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Selection of Health Insurance Policy: Using Analytic Hierarchy Process and Combined Compromised Solution Approach Under Spherical Fuzzy Environment

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Abstract: The process of health insurance policy selection is a critical decision with far–reaching financial implications. The complexity of health insurance policy selection necessitates a structured approach to facilitate informed decision-making amidst numerous criteria and provider options. This study addresses the health insurance policy selection problem by employing a comprehensive methodology integrating Spherical Fuzzy Analytic Hierarchy Process (SF–AHP) and Combined Compromise Solution (CoCoSo) Algorithm. Eight experienced experts, four from academia and industry each, were engaged, and eleven critical factors were identified through literature review, survey, and expert opinions. SF–AHP was utilized to assign weights to these factors, with Claim settlement ratio (C9) deemed the most significant. Subsequently, CoCoSo Algorithm facilitated the ranking of insurance service providers, with alternative A6 emerging as the superior choice. The research undertakes sensitivity analysis, confirming the stability of the model across various scenarios. Notably, alternative A6 consistently demonstrates superior performance, reaffirming the reliability of the decision-making process. The study's conclusion emphasizes the efficacy of the joint SF–AHP and CoCoSo approach in facilitating informed health insurance policy selection, considering multiple criteria and their interdependencies. Practical implications of the research extend to individuals, insurance companies, and policymakers. Individuals benefit from making more informed choices aligned with their healthcare needs and financial constraints. Insurance companies can tailor policies to customer preferences, enhancing competitiveness and customer satisfaction. Policymakers gain insights to inform regulatory decisions, promoting fair practices and consumer protection in the insurance market. This study underscores the significance of a structured approach in navigating the intricate health insurance landscape, offering practical insights for stakeholders and laying a foundation for future research advancements.

Index Terms: Spherical Fuzzy Sets, AHP, CoCoSo, Insurance Policy, MCDM.

1. Introduction

In today's complex healthcare landscape, choosing an optimal health insurance policy is a critical decision that can significantly impact an individual's financial well–being and access to quality medical care [1]. The multitude of available insurance plans, each varying in terms of coverage benefits, premium costs, and network providers, presents a daunting challenge for individuals seeking the most suitable policy that aligns with their specific needs and preferences [2]. To address this multifaceted decision–making process, researchers and practitioners have turned to innovative methodologies that can effectively handle the complexity and uncertainty inherent in such choices [3]. The significance of health insurance policy selection lies in its ability to provide financial protection, access to healthcare, and peace of mind. It also affects legal compliance, job satisfaction, and long–term financial planning. Therefore, careful consideration of your needs and a thorough understanding of available options are crucial when choosing a health insurance policy. Health insurance policy selection is a quintessential problem for individuals, families, and even organizations seeking to provide comprehensive coverage to their members. The decision–making process involves the consideration of multiple interrelated criteria, such as coverage benefits, premium costs, policy terms, and the breadth of the healthcare provider network [4]. Moreover, the inherently uncertain nature of the healthcare industry, coupled with the varying preferences and subjective judgments of stakeholders, further complicates the selection process.

The use of the Analytic Hierarchy Process (AHP) as a decision–making tool is well–established, and it has been extensively employed in various domains to aid in multi–criteria decision–making [5,6]. However, its traditional application assumes precise numerical data and does not directly address the challenges posed by linguistic uncertainty and vagueness. This paper, therefore, explores the incorporation of Spherical Fuzzy sets into the AHP framework to accommodate linguistic variables and address imprecision in the decision–making process. This research paper delves into the problem of health insurance policy selection and proposes a comprehensive approach that combines the Analytic Hierarchy Process (AHP) and the Combined Compromised Solution (CoCoSo) approach within a Spherical Fuzzy (SF) environment. The integration of these methodologies aims to provide decision–makers with a robust and adaptive framework to make informed choices amid uncertain and subjective factors. The next section further discusses the need of joint approach.

1.1. Why a Joint CoCoSo–spherical Fuzzy AHP Approach?

A joint spherical fuzzy AHP with COCOSO approach would be an effective combination to address the complexities and uncertainties [7]. Traditional AHP can handle crisp data, but it may not adequately capture the vagueness and linguistic uncertainty prevalent in decision–making. By introducing Spherical Fuzzy sets into the AHP framework, decision–makers can represent linguistic variables, fuzzy linguistic terms, and vague comparisons more effectively [8,9]. Spherical Fuzzy AHP enables a more flexible and realistic representation of decision–makers' preferences and judgments, leading to more robust and accurate results [10,11]. The COCOSO approach is specifically designed to handle situations by seeking a balanced compromise among competing objectives [12]. It explores a range of compromise solutions that strike a harmonious balance between the conflicting interests of different stakeholders. This makes it a suitable choice for health insurance policy selection, where stakeholders may have diverse preferences. By combining Spherical Fuzzy AHP with the COCOSO approach, the decision–making framework becomes more comprehensive. Spherical Fuzzy AHP provides a robust method to determine the relative importance of criteria and alternatives using fuzzy linguistic terms. On the other hand, the COCOSO approach helps identify compromise solutions that meet multiple objectives, satisfying various stakeholders to a reasonable extent. The synergy between the two approaches enhances the decision–making process by accommodating uncertainties and balancing diverse objectives.

