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Analysis of health insurance reform strategies from a risk-sharing perspective based on the Markov model

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Abstract: China's healthcare system faces increasing challenges, including surging medical costs, resource allocation imbalances favoring large hospitals, and ineffective referral mechanisms. The lack of a unified strategy integrating standardized coverage with personalized payment compounds these issues. To this end, this study proposes a risk-sharing reform strategy that combines equal coverage for the same disease (ECSD) with an individualized out-of-pocket (I-OOP) model. Specifically, the study employs a Markov model to capture patient transitions across health states and care levels. The findings show that ECSD and I-OOP enhance equity by standardizing disease coverage while tailoring costs to patient income and facility type. This approach alleviates demand on high-tier hospitals, promoting primary care utilization and enabling balanced resource distribution. The study's findings provide a reference for policymakers and healthcare administrators by presenting a scalable framework that is aligned with China's development goals with the aim of fostering an efficient, sustainable healthcare system that is adaptable to regional needs.

Key words: equal coverage for the same disease (ECSD); individualized out-of-pocket (I-OOP); health insurance reform; risk sharing; Markov model

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As the economy enters a phase of high-quality development, China's medical security system faces increasing challenges due to urbanization, an aging population, diverse employment patterns, and shifting disease profiles, thus leading to increased and varied healthcare demands. These factors significantly pressure health insurance funds. However, as these funds currently rely on resource allocation decisions dominated by tertiary hospitals, the role of health insurance as a strategic purchaser is limited[1-2]. According to the China Health Statistical Yearbook (2009—2021), patient visits to tertiary hospitals rose from 34. 87% in 2008 to 57. 46% in 2021. Meanwhile, visits to secondary, primary, and ungraded institutions declined, exacerbating the imbalance. The increasing medical costs that outpace funding growth threaten the financial sustainability of health insurance funds[3-5].

Studies have revealed that downward referrals are significantly lower than upward referrals, highlighting a trend of "easy upward, difficult downward" referrals. This trend indicates the referral management system's failure to promote rational patient distribution[6]. Moreover, economic incentives and the absence of unified standards have resulted in insufficient awareness of bidirectional referrals among doctors and patients, hindering implementation of "minor illnesses go to the community, major illnesses go to the hospital"[7].

Additionally, the delegation of referral approvals to medical institutions has caused procedural confusion, with approvals often influenced by "connections"[8]. While inter-regional direct settlements reduce costs and improve satisfaction, they introduce moral hazards under information asymmetry, leading some patients to seek unnecessary treatments outside their regions or pursue referrals due to price and income elasticity effects[9]. Price-insensitive patients, especially those driven by survival concerns, prefer higher-cost healthcare services.

In an attempt to address these issues, prior studies have focused on risk-sharing and cost transparency to improve access and control expenses. Standardized reimbursement optimizes resource allocation and reduces patient burdens but lacks differentiation based on income or facility levels[10-11]. Individualized out-of-pocket (I-OOP) payments enhance equity by tailoring costs to income, particularly for low-income groups. However, a unified model combining both approaches has not been developed[12]. Cost transparency frameworks such as diagnosis-related groups (DRG) empower informed choices and optimize resources but struggle to adapt dynamically to evolving healthcare needs[13].

To overcome these limitations, this study proposes an innovative reform strategy integrating equal coverage for the same disease (ECSD) based payment with I-OOP within a risk-sharing framework. Unlike previous stud-

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ies, this strategy standardizes reimbursement rates across healthcare institutions while adjusting out-of-pocket costs based on patients' income levels and treatment settings. Accordingly, the approach aims to strike a balance between healthcare equity and resource optimization, addressing existing gaps in cost management models that lack personalization and standardization[14].

To validate this strategy, this study uses a Markov model to dynamically track patient health progression across states to reflect evolving healthcare needs and costs. Specifically, the model simulates patient movement across levels by incorporating transition probabilities, offering insights into healthcare utilization and cost distribution[15-16].

1 Health Insurance Reform Strategy Based on Risk-Sharing

1.1 Design ideas for a reform strategy

The ECSD mechanism standardizes reimbursement rates for the same disease, whereas the I-OOP mechanism adjusts out-of-pocket costs based on income and treatment context, guiding patients toward appropriate healthcare levels. For instance, a middle-income diabetic patient receiving basic care at a primary facility may face lower out-of-pocket costs (e.g., 20%), whereas opting for a tertiary hospital could increase costs to 40%, promoting cost-effective care choices. A detailed diagram of the strategic design for healthcare reform is shown in Fig. 1.

