e.g., some non-employed residents), even with insurance, high out-of-pocket costs remain an insurmountable barrier to healthcare when household financial risks are elevated. Alternatively, their access to better preventive services may reduce hospitalization needs, consistent with Yaxin Zhao's research[30]. Reimbursement policies for URBMI enrollees require further optimization to alleviate their financial burden for hospitalization.

Gender subgroup analysis further refined population differences in factors influencing healthcare utilization. Results indicate women generally exhibit higher sensitivity to financial risks than men, with the "demand-release effect" of health insurance being more pronounced among women. Women demonstrate greater attention to health issues and more cautious medical decision-making. When financial risks increase or insurance coverage is provided, they are more inclined to address health problems through outpatient or inpatient care. This aligns with Baohua Qiu's conclusion that "women exhibit stronger tendencies toward health service utilization"[16] and provides empirical evidence for developing gender-differentiated health insurance policies.

From a policy perspective, the findings of this study provide clear guidance for optimizing the medical insurance system and steering rational healthcare-seeking behavior. First, addressing the contradictory hospitalization patterns among NCMS enrollees requires further increasing the reimbursement rate for inpatient care in rural areas and lowering deductibles, particularly for households with high financial risk. Expanding the scope of reimbursement for chronic disease hospitalization could reduce the economic burden of hospitalization for rural elderly individuals. Second, for UEMBI participants, tiered diagnosis and treatment policies should guide increased reimbursement rates for primary care initial visits. This would curb excessive medical consumption among middle-income groups and prevent healthcare resource wastage, aligning with scholar Lizhu Guo's perspective that "policy guidance optimizes healthcare resource allocation"[31]. Third, establish a dynamic monitoring mechanism for household financial risks. Leverage medical insurance big data to identify high-risk

families and provide targeted interventions such as medical expense subsidies and free chronic disease management. Supplement this with commercial health insurance to alleviate financial pressure[32].

This study has certain limitations. First, due to the absence of healthcare facility choice data in CHARLS 2020, it does not address residents' choice of medical institutions, making it difficult to fully reflect variations in healthcare-seeking behavior. Second, the findings represent statistical analysis rather than "causal" analysis. Few studies have examined the combined impact of health insurance and household financial risks on healthcare-seeking behavior, making statistical analysis a reasonable initial step. Future research should utilize longitudinal tracking data from CFPS and CHARLS to validate the long-term effects of health insurance and household financial risks on healthcare-seeking behavior. Finally, this study focuses on the demand side and does not incorporate the influence of healthcare providers' supply-side behaviors. These aspects require further refinement in subsequent research.

5 Conclusion

This study integrates the Anderson model with two major Chinese databases—CFPS 2022 and CHARLS 2020—to examine the impact of health insurance and household financial risk on healthcare utilization among Chinese residents. Results indicate a significant positive correlation between household health financial risk and hospitalization behavior. The influence of health insurance type exhibits heterogeneity, with an interaction effect between the two variables and pronounced gender differences: women demonstrate greater sensitivity to household health financial risk, and the "demand-release effect" of health insurance is more pronounced among them. This study provides empirical evidence for optimizing differentiated health insurance policies and alleviating household medical burdens, offering reference for other regions globally. Future efforts should focus on refining health insurance system design, strengthening financial risk interventions, enhancing primary healthcare service capacity, and promoting equity and efficiency in healthcare utilization.

Abbreviations

CHARLS:China Health and Retirement Longitudinal Study

CFPS:China Family Panel Studies

UHC:Universal Health Coverage

UEBMI:Urban Employee Basic Medical Insurance

New Rural Cooperative Medical Scheme (NCMS)

Urban Resident Basic Medical Insurance (URBMI)

unified Urban-Rural Resident Basic Medical Insurance (URRBMI)

Government-funded Medical Insurance (GFMI)

Declarations

1.Ethics approval and consent to participate.

The CFPs (ethical approval code: IRB00001052-14010) and CHARLS (ethical approvalcode: IRB00001052-11015) have been approved by the Biomedical Ethics Committee olPeking University, and all participants signed an informed consent form.

Clinical trial number: not applicable.

2. Consent for publication.

Not applicable.

3. Availability of data and materials.

The data used and/or analyzed during the study are available from the corresponding author upon reasonable request.

4. Competing interests.

The authors declare that they have no competing interests.

5. Funding.

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6. Authors' contributions.

Mengfan Yu: Conceptualization, Methodology, Formal analysis, Writing – original draft.

Ruixue Zhou: Data curation, Investigation, Writing – review & editing.

Di Shen: Software, Validation, Visualization.

Xiduo Yang: Formal analysis, Investigation.

Zijing Wu: Data curation, Writing – review & editing.

Liangru Zhou: Conceptualization, Supervision, Writing – review & editing, Funding acquisition.

Yuwei Wang: Conceptualization, Methodology, Supervision, Writing – review & editing, Funding acquisition.

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Figures

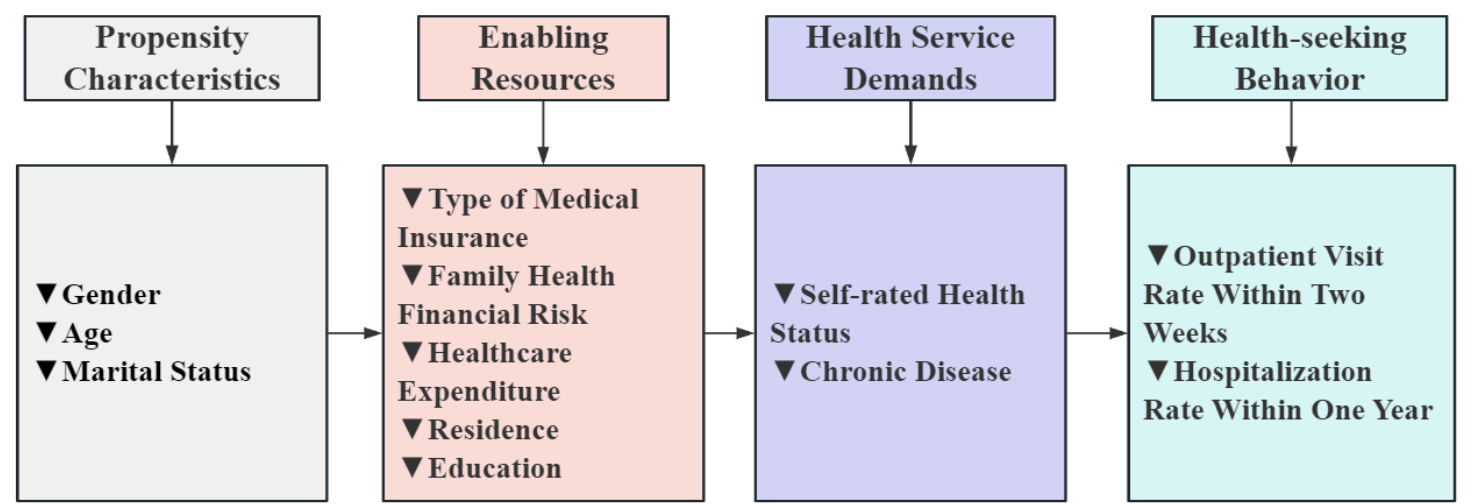


Figure 1

Anderson’s Health-seeking Behavior Model

Supplementary Files

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- [AppendixADefinitionoftheVariables.docx](#)