1.2. Objectives of the Research

The primary objective of this research paper is to propose and demonstrate a holistic decision–making framework for health insurance policy selection. The study aims to achieve the following specific goals:

- Integrate the Analytic Hierarchy Process (AHP) with Spherical Fuzzy sets to handle uncertain and vague inputs in the health insurance policy evaluation and calculate weights of the criteria.
- Apply the Combined Compromised Solution (CoCoSo) approach to rank the alternatives.
- Demonstrate the applicability and effectiveness of the proposed approach through a case study.

2. Materials and Methods

The process of choosing a health insurance policy is of great importance due to its significant financial consequences. However, this decision–making process is complex as it involves both quantitative and qualitative factors. The research methodology used in the study is depicted in Fig. 1 and Fig. 2 respectively.

2.1. Spherical Fuzzy Sets (SFS)

Traditional fuzzy sets, introduced by Zadeh in 1965, are widely used in decision-making problems where uncertainty and vagueness are present. In traditional fuzzy sets, each element has a degree of membership (ranging between 0 and 1), which indicates how much that element belongs to a set. The concept is extended through different variants such as Intuitionistic Fuzzy Sets (IFS), Type-2 Fuzzy Sets, and Pythagorean Fuzzy Sets (PFS), each adding new dimensions to better handle uncertainty by incorporating additional parameters such as non-membership and hesitation. Spherical Fuzzy Sets (SFS), on the other hand, offer a further extension by allowing a more comprehensive representation of the uncertainty inherent in decision-making. In SFS, each element is described by three parameters:

- Membership degree (μ): Reflects the extent to which an element belongs to a set.

- Non-membership degree (v): Captures the extent to which an element does not belong to a set.
- Hesitation degree (π): Represents the uncertainty or hesitation in determining whether an element belongs to the set.

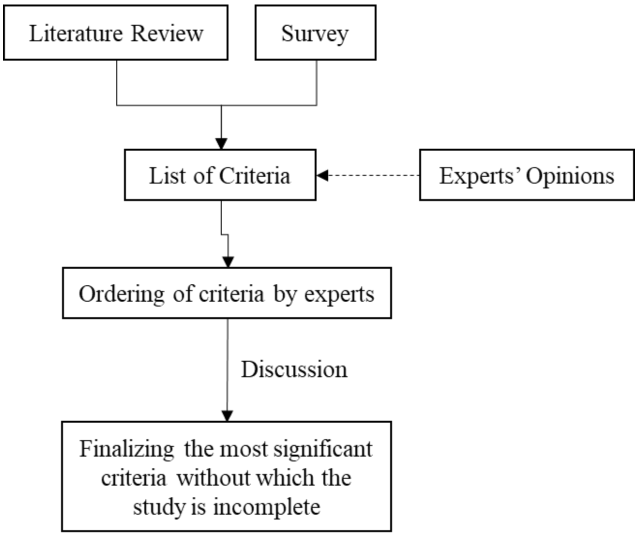

Fig.1. Methodology for criteria selection

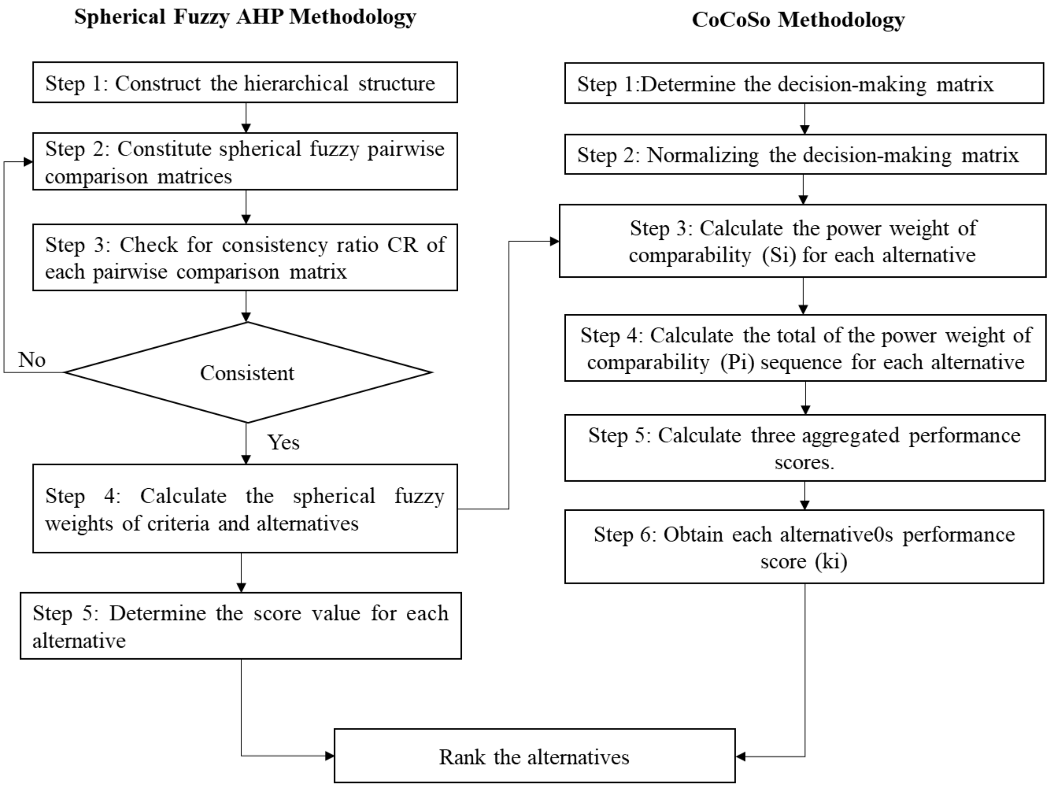

Fig.2. Methodology for criteria selection

These parameters satisfy the condition that the square sum of the membership, non-membership, and hesitation degrees must be less than or equal to 1. This spherical condition is what sets SFS apart from other fuzzy set theories like IFS and PFS, where the sum of the membership and non-membership degrees (with hesitation as a supplementary component) must be less than or equal to 1. In the realm of decision–making, fuzzy sets have emerged as a means to address uncertainties. Recently, the development of SFS has drawn the interest of researchers. SFS is an extension of fuzzy sets that combines Pythagorean fuzzy sets (PFS) and Neuromorphic sets [8]. SFS enables decision–makers to express their uncertain opinions through following settings.