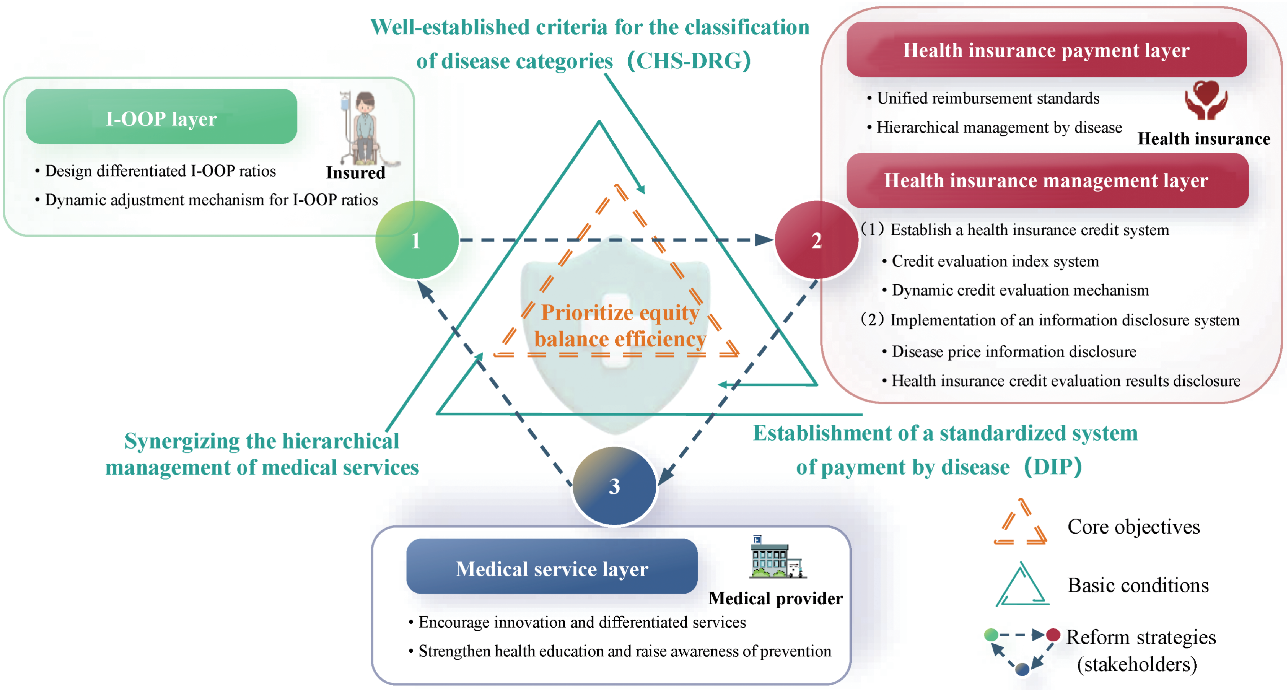

Fig. 1 Idea map for designing healthcare reform strategies based on risk-sharing

1.1.1 Health insurance management layer

Information asymmetry between doctors and patients remains a key issue in medical resource allocation and patient decision-making. To address this issue, a comprehensive health insurance credit system and information disclosure mechanism for designated medical institutions will be established. By regularly publishing disease price information and health insurance credit evaluations, patients can make more informed and rational medical choices.

1.1.2 I-OOP layer

The health insurance system supplements and improves the existing referral management framework, respecting patients' right to choose medical services. The improved system links the I-OOP portion of medical costs to patients' medical choices, enabling personal autonomy while sharing financial risks. Key measures include implementing differentiated I-OOP ratios based on income level and disease severity and establishing a dynamic I-OOP adjustment mechanism to align with economic development and medical cost trends.

1.1.3 Health insurance payment layer

Reforms in payment methods ensure consistent reimbursement standards for the same disease across hospital and surgical grades. Diseases that can be treated at primary or lower-level institutions will incur lower costs, whereas treatment at larger hospitals will be more expensive; however, the health insurance reimbursement for the same disease will remain consistent, with additional costs covered by the patient.

1.1.4 Medical service layer

Promoting a competitive market mechanism in medical services is critical for optimizing resource allocation and controlling medical costs. Competition among healthcare providers is encouraged within the framework of ECSD and improves the quality and efficiency of services. The specific implementation plan includes providing innovative, differentiated services and strengthening health education and prevention awareness[17-18].

1.2 Necessary infrastructure and expansion

Certain conditions are required to implement risk sharing-based health insurance reform. These conditions mainly involve three aspects: classification of disease types, grading of medical services, and payment standards for health insurance by disease type.

1.2.1 Well-established criteria for the classification of disease categories

China is implementing the China Healthcare Security DRG (CHS-DRG) and Big Data Diagnosis-Intervention Packet (DIP) systems under total budget management. The National Healthcare Security Administration (NHSA) has launched the CHS-DRG Subgroup Program (Version 1.0) and the DIP Catalog Library (Version 1.0), creating a DIP-based comparison system. This system transforms previously "incomparable" clinical practices into "comparable" data, enabling a quantitative evaluation of case volumes, treatment complexity, and care levels across hospitals for the same disease group[19].

1.2.2 Synergizing the hierarchical management of medical services

In 1989, the former Ministry of Health issued the Measures for the Hierarchical Management of Hospitals, clarifying that level Ⅰ hospitals provide primary care, level Ⅱ hospitals offer regional comprehensive services, and level Ⅲ hospitals specialize in advanced care. The 2012 Measures for the Management of Surgical Classification further defined surgical scopes: tertiary hospitals handle complex surgeries (levels Ⅲ and Ⅳ), secondary hospitals focus on intermediate surgeries (levels Ⅱ and Ⅲ), and primary hospitals perform basic surgeries (levels Ⅰ and Ⅱ).