Spherical Fuzzy Sets (SFS) offer distinct advantages in health insurance selection by handling uncertainty more effectively than traditional fuzzy sets. They explicitly incorporate hesitation alongside membership and non-membership degrees, allowing for better representation of the ambiguity inherent in decision-making. SFS enable more precise modeling of preferences by considering uncertainties such as future premium changes, offering a nuanced evaluation that traditional methods may miss. Their flexible structure accommodates subjective judgments and incomplete information, making them ideal for multi-criteria decision-making scenarios. Ultimately, SFS improve decision accuracy by capturing complex trade-offs, aligning choices more closely with the decision-maker's preferences and risk tolerance.

2.2. Spherical Fuzzy AHP

The SF–AHP method extends the Analytic Hierarchy Process (AHP) by incorporating spherical fuzzy sets. Various studies have been carried out in the past such as study [13,14] for technology selection, studies [15,16] for supplier selection. In this research, the SF–AHP method is applied to determine the weights of the criteria for health insurance policy selection. The SF–AHP method encompasses following steps:

- Establish the hierarchical structure of the model. A hierarchical structure with three levels is created. The top–level represents the model's goal, which is determined by a scoring index. The second level consists of n criteria that are utilized to evaluate the alternatives defined in the third level of the structure.
- Formulate pairwise comparison matrices for the criteria using spherical fuzzy judgment, utilizing linguistic terms (as demonstrated in Table 1): The calculation of the score indices (SI) for each alternative is performed using (1) for AM, VH, HI, SM, and EI and (2) for SL, LI, VL, and AL.

Table 1. Linguistic measures of importance

Definition	(μ,v,π)	Score Index (SI)
Absolutely more importance (AM)	(0.9, 0.1, 0.0)	9
Very high importance (VH)	(0.8, 0.2, 0.1)	7
High importance (HI)	(0.7, 0.3, 0.2)	5
Slightly more importance (SM)	(0.6, 0.4, 0.3)	3
Equally importance (EI)	(0.5, 0.4, 0.4)	1
Slightly lower importance (SL)	(0.4, 0.6, 0.3)	1/3
Low importance (LI)	(0.3, 0.7, 0.2)	1/5
Very low importance (VL)	(0.2, 0.8, 0.1)	1/7
Absolutely low importance (AL)	(0.1, 0.9, 0.0)	1/9

$$\mathrm{SI} = \sqrt{\left|100 * \left[\left(\mu_{\tilde{A}_s} - \pi_{\tilde{A}_s}\right)^2 - \left(v_{\tilde{A}_s} - \pi_{\tilde{A}_s}\right)^2\right]\right|} \tag{1}$$

$$\frac{1}{\mathrm{SI}} = \frac{1}{\sqrt{\left|100*\left[\left(\mu_{\tilde{A}_s}-\pi_{\tilde{A}_s}\right)^2-\left(v_{\tilde{A}_s}-\pi_{\tilde{A}_s}\right)^2\right]\right|}} \tag{2}$$

- It involves assessing the consistency of each pairwise comparison matrix using the classical consistency check. The Consistency Ratio (CR) threshold of 10% is utilized for this purpose using (3). The Consistency Index (CI) is calculated using (4).

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{3}$$

$$CI = \frac{\lambda_{\max}-n}{n-1} \tag{4}$$

where the maximum eigenvalue of the matrix, denoted as $\lambda_{\max}$, is used in conjunction with the number of criteria n in the calculation. The Random Index (RI) used in (3) is determined by considering the number of criteria utilized in the research study.

- It involves obtaining the fuzzy weights for both the criteria and alternatives. The weights of each alternative with respect to each criterion is obtained using (7).
- The determination of the final ranking of the alternatives is conducted by consolidating the spherical weights at each level of the hierarchical structure. At this stage, there are two viable methods for performing the computation. The initial method involves employing the score function outlined in (5) to deconstruct the criteria weights and obtain a crisp value.

$$S(\tilde{w}_j^S) = \sqrt{\left|100 * \left[\left(3\mu_{\tilde{A}_s} - \frac{\pi_{\tilde{A}_s}}{2}\right)^2 - \left(\frac{v_{\tilde{A}_s}}{2} - \pi_{\tilde{A}_s}\right)^2\right]\right|} \tag{5}$$

Next, the normalization of criteria weights is carried out using Equation (6), followed by the application of spherical fuzzy multiplication described in Equation (7).