1.2.3 Establishment of a standardized system of payment by disease

The current DRG/DIP payment reform focuses on establishing a Chinese-style settlement method where medical insurers and providers settle payments based on the value of disease categories. The "ECSD & I-OOP" reform replaces payments based on institution level and expense proportions, with standardized payments determined by disease type, ensuring "same disease, same payment" across insurance types.

2 Mathematical Model

This study constructs a multi-participant model to optimize the allocation of medical resources and encourage patients to choose appropriate medical institutions based on their disease severity. The participants include the government health insurance provider, the insured, and medical service providers. We use the Markov decision process (MDP) to establish a mathematical model and solve the optimal strategy through numerical simulations, exploring each participant's optimal strategy and the system's overall benefits[20-24].

2.1 State space

The state space S is defined as the combination of disease states S_i and medical institution levels L_j. Suppose there are n types of disease states and m levels of medical institutions. Then, the state space is defined as follows:

$$S = \{S_i L_j | i \in \{1, 2, \cdots, n\}, j \in \{1, 2, \cdots, m\}\} \quad (1)$$

Disease states S_i are classified by severity: mild diseases S_1 require basic care, moderate diseases S_2 need specialized treatments, severe diseases S_3 demand advanced care at specialized institutions, acute diseases S_4 require immediate emergency treatment, and finally, chronic diseases S_5 involve long-term management and care.

Medical institution levels L_j are categorized by scale and capability: community health centers L_1 offer basic care, county-level hospitals L_2 provide comprehensive services with some specialization, city-level hospitals L_3 deliver higher-level specialized care, provincial hospitals L_4 offer advanced, resource-rich services, and national-level hospitals L_5 represent the highest level of specialized and comprehensive care.

Assuming the state space S has five types of disease states and five levels of medical institutions, S can be expressed as follows:

$$S = \{S_1L_1, S_1L_2, S_1L_3, S_1L_4, S_1L_5, S_2L_1, S_2L_2, S_2L_3, S_2L_4, S_2L_5, \cdots, S_5L_1, S_5L_2, S_5L_3, S_5L_4, S_5L_5\} \quad (2)$$

2.2 Action space

The action space involves decisions made by the government health insurance provider, the insured, and medical service providers. The government health insurance provider selects among three payment standards: basic (A_1), enhanced (A_2), or premium (A_3). The insured chooses specific doctors, treatment plans, and medical institution levels, ranging from community health service centers to national hospitals (L_j), with decisions based on the doctor's expertise and reputation (D_k) and the available treatment plans (T_m). Meanwhile, medical service providers decide on combinations of service quality (high, medium, or low, denoted as Q_p) and cost structures (C_q).

Assuming there are three types of payment standards, five levels of medical institutions, three types of doctor selections, and four treatment plans, the action space can be expressed as follows:

$$A = \{A_1, A_2, A_3, L_1, L_2, L_3, L_4, L_5, D_1, D_2, D_3, T_1, T_2, T_3, T_4\} \quad (3)$$

2.3 Transition probability matrix

The transition probability matrix $\boldsymbol{T}$ is a crucial part of the model that is used to describe the probability of transitioning from one state to another. To achieve the optimization goal of encouraging patients to choose appropriate medical institutions based on their disease's severity, we set transition probabilities during the model construction stage. Specifically, the transition probability matrix is defined as follows:

$$\boldsymbol{T}(s'|s,a) \tag{4}$$

where $\boldsymbol{T}(s'|s,a)$ represents the probability of transitioning from state s to state s' through action a.

The transition probabilities are derived from real-world health data, including hospital records, electronic health records, clinical studies, and health surveys. For example, in relation to diabetes, literature-based probabilities show that the probability of transitioning from a no-complication state to mild complications is 0.164, that of transitioning from mild to moderate complications is 0.324, and that of transitioning from moderate to severe complications is 0.456. The probability of progressing from severe complications to a state with four or more complications is 0.259[25].

2.4 Reward functions

When constructing reward functions, more practical factors (including the patient's health status, efficiency of medical resource use, cost control, medical quality, and the interaction between different stakeholders) must be considered. In this paper, the reward functions for each participant are defined as follows.

2.4.1 Government health insurance provider

The reward function considers savings in medical expenses, improvements in medical service quality, and patient satisfaction. The function expression is defined as follows:

$$R_1(s,a) = -C(s,a) + \lambda_1 Q(s,a) + \lambda_2 S(s,a) - \lambda_3 D(s,a) \tag{5}$$

where $C(s,a)$ represents medical expenses, $Q(s,a)$ represents service quality, $S(s,a)$ represents patient satisfaction, $D(s,a)$ represents the volatility of medical expenses (the greater the volatility, the lower the reward), and λ_1, λ_2, and λ_3 are weight factors.

2.4.2 Insured

The reward function is the balance between obtaining high-quality medical services and paying costs, as well as the medical experience. The function is defined as follows:

$$R_2(s,a) = \alpha Q(s,a) - \beta P(s,a) + \gamma E(s,a) - \delta T(s,a) \tag{6}$$

where $P(s,a)$ denotes payment costs, $E(s,a)$ represents medical experience (including service attitude and environment), $T(s,a)$ represents waiting time (the longer the time, the lower the reward), and $\alpha, \beta, \gamma, \delta$ are weight factors.

2.4.3 Medical service providers

The reward function is the profit from providing services, the efficiency of resource utilization, and patient satisfaction. The function is defined as follows:

$$R_3(s,a) = P(s,a)(1 - C(s,a)) + \theta U(s,a) + \phi S(s,a) \tag{7}$$

where $P(s,a)$ represents service profit, $C(s,a)$ represents costs, $U(s,a)$ represents resource utilization efficiency, and θ, ϕ are weight factors.

2.5 Utility functions

2.5.1 Utility function of government health insurance provider

The utility function of government health insurance provider U_1 is expressed as

$$U_1(S_i,A_j) = -C_1(S_i,A_j) + \lambda_1 R_1(S_i,A_j) + \lambda_2 S_1(S_i,A_j) - \lambda_3 D_1(S_i,A_j) \tag{8}$$

The utility function $U_1(S_i,A_j)$ represents the objective of the government health insurance provider in balancing various factors that impact its overall performance. This includes minimizing medical expenses $C_1(S_i,A_j)$, maximizing immediate rewards $R_1(S_i,A_j)$, ensuring patient satisfaction $S_1(S_i,A_j)$, and reducing the volatility of medical expenses $D_1(S_i,A_j)$. By appropriately weighting these factors using λ_1, λ_2, and λ_3, the government health insurance provider seeks to optimize its utility and achieve sustainable operations.

2.5.2 Utility function of insured

The utility function of insured U_2 is expressed as

$$U_2(S_i,A_j) = \alpha Q(S_i,A_j) - \beta P(S_i,A_j) + \gamma E(S_i,A_j) - \delta T(S_i,A_j) + \eta H(S_i,A_j) \tag{9}$$

where $Q(S_i,A_j)$ represents service quality, $P(S_i,A_j)$ represents payment costs, $E(S_i,A_j)$ represents medical experience, $T(S_i,A_j)$ represents waiting time, and $H(S_i,A_j)$ represents health improvement degree (i.e., treatment effect). Weight factors $\alpha, \beta, \gamma, \delta, \eta$ are used to adjust the influence of these factors, enabling the insured to find the optimal balance between payment costs, service quality, and health improvement.

2.5.3 Utility function of medical service providers

The utility function of medical service providers U_3 is expressed as

$$U_3(S_i,A_j) = P(S_i,A_j)(1 - C_1(S_i,A_j)) + \theta U(S_i,A_j) + \phi S(S_i,A_j) \tag{10}$$

where $P(S_i,A_j)$ represents service profit, $C_1(S_i,A_j)$ represents costs, and $U(S_i, A_j)$ represents resource utilization efficiency. Weight factors θ and ϕ are used to balance profit, cost, resource utilization efficiency, and patient satisfaction, thereby maximizing the overall utility for medical service providers.

3 Numerical Simulation

3.1 Parameter assumptions

3.1.1 Transition probabilities

The transition probability matrix $\boldsymbol{T}(s'|s, a)$ describes the probability of transitioning from one state to another. These probabilities must be adjusted based on actual data to more accurately reflect the treatment effects of different medical institutions on different disease states.

3.1.2 Service quality and cost settings

Payment standard A_1 refers to the existing regular health insurance payment strategy, allowing patients to save 100 yuan in medical costs.

Payment standard A_2 involves implementing partial payment reforms based on regular health insurance payment methods, allowing patients to save 200 yuan in medical costs.

Payment standard A_3 adopts the ECSD & I-OOP strategy, allowing patients to save 300 yuan, in medical costs.

3.1.3 Service quality settings

For S_1, $Q(S_1, L_1)=0.7$, $Q(S_1, L_2)=0.8$, $Q(S_1, L_3)=0.9$, $Q(S_1, L_4)=1.0$, and $Q(S_1, L_5)=1.1$.

For S_2, $Q(S_2, L_1)=0.6$, $Q(S_2, L_2)=0.7$, $Q(S_2, L_3)=0.8$, $Q(S_2, L_4)=0.9$, and $Q(S_2, L_5)=1.0$.

For S_3, $Q(S_3, L_1)=0.5$, $Q(S_3, L_2)=0.6$, $Q(S_3, L_3)=0.7$, $Q(S_3, L_4)=0.8$, and $Q(S_3, L_5)=0.9$.

3.1.4 Discount factor

The discount factor is set to $\gamma = 0.95$ to balance the relative importance of current rewards and future rewards. Sensitivity analysis was also done using $\gamma = 0.85$.