$$\bar{w}_j^s = \frac{s\left(\tilde{w}_j^s\right)}{\sum_{j=1}^{n} s\left(\tilde{w}_j^s\right)} \tag{6}$$

$$\widetilde{A}_{S_{ij}} = \bar{w}_j^s * \tilde{A}_{S_i}$$

$$= \left(1 - \left(1 - \mu_{\tilde{A}_{S_i}}^2\right)^{\bar{w}_j^s}\right)^{1/2}, v_{\tilde{A}'_{S'_i}}^{\bar{w}'_j}\left(\left(1 - \mu_{\tilde{A}^2_{S_i}}^2\right)^{\bar{w}_j^s} - \left(1 - \mu_{\tilde{A}^2_{S_i}}^2 - \pi_{\tilde{A}^2_{S_i}}^2\right)^{\bar{w}_j^s}\right)^{1/2} \tag{7}$$

The calculation of the final ranking score ($\tilde{F}$) for each alternative A_i is performed using Equation (8):

$$\tilde{F} = \sum_{j=1}^{n} \tilde{A}_{S_{ij}} = \tilde{A}_{S_{i1}} + \tilde{A}_{S_{i2}} + \cdots + \tilde{A}_{S_{in}} \tag{8}$$

Another approach is to proceed with the calculation without performing the defuzzification of the criteria weights (Equation 9). Instead, the spherical fuzzy global weights are determined using the following method:

$$\prod_{j=1}^{n} \tilde{A}_{S_{ij}} = \tilde{A}_{S_{i1}} * \tilde{A}_{S_{i2}} * \ldots * \tilde{A}_{S_{in}} \tag{9}$$

2.3. *Combined Compromised Solution (COCOSO)*

The Combined Compromise Solution (CoCoSo) method, developed by Yazdani[17], is an advanced multicriteria decision-making (MCDM) approach designed to tackle complex decision problems by integrating multiple compromise solutions. This method aims to balance various conflicting criteria rather than optimizing a single criterion at the expense of others. CoCoSo achieves this by combining different compromise approaches, providing a robust decision support framework that considers diverse criteria simultaneously. Key components of the CoCoSo method include defining criteria and alternatives, normalizing data to ensure comparability, and assigning weights to reflect the importance of each criterion. The method uses weighted aggregation techniques to evaluate alternatives based on their distance from both ideal and nadir solutions, offering a balanced assessment of performance. In traditional MCDM methods, a compromise solution is one that meets most criteria to a reasonable extent, rather than achieving the best possible outcome for a single criterion while neglecting others. CoCoSo extends this idea by integrating multiple compromise solutions, thus enhancing its ability to handle complex decision scenarios.

CoCoSo has been effectively applied across various fields, including business, engineering, healthcare, and environmental management, due to its ability to handle complex criteria and provide well-rounded solutions. Its strengths lie in its comprehensive approach to integrating multiple compromise solutions, which enhances decision making accuracy. However, the method's complexity and dependence on accurate data can be seen as limitations. Compared to traditional MCDM methods such as AHP and TOPSIS, CoCoSo offers a more nuanced evaluation by combining different compromise solutions, making it particularly valuable for complex decision scenarios involving multiple conflicting criteria. Various studies involved COCOSO approach in the research [18] for supplier selection, studies [19,20] for location selection. In this research, the CoCoSo method is employed as a robust framework to ascertain the ranking of health insurance service providers. The CoCoSo model, designed for scenarios with a multitude of alternatives (m) and criteria (n), encompasses five fundamental steps. These steps encompass the entire decision–making process, from the formulation of the decision problem to the computation of the final rankings. By leveraging the CoCoSo approach, the research aims to provide valuable insights and recommendations for selecting best insurance policy/service provider. The method's ability to incorporate various criteria and combine them into a unified ranking enables a thorough and reliable assessment of the alternatives. Through its step–by–step execution, the CoCoSo method ensures a rigorous and comprehensive evaluation process that ultimately leads to more robust decision outcomes.

- It involves determining the decision–making matrix X, denoted as X = (xij), with dimensions' m × n, where xij represents the value associated with the i^{th} alternative and the j^{th} criterion.

$$x_{ij} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{10}$$

- Normalizing the decision–making matrix using (11) for beneficial criterion and (12) for non–beneficial criterion.

$$r_{ij} = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{11}$$

$$r_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{12}$$

- The calculation of the power weight of comparability (Si) and the total power weight of comparability (Pi) sequence for each alternative is performed using (13) and (14) respectively.

$$S_i = \sum_{j=1}^{n} \left(w_j r_{ij}\right) \tag{13}$$

$$P_i = \sum_{j=1}^{n} \left(r_{ij}^{\ w_j}\right) \tag{14}$$

- Calculate three aggregated performance scores, with k_{ia} as the relative performance scores of the *i*-th alternative, calculated as the arithmetic mean of the sums of S_i and P_i scores using (15):

$$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m} (P_i + S_i)'} \tag{15}$$

k_{ib} is the relative performance score of the *i*-th alternative calculated as the sum of the relative scores of S_i and P_i
scores in comparison to the ideal performance values using (16):

$$k_{ib} = \frac{S_i}{minS_i} + \frac{Pi}{minP_i} \tag{16}$$

k_{ic} is the relative performance score of the *i*-th alternative calculated as the compromise of S_i and P_i performance scores. In Equation (17), the parameter λ is selected by the decision makers and has a value between 0 and 1 (usually $\lambda = 0.5$):

$$k_{ic} = \frac{\lambda(S_i) + (1-\lambda)P_i}{\lambda \max S_i + (1-\lambda)\max P_i} \tag{17}$$

- Obtain each alternative's performance score (ki):

$$k_i = (k_{ia} k_{ib} k_{ic})^{\frac{1}{3}} + \frac{1}{3}(k_{ia} + k_{ib} + k_{ic}) \tag{18}$$

The final ranking of the alternatives is based on the calculated performance scores with the optimal alternative having the highest score.

3. Case Study

3.1. *Context and Participant Demographics*

In the case study, the focus was on health insurance policy selection in India, specifically within the metropolitan regions of Maharashtra State. The participants consisted of 467 individuals from various socio-economic backgrounds, ranging in age from 25 to 60 years. The sample included both salaried professionals and self-employed individuals, ensuring a diverse representation of the urban population. The health insurance market in India was examined with a particular emphasis on private and government sponsored insurance schemes, such as those provided by large insurance companies and programs like Ayushman Bharat. This diverse participant base allowed us to capture a wide spectrum of preferences and factors influencing health insurance policy decisions, including premium affordability, coverage options, and network hospitals.

3.2. *Ethical Considerations*

This study addresses key ethical concerns related to expert judgment, data privacy, and biases in decision-making. Experts from diverse backgrounds were chosen to minimize bias, and a structured elicitation process was followed. Participant data were anonymized. We also implemented measures to identify and reduce biases that could affect policyholders, ensuring that the study's findings are fair and transparent.

3.3. *Model Application*

In this study, the health insurance policy selection problem is addressed by engaging eight experts—four from academia and four from industry—each with over 10 years of experience. A total of 19 factors were initially identified through a literature review, survey, and expert opinions. The experts were asked to create pairwise comparison matrices using Saaty's scale(Table 1). Based on the resulting matrices, the weights of the factors were calculated. Factors with weights less than 5% were eliminated with the experts' agreement. After this elimination, eleven significant factors were finalized, as shown in Table 2.

In the initial phase of this research, the author employed the Spherical Fuzzy Analytic Hierarchy Process (SF–AHP) to assess and determine the weights of eleven criteria. For this, pairwise comparison matrix was obtained from each of the decision makers. The ultimate pairwise comparison matrix was derived, taking into account the majority rule. Minor experts' bias was observed which was not affecting the output of the study. The information presented in Table 3 displays the Spherical Fuzzy Pairwise Comparison Matrix, which was generated based on the predominant preferences of decision–makers during comparisons. Matrix thus obtained is assigned with spherical number with (μ, v, π) values as per Table 1. The result of this is presented in Table 4. Following the methodology of spherical fuzzy AHP, the final outcomes of this analysis are presented in Table 5, providing valuable insights into the relative importance and significance of each criterion within the decision–making framework. The rankings of the alternatives were also obtained. The weight of the criteria in Crisp weight column indicates the weightages assigned or relative importance. Highest weight is associated with Claim settlement ratio (C9) followed by Premium Cost (C2), Coverage Benefits (C1), Maximum Coverage Limits (C6), Network of Healthcare Providers (C4), Family Coverage (C11), Waiting Periods(C7), Customer Service and Reputation (C8), Pre–existing Conditions Coverage(C5), Deductibles and Copayments (C3), Flexibility and Customization (C10) respectively.

Table 2. Details of factors identified

Factor	Description	Reference
Coverage Benefits (C1)	The extent of medical services and treatments covered by the policy, including hospitalization, outpatient care, prescription drugs, preventive care, maternity services, and mental health services.	[21]
Premium Cost (C2)	The amount of money paid as a premium to the insurance company for coverage. Individuals often consider affordability and the balance between cost and benefits.	[22]
Deductibles and Copayments (C3)	The amount a policyholder must pay out of pocket before the insurance coverage kicks in (deductibles) and the portion of costs paid by the policyholder for each medical service (copayments).	[23]
Network of Healthcare Providers (C4)	The availability of a broad network of hospitals, doctors, specialists, and healthcare facilities where the policyholder can receive medical services at a discounted rate.	[24]
Pre–existing Conditions Coverage (C5)	The policy's provisions for covering pre–existing medical conditions, as some plans may impose waiting periods or limitations.	[25]
Maximum Coverage Limits (C6)	The maximum amount the insurance company will pay for medical expenses in a given period, either annually or throughout the policy's lifetime.	[26]
Waiting Periods (C7)	The duration policyholders must wait before certain benefits become available.	[27]
Customer Service and Reputation (C8)	The track record of the insurance company in terms of customer service, claims handling, and reputation for reliability.	[28]
Claim Settlement Ratio (C9)	It is a key performance indicator used in the insurance industry to measure the efficiency of an insurance company in settling claims.	[29]
Flexibility and Customization (C10)	The ability to customize the policy to suit individual needs and preferences.	Discussion
Family Coverage (C11)	The options available for including family members or dependents under the same policy.	[30]

Table 3. Spherical fuzzy pairwise comparison matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
C1	EI	SM	VH	EI	HI	SM	SM	SM	EI	VH	HI
C2	SL	EI	VH	HI	SM	EI	HI	SM	SM	HI	VH
C3	VL	VL	EI	LI	SL	LI	EI	SM	LI	SM	LI
C4	EI	LI	HI	EI	SM	SL	HI	SM	LI	VH	EI
C5	LI	SL	SM	SL	EI	LI	EI	SM	LI	LI	SL
C6	SL	EI	HI	SM	HI	EI	SM	HI	SL	HI	EI
C7	SL	LI	EI	LI	EI	SL	EI	EI	LI	SM	SM
C8	SL	SL	SL	SL	SL	LI	EI	EI	LI	HI	EI
C9	EI	SL	HI	HI	HI	SM	HI	HI	EI	AM	SL
C10	VL	LI	SL	VL	HI	LI	SL	LI	AL	EI	SL
C11	LI	VL	HI	EI	SM	EI	SL	EI	SM	SM	EI