By performing a sensitivity analysis on the discount factor (Fig. 2), we can observe that the long-term cost metric significantly increases as the discount factor approaches 1.0. Notably, high discount factors (0.95-0.99) might be more suitable in contexts where long-term health outcomes and sustainability are prioritized, even if they increase short-term expenditures. Conversely, lower discount factors (0.85-0.90) are preferable where immediate cost control is critical because they de-emphasize future costs.

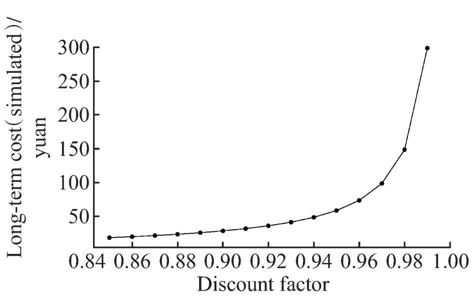

Fig. 2 Discount factor analysis chart

3.1.5 Immediate incentive

The function expression of the following is defined as follows.

For the government,

$$R_1(s, a) = -C(s, a) + \lambda_1 Q(s, a) + \lambda_2 S_1(s, a) - \lambda_3 D_1(s, a) \tag{11}$$

For the insured,

$$R_2(s, a) = \alpha Q(s, a) - \beta P(s, a) + \gamma E(s, a) - \delta T(s, a) + \eta H(s, a) \tag{12}$$

For the medical service providers,

$$R_3(s, a) = P(s, a)(1 - C(s, a)) + \theta U(s, a) + \phi S(s, a) \tag{13}$$

3.2 Value iteration algorithm

Value iteration is a standard method for solving MDP[26], which finds the optimal strategy by repeatedly updating the value function until convergence.

The process begins by initializing the value function $V(s)$, which is typically set to zero or random values. The value function is then updated iteratively until convergence using the following equation:

$$V_{k+1}(s) = \max_a \left[R(s, a) + \gamma \sum_{s'} P(s'|s, a) V_k(s') \right] \tag{14}$$

where $V_k(s)$ is the value function of state s in the k-th iteration, $R(s, a)$ is the immediate reward for performing action a in state s, γ is the discount factor, and $P(s'|s, a)$ is the probability of transitioning from state s to state s' after performing action a.

After the value function converges, we extract the optimal policy $\pi(s)$, which selects the action that maximizes the value function in each state.

$$\pi(s) = \arg\max_a \left[R(s, a) + \gamma \sum_{s'} P(s'|s, a) V_k(s') \right] \tag{15}$$

3.3 Numerical simulation results and analysis

The findings under different parameters are compared and analyzed through the value iteration method. Consequently, the optimal strategy for each participant is obtained as follows.

3.3.1 Optimal strategy for government health insurance provider

The simulation results show that with a high discount factor ($\gamma = 0.95$), long-term gains are higher, making it optimal for the government health insurer to select high-quality healthcare services despite higher short-term costs. In contrast, with a low discount factor ($\gamma = 0.85$), short-term returns are prioritized, favoring strategies that save healthcare costs (Fig. 3). Therefore, the premium payment method A_3 is the optimal strategy for the health insurance provider as it delivers the maximum overall benefit.

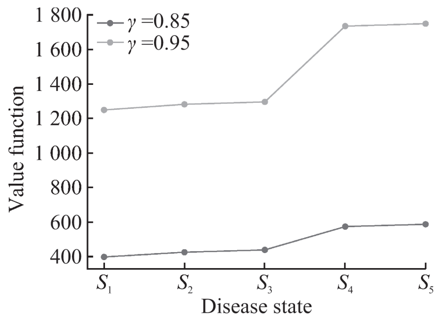

Fig. 3 Value functions at different discount factors

3.3.2 Optimal strategy for insured

The simulation results indicate that with a high discount factor ($\gamma = 0.95$), long-term gains are greater, making it optimal for insured patients to select high-quality services despite higher short-term costs. Conversely, at a low discount factor ($\gamma = 0.85$), short-term benefits are prioritized, leading insured patients to opt for low-cost, low-quality providers to minimize immediate expenses.

For severe S_3 and acute S_4, gains were significantly higher under the high discount factor, suggesting that long-term considerations favor higher-quality care (Fig. 3). For S_1, S_2, and S_5, the optimal strategy is A_3 under both discount factors, maximizing benefits regardless of time horizon (Fig. 4). Thus, the insured's optimal strategy P_1 is determined by solving the utility maximization problem under given conditions, including disease severity (S_1, S_2, ⋯, S_5), payment standards (A_1, A_2, A_3), and the discount factor (γ). The strategy's value (e. g., A_1, A_2, A_3) reflects the insured's decision to select the payment standard that maximizes their overall benefit, balancing short-term costs and long-term gains. For visualization purposes, the strategies are encoded numerically as follows: A_1=0, A_2=1, A_3=2.