Table 4. Aggregated evaluations of the decision makers

		C1			C2			C3			C4			C5			C6			C7			C8			C9			C10			C11	
C1	0.5	0.4	0.4	0.6	0.4	0.3	0.8	0.2	0.1	0.5	0.4	0.4	0.7	0.3	0.2	0.6	0.4	0.3	0.6	0.4	0.3	0.6	0.4	0.3	0.5	0.4	0.4	0.8	0.2	0.1	0.7	0.3	0.2
C2	0.4	0.6	0.3	0.5	0.4	0.4	0.8	0.2	0.1	0.7	0.3	0.2	0.6	0.4	0.3	0.5	0.4	0.4	0.7	0.3	0.2	0.6	0.4	0.3	0.6	0.4	0.3	0.7	0.3	0.2	0.8	0.2	0.1
C3	0.2	0.8	0.1	0.2	0.8	0.1	0.5	0.4	0.4	0.3	0.7	0.2	0.4	0.6	0.3	0.3	0.7	0.2	0.5	0.4	0.4	0.6	0.4	0.3	0.3	0.7	0.2	0.6	0.4	0.3	0.3	0.7	0.2
C4	0.5	0.4	0.4	0.3	0.7	0.2	0.7	0.3	0.2	0.5	0.4	0.4	0.6	0.4	0.3	0.4	0.6	0.3	0.7	0.3	0.2	0.6	0.4	0.3	0.3	0.7	0.2	0.8	0.2	0.1	0.5	0.4	0.4
C5	0.3	0.7	0.2	0.4	0.6	0.3	0.6	0.4	0.3	0.4	0.6	0.3	0.5	0.4	0.4	0.3	0.7	0.2	0.5	0.4	0.4	0.6	0.4	0.3	0.3	0.7	0.2	0.3	0.7	0.2	0.4	0.6	0.3
C6	0.4	0.6	0.3	0.5	0.4	0.4	0.7	0.3	0.2	0.6	0.4	0.3	0.7	0.3	0.2	0.5	0.4	0.4	0.6	0.4	0.3	0.7	0.3	0.2	0.4	0.6	0.3	0.7	0.3	0.2	0.5	0.4	0.4
C7	0.4	0.6	0.3	0.3	0.7	0.2	0.5	0.4	0.4	0.3	0.7	0.2	0.5	0.4	0.4	0.4	0.6	0.3	0.5	0.4	0.4	0.5	0.4	0.4	0.3	0.7	0.2	0.6	0.4	0.3	0.6	0.4	0.3
C8	0.4	0.6	0.3	0.4	0.6	0.3	0.4	0.6	0.3	0.4	0.6	0.3	0.4	0.6	0.3	0.3	0.7	0.2	0.5	0.4	0.4	0.5	0.4	0.4	0.3	0.7	0.2	0.7	0.3	0.2	0.5	0.4	0.4
C9	0.5	0.4	0.4	0.4	0.6	0.3	0.7	0.3	0.2	0.7	0.3	0.2	0.7	0.3	0.2	0.6	0.4	0.3	0.7	0.3	0.2	0.7	0.3	0.2	0.5	0.4	0.4	0.9	0.1	0	0.4	0.6	0.3
C10	0.2	0.8	0.1	0.3	0.7	0.2	0.4	0.6	0.3	0.2	0.8	0.1	0.7	0.3	0.2	0.3	0.7	0.2	0.4	0.6	0.3	0.3	0.7	0.2	0.1	0.9	0	0.5	0.4	0.4	0.4	0.6	0.3
C11	0.3	0.7	0.2	0.2	0.8	0.1	0.7	0.3	0.2	0.5	0.4	0.4	0.6	0.4	0.3	0.5	0.4	0.4	0.4	0.6	0.3	0.5	0.4	0.4	0.6	0.4	0.3	0.6	0.4	0.3	0.5	0.4	0.4

Following the SF–AHP analysis, the research progresses to the next stage, where the Combined Compromise Solution (CoCoSo) Algorithm is applied to determine the ranking of insurance service providers. The steps provided in methodology section are utilized to obtain the final ranking. This algorithm takes into account the normalized matrix, as well as the weighted comparability sequence (Si) and exponentially weighted comparability sequence (Pi). The corresponding values for these parameters are presented in Tables 6, Table 7, and Table 8 respectively. Table 6 showcases the normalized matrix, which provides a comprehensive view of the relative performance of each alternative in relation to the established criteria. The weighted comparability sequence (Si) in Table 7 represents the power weight of comparability for each alternative, indicating their individual suitability for the decision–making process. Furthermore, Table 8 displays the exponentially weighted comparability sequence (Pi), illustrating the cumulative power weight of comparability for each alternative. By utilizing the CoCoSo Algorithm in conjunction with these tables, the research ensures a systematic and objective approach to ranking. This integrated methodology allows for a thorough evaluation, considering both individual and cumulative weights, thus enabling informed decision–making in selecting the most suitable service provider.

In the concluding stage, an aggregated multiplication rule is utilized to generate the ranking of the alternatives and finalize the decision–making process. Based on the findings presented in Table 9, it is evident that alternative A6 emerges as the superior service provider. The application of the aggregated multiplication rule allows for the comprehensive evaluation and comparison of the alternatives, ultimately leading to the identification of the most favorable option. The ranks of the alternatives are as per sequence mentioned below: A6 > A4 > A2 > A5 > A3 > A1.

Table 5. Results from the SF–AHP model

Criteria	Spherical Fuzzy Weights			Defuzzified values	Crisp Weights
	Membership	Non–Membership	Degree of Hesitancy		
C1	0.650	0.335	0.275	18.122	0.114
C2	0.655	0.338	0.257	18.350	0.115
C3	0.417	0.577	0.280	11.110	0.070
C4	0.579	0.409	0.284	15.945	0.100
C5	0.440	0.548	0.300	11.703	0.073
C6	0.595	0.388	0.294	16.367	0.103
C7	0.465	0.502	0.328	12.298	0.077
C8	0.459	0.519	0.313	12.191	0.076
C9	0.664	0.333	0.247	18.690	0.117
C10	0.394	0.619	0.246	10.599	0.067
C11	0.520	0.453	0.320	14.008	0.088

Table 6. Normalized input decision matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
A1	1.000	0.617	0.000	0.983	0.000	0.000	0.500	0.000	0.948	0.000	0.000
A2	0.000	0.685	0.667	0.488	0.000	0.048	0.000	0.800	1.000	1.000	1.000
A3	0.000	0.555	0.333	0.056	0.333	0.000	0.500	1.000	0.517	0.500	0.000
A4	1.000	1.000	0.333	0.210	1.000	0.000	0.500	0.600	0.879	0.000	0.000
A5	0.000	0.000	0.667	0.000	0.667	1.000	1.000	0.400	0.000	0.500	1.000
A6	0.000	0.751	1.000	1.000	0.333	0.000	0.500	0.200	0.414	1.000	1.000

Table 7. Weighted comparability sequence and Si value

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	Si
A1	0.114	0.071	0.000	0.098	0.000	0.000	0.039	0	0.111	0	0	0.433
A2	0.000	0.079	0.047	0.049	0.000	0.005	0.000	0.0608	0.117	0.067	0.088	0.512
A3	0.000	0.064	0.023	0.006	0.024	0.000	0.039	0.076	0.061	0.0335	0	0.326
A4	0.114	0.115	0.023	0.021	0.073	0.000	0.039	0.0456	0.103	0	0	0.533
A5	0.000	0.000	0.047	0.000	0.049	0.103	0.077	0.0304	0.000	0.0335	0.088	0.427
A6	0.000	0.086	0.070	0.100	0.024	0.000	0.039	0.0152	0.048	0.067	0.088	0.538

4. Sensitivity Analysis

This section focuses on conducting a sensitivity analysis to validate the results of the model. The purpose of the sensitivity analysis is to allow decision-makers to assess the robustness and reliability of the decision-making process by altering the parameters of the original model. In this study, various values of the parameter λ within the range of 0 to 1 are employed to perform the sensitivity test. Table 10 presents the performance scores of each alternative under different values of" λ". By examining the performance scores across these variations, decision–makers can gain insights into how changes in the parameter affect the relative rankings of the alternatives. This sensitivity analysis aids in verifying the stability and consistency of the model, enhancing the confidence in the final decision outcome.

The rankings of each alternative remain unchanged across different values of λ, as depicted in Fig. 3, based on the results presented in Table 10. This indicates the robustness and stability of the decision–making process, as variations in the parameter" λ" do not significantly impact the relative rankings of the alternatives. The consistency of the rankings across different scenarios enhances the confidence in the validity and reliability of the model, reinforcing the trustworthiness of the final decision outcome.

Table 8. Exponentially weighted comparability sequence and Pi values

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	Pi
A1	1.000	0.946	0.000	0.998	0.000	0.000	0.948	0.000	0.994	0.000	0.000	4.886
A2	0.000	0.957	0.972	0.931	0.000	0.731	0.000	0.983	1.000	1.000	1.000	7.574
A3	0.000	0.934	0.926	0.750	0.923	0.000	0.948	1.000	0.926	0.955	0.000	7.362
A4	1.000	1.000	0.926	0.856	1.000	0.000	0.948	0.962	0.985	0.000	0.000	7.677
A5	0.000	0.000	0.972	0.000	0.971	1.000	1.000	0.933	0.000	0.955	1.000	6.830
A6	0.000	0.968	1.000	1.000	0.923	0.000	0.948	0.885	0.902	1.000	1.000	8.625

Table 9. Final aggregation and ranking

	Ka	Rank	Kb	Rank	Kc	Rank	Ki	Rank
A1	0.116	6	2.329	6	0.580	6	1.548	6
A2	0.177	3	3.122	3	0.882	3	2.181	3
A3	0.168	4	2.507	5	0.839	4	1.878	5
A4	0.180	2	3.209	2	0.896	2	2.230	2
A5	0.159	5	2.710	4	0.792	5	1.919	4
A6	0.200	1	3.417	1	1.000	1	2.421	1

Table 10. Final performance score (Ki) with different λ values

Alternative	Final Performance Score (Ki)										
	$\lambda = 0$	$\lambda = 0.1$	$\lambda = 0.2$	$\lambda = 0.3$	$\lambda = 0.4$	$\lambda = 0.5$	$\lambda = 0.6$	$\lambda = 0.7$	$\lambda = 0.8$	$\lambda = 0.9$	$\lambda = 1.0$
A1	1.539	1.540	1.542	1.543	1.545	1.548	1.552	1.559	1.570	1.594	1.685
A2	2.178	2.178	2.179	2.179	2.180	2.181	2.182	2.184	2.187	2.195	2.224
A3	1.887	1.886	1.885	1.883	1.881	1.878	1.874	1.868	1.857	1.832	1.728
A4	2.227	2.227	2.228	2.228	2.229	2.230	2.232	2.235	2.239	2.250	2.290
A5	1.919	1.919	1.919	1.919	1.919	1.919	1.919	1.919	1.919	1.919	1.920
A6	2.421	2.421	2.421	2.421	2.421	2.421	2.421	2.421	2.421	2.421	2.421