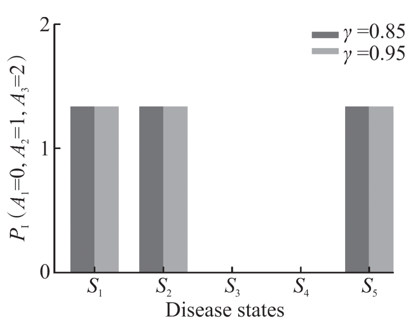

Fig. 4 Strategies at different discount factors

3.3.3 Optimal strategy for medical service providers

Likewise, the simulation results show that patient satisfaction S_1 and health status improvement $H(S_i, A_j)$ vary across disease states, influencing the choices of insured parties. The advanced payment method A_3 consistently leads to higher patient satisfaction and improved health outcomes (Fig. 5 and Fig. 6). Therefore, for medical service providers, the optimal strategy is to enhance patient satisfaction and health improvement by balancing Q_p and C_q.

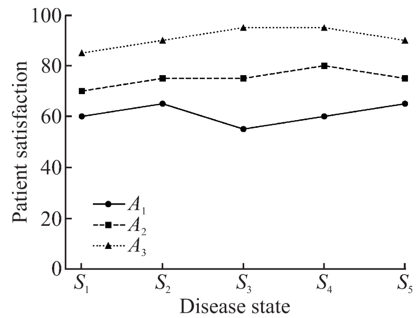

Fig. 5 Patient satisfaction at different discount factors

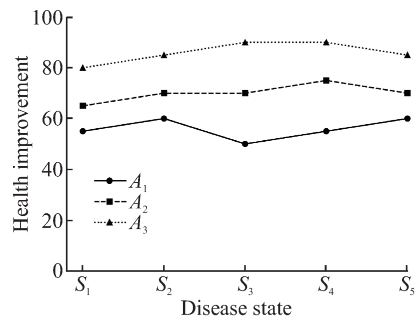

Fig. 6 Health improvement at different discount factors

To summarize, the government health insurer's adoption of payment method A_3 achieves an optimal balance of long-term cost savings, improved service quality, and enhanced patient satisfaction. The insured party selects appropriate healthcare providers based on disease severity, balancing costs, service quality, and health outcomes. Healthcare providers at different levels deliver services with appropriate quality and cost, maximizing their revenue while improving patient satisfaction and health outcomes (Fig. 7).

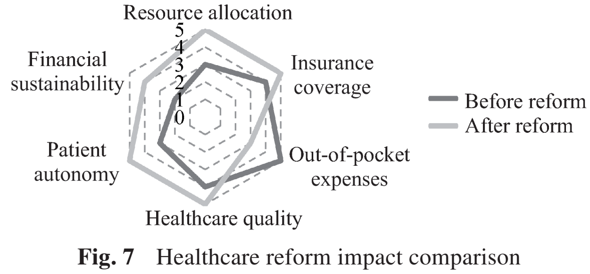

Fig. 7 Healthcare reform impact comparison

4 Empirical Case Studies

Currently, pilot projects for health insurance reform based on risk-sharing are primarily concentrated in some counties and cities in Anhui Province and Sanming City, Fujian Province.

4.1 Practical exploration in Anhui Province

Anhui Province's health insurance reform is centered on ECSD, focusing on disease-based group payments and unified standards. By January 2020, ECSD was implemented in 18 provincial hospitals, covering 422 diseases[27]. Regions such as Fuyang, Lu'an, and Xuancheng actively explored reforms. In Fuyang City, county-level medical institutions completed 26 970 cases with an 83.79% reimbursement ratio, reducing patient expenses by 15 million yuan, easing financial burdens, and improving primary care utilization[28]. In Jingde County, as of July 31, 2021, ECSD covered 2 411 cases with total costs of 24.89 million yuan, achieving a 67.37% reimbursement ratio (18.73% higher than out-of-county hospitalization), thereby saving 5.18 million yuan for the fund and enhancing cost efficiency and affordability[29].

4.2 Practical exploration in Sanming City, Fujian Province

In Sanming City, the reform centered on implementing China DRG (C-DRG) to enhance cost transparency and patient satisfaction by setting fixed treatment prices upfront. This approach provides patients with clarity on treatment costs, enabling informed decisions and reducing unnecessary expenses[30-31]. In 2020, the reform saved approximately 69.71 million yuan for the health insurance fund. The actual reimbursement ratio for patients covered under employees' health insurance increased from 66.21% (level Ⅲ hospitals) and 68.82% (level Ⅱ hospitals) to 70%. Similarly, for residents' health insurance, the ratio rose from 47.69% to 50% for level Ⅲ hospitals and 64.68% to 70% for level Ⅱ hospitals[32].

4.3 Comparative analysis of reform differences, challenges, and outcomes

Evidently, the reforms in Anhui Province and Sanming City differed in focus, challenges, and outcomes. Anhui prioritized standardized reimbursement across disease types to promote healthcare equity, whereas Sanming focused on cost transparency through the C-DRG model, empowering patients with fixed treatment prices. Anhui faced challenges in applying uniform standards due to regional disparities, whereas Sanming struggled with resource constraints in lower-level facilities. Finally, Anhui's broad coverage increased demand, particularly at primary institutions, improving access but straining resources. In contrast, Sanming's pricing model reduced unnecessary visits by encouraging cost-effective choices. While Anhui's I-OOP structure maintained high patient satisfaction, it led to higher costs at tertiary hospitals, whereas Sanming's approach consistently lowered financial burdens across all hospital levels.

5 Conclusions

This study proposes a health insurance reform strategy integrating ECSD with an I-OOP model to enhance equity, manage healthcare costs, and optimize resource allocation in China's healthcare system.

(1) The I-OOP mechanism strengthens individual responsibility within the medical security framework, bridging cost gaps introduced by ECSD while controlling medical expenses and maintaining service quality. Simulations and evidence show that appropriate premium standards can reduce long-term costs, improve service quality, and ensure sustainable fund management[33].

(2) The reform enhances patient autonomy for insured individuals, allowing them to choose medical institutions based on their needs and disease severity. This approach balances costs, service quality, and health outcomes while protecting low-income groups, reducing medical expenses, and promoting healthcare equity.

(3) For healthcare providers, the reform encourages market-aligned pricing and the development of specialty services. Community health centers focus on cost-effective care, city-level hospitals manage moderate cases, and national hospitals treat complex cases, improving resource allocation and service quality. Unified reimbursement standards and the I-OOP model guide patients to primary care, fostering a tiered healthcare system and motivating providers to align with systemic goals[34].

(4) While promising results have been observed in pilot regions, further research is needed to adapt this model to diverse demographic and regional contexts, particularly in rural areas and regions with aging populations. Clearly, unique socioeconomic conditions and healthcare infrastructure in certain areas require tailored implementation strategies.

References

[1] ZHAO J Y, GUO K. Study on the influencing factors of Chinese medical insurance fund development: Based on provincial panel data[J]. Management Review, 2023, 35(8): 71-84. (in Chinese)

[2] WANG Z, ZHU F M. Calculation of the income and expenditure of the fund for the reform of the medical insurance outpatient security mode[J]. China Health Insurance, 2020(11): 41-48. (in Chinese)

[3] Health Ministry of People's Republic of China. China health statistics yearbook[M]. Beijing: Peking Union Medical College Press, 2011: 118. (in Chinese)

[4] National Health and Family Planning Commission. China health and family planning statistical yearbook[M]. Beijing: Peking Union Medical College Press, 2016: 122. (in Chinese)

[5] National Health Commission. China health statistics yearbook[M]. Beijing: Peking Union Medical College Press, 2022: 126. (in Chinese)

[6] GAO X T, HAO X Q. Willingness of Chinese patients for downward referral and its influencing factors: A meta analysis[J]. Modern Hospitals, 2022, 22(5): 671-675. (in Chinese)

[7] WEI J T, GE M Y, LIU Z L, et al. Current situation and analysis of the two-way referral system in Luohe based on the mode of health alliance[J]. Chinese Journal of General Practice, 2022, 20(4): 635-638. (in Chinese)

[8] GONG G W. Value-based orientation study on the formation mechanism of saving in the global budget of medical insurance in county medical community[D]. Wuhan: Huazhong University of Science and Technology, 2021. (in Chinese)

[9] LÜ S N, FENG J. Effect of the policy for cross-provincial direct settlement of outpatient expenses on basic medical insurance expenditure[J]. Journal of Financial Research, 2023, 517(7): 97-115. (in Chinese)

[10] SUN J, FU X Z, YAO Q. Burden of hospitalization and countermeasures for chronic diseases in megacities from the perspective of medical insurance: A case study of W city in Central China[J]. Chinese Journal of Health Policy, 2023, 16(4): 1-8. (in Chinese)

[11] FENG J, CHEN X X, HU B. The medical insurance based on efficiency and equity: evidence from the integration of the national basic medical insurance program for urban and rural residents[J]. Economic Research Journal, 2022, 57(6): 154-172. (in Chinese)

[12] ZHENG G C. Comprehensively deepening health care reforms: Progress, challenges and advancement[J]. Administration Reform, 2021, 10(10): 12-25. (in Chinese)

[13] QIN Y F. DRG disease payment system reform: "Same price for same disease" to alleviate "expensive medical treatment" [EB/OL]. (2018-04-18) [2024-06-01]. https://www. zgylbx. com/index. php? m=content&c=index&a=show&catid=17&id=32989. (in Chinese)

[14] China Medical Insurance. DIP reform reinforces policy synergies and can be informed by these experiences[EB/OL]. (2024-03-01) [2024-06-01]. http://www. drugnet. com. cn/news/detail/221528. (in Chinese)

[15] SONNENBERG F A, BECK J R. Markov models in medical decision making: A practical guide[J]. Medical Decision Making, 1993, 13(4): 322-338.