Alternative 6 (A6) is consistently the better solution in all the cases of λ. Consequently, based on the findings and results obtained, it can be concluded that the performance of the proposed model is deemed satisfactory and reliable. The model demonstrates its effectiveness in providing valuable insights and rankings for decision–making in real–world

scenarios. The successful application of the model to this study suggests its potential applicability and relevance to similar real–world cases. This conclusion further strengthens the confidence in the proposed model's viability and encourages its adoption in practical decision–making contexts.

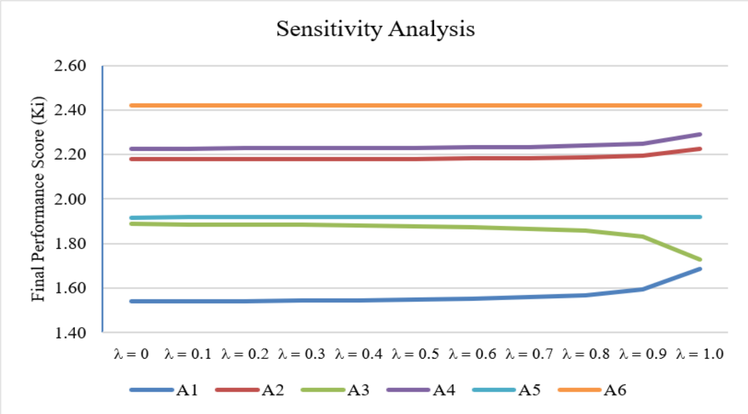

Fig.3. Sensitivity analysis

5. Conclusions

The joint SF–AHP and COCOSO approach offers a robust framework for health insurance policy selection. By combining the SF–AHP method's ability to handle uncertainty and the COCOSO method's capability to address conflicting objectives, this approach empowers decision–makers to make informed choices. The joint approach provides a structured and comprehensive analysis of various health insurance policies, taking into account multiple criteria and their interdependencies. With the increasing complexity of the insurance market, the joint approach serves as a valuable tool for individuals, insurance companies, and policymakers to facilitate optimal health insurance policy selection. SF–AHP was utilized to provide weights to eleven factors. Highest weight is associated with Claim settlement ratio (C9) followed by Premium Cost (C2), Coverage Benefits (C1), Maximum Coverage Limits (C6), Network of Healthcare Providers (C4), Family Coverage (C11), Waiting Periods(C7), Customer Service and Reputation (C8), Pre–existing Conditions Coverage(C5), Deductibles and Copayments (C3), Flexibility and Customization (C10) respectively. With these weights, ranking of the alternatives were obtained. The alternative A6 proved to be better than the other five alternatives. The sensitivity analysis also confirmed the final decision outcome. The rankings of each alternative remain unchanged across different values of" λ". The alternative A1 had less value of performance score leading to least selection possibility.

5.1. Practical Implications

The research findings, which leverage the joint SF–AHP and CoCoSo approach for health insurance policy selection, have significant practical implications for individuals, insurance companies, and policymakers in navigating the intricate insurance market. Individuals can make more informed choices when selecting health insurance policies. The approach provides a structured analysis of policy options, considering multiple criteria and their interdependencies. This helps individuals choose plans that align with their specific healthcare needs and financial constraints. By selecting policies that best match their requirements, individuals reduce the risk of being underinsured or overpaying for coverage. This ensures they receive the necessary financial protection in times of illness or medical emergencies. The approach helps individuals optimize their coverage by considering factors like claim settlement ratios, premium costs, coverage benefits, and network providers. This ensures they receive the best value for their insurance premiums. Insurance companies can use the insights generated by this approach to tailor their policies to customer preferences and market trends. This helps in the development of competitive and customer–centric insurance products. By understanding customer preferences and the factors that drive policy selection, insurance companies can better manage their risk profiles and pricing strategies. This can lead to more accurate risk assessment and premium setting. Offering policies that align with customer needs and priorities can enhance customer satisfaction and retention. This approach allows insurance companies to align their offerings with market demand, fostering long–term customer relationships. Policymakers can use the findings from this approach to inform regulatory decisions and policies related to health insurance. It provides insights into what criteria individuals prioritize, which can influence policy regulations. With a better understanding of how individuals make health insurance choices, policymakers can monitor and regulate the insurance market more effectively. This ensures fair practices and consumer protection. Policymakers can leverage the approach to encourage insurance companies to expand their networks of healthcare providers, improving access to medical services for policyholders. By promoting the selection of policies that align with cost–effective healthcare options, policymakers can contribute to overall healthcare cost management and sustainability.

5.2. Limitations and Future Scope

The joint SF–AHP and COCOSO approach for health insurance policy selection, while robust, has limitations such as its complexity, reliance on static data, and subjectivity in criteria weighting. In the future, potential improvements include developing user–friendly tools to automate the process, integrating real–time data for greater accuracy, employing machine learning for dynamic decision–making, enhancing sensitivity analysis techniques, promoting user education, and offering customization options to adapt to evolving criteria and preferences, thereby making the approach more accessible and adaptable to a wider range of users and changing healthcare landscapes.

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