[16] LIU G E. China pharmacoeconomic evaluation guide 2020[M]. Beijing: Market Press, 2020: 8-10. (in Chinese)

[17] SUN H, WANG H Y. Enhancing customers' prevention efforts: An incentive feedback mechanism design[J]. Journal of Southeast University (English Edition), 2021, 37(4): 436-444.

[18] GONG X, ZHAO L D. Return models of health data platform considering online-and-offline interaction[J]. Journal of Southeast University (Natural Science Edition), 2022, 52(1): 196-202. (in Chinese)

[19] GUO W, ZHONG Y M, ZHOU B. Economic operation of Chinese pharmaceutical industry from January to September 2019[J]. Chinese Journal of Pharmaceuticals, 2019, 50(12): 1530-1536. (in Chinese)

[20] BELLMAN R, DREYFUS S E. Applied dynamic programming[M]. Princeton, NJ, USA: Princeton University Press, 1962: 13-14.

[21] SUTTON R S, BARTO A G. Reinforcement learning: An introduction[M]. Cambridge, MA, USA: MIT Press, 2014: 73-88.

[22] PUTERMAN M L. Markov decision processes: Discrete stochastic dynamic programming[M]. Danvers, MA, USA: John Wiley & Sons Inc, 1994: 25-50.

[23] NASH J F. Equilibrium points in N-person games[J]. Proceedings of the National Academy of Sciences of the United States of America, 1950, 36(1): 48-49.

[24] LIANG Y X, ZHAO L D. Sustainability of health information exchange platform based on information cooperation[J]. Journal of Southeast University (English Edition), 2021, 37(3): 332-338.

[25] SHI S Y, ZHAO H Y, LIU Z K, et al. Application of multi-state Markov model in studying transition of number of chronic complications and influencing factors in type 2 diabetes mellitus patients[J]. Chinese Journal of Epidemiology, 2021, 42(7): 1274-1279. (in Chinese)

[26] FUDENBERG D, TIROLE J. Game theory[M]. Cambridge, MA, USA: MIT Press, 1991: 105-107.

[27] Anhui Medical Insurance Bureau. Notice on the issuance of Anhui Province basic medical insurance payment for diseases according to disease grouping and medical insurance payment standards (first batch) [EB/OL]. (2019-11-20) [2024-06-01]. https://ybj. ah. gov. cn/public/7071/117236261. html. (in Chinese)

[28] Fuyang Medical Insurance Bureau. Our city is trying to implement the same insurance for the same disease to effectively alleviate the "expensive medical treatment"[EB/OL]. (2020-08-06) [2024-06-01]. https://www. fy. gov. cn/content/detail/5f2ba3227f8b9a29168b4585. html. (in Chinese)

[29] Xuancheng Municipal Health Commission. Reply to the municipal CPPCC proposal No. 167 in 2021[EB/OL]. (2021-08-24) [2024-06-01]. https://www. xuancheng. gov. cn/OpennessContent/show/2207148. html. (in Chinese)

[30] XU Z L, WENG Z X, ZHUO C. Experiences and introduction of C-DRG collection and payment reform in Sanming[J]. Chinese Health Economics, 2022, 41(1): 28-31. (in Chinese)

[31] CHEN X J, HUA L, LIU H L. Difficulties and countermeasures of C-DRG implementation in Sanming[J]. Chinese Health Economics, 2022, 41(1): 36-40. (in Chinese)

[32] ZHANG Y M. Sanming medical reform and C-DRG payment system reform [EB/OL]. (2021-11-09) [2024-06-01]. https://www. cn-healthcare. com/articlewm/20211109/content-1282943. html. (in Chinese)

[33] PAN S F, WANG H Y, LIN X X. Effects of medical insurance payment on preventive efforts of patients with chronic diseases and hospitals[J]. Journal of Southeast University (Natural Science Edition), 2020, 50(4): 789-796. (in Chinese)

[34] WANG K, XIAO Y T, ZHAO L D. Value on investment decision for internet hospitals under online /offline direct-to-patient mode[J]. Journal of Southeast University(English Edition), 2023, 39(1): 98-106.

风险共担视角下医保制度改革策略分析
——基于马尔可夫模型

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摘要：中国的医疗体系面临着不断升级的挑战，包括医疗费用激增、资源分配失衡、偏向大医院以及转诊机制失效，由于缺乏将标准化保障与个性化支付相结合的统一战略，这些问题变得更加复杂。本研究提出了一种将同病同保障（ECSD）与差异化自付（I-OOP）模式相结合的风险共担医保改革策略。采用马尔可夫模型捕捉病人在不同健康状态和护理级别之间的转变。研究结果表明，同病同保障和差异化自付模式通过标准化疾病覆盖范围来提高公平性，同时根据患者收入和医疗机构类型调整费用成本。该方法减轻了大医院的需求压力，促进了基层卫生服务利用率，并实现了更均衡的资源分配。该研究提出了一个与中国发展目标相一致的可扩展框架，为政策制定者和医疗管理者提供了参考，以促进建立一个适应区域需求的高效、可持续的医疗体系。

关键词：同病同保障；差异化自付；医保改革；风险共担；马尔科夫模型

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