



FUZZY MULTIATTRIBUTE CONSUMER CHOICE AMONG HEALTH INSURANCE OPTIONS

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Abstract. People buy insurance to protect themselves against possible financial loss in the future. Health insurance provides protection against the possibility of financial loss due to health care use. A selection among health insurance options is a multiattribute decision making problem including many conflicting criteria. This problem can be better solved using the fuzzy set theory since human decision making is generally based on vague and linguistic data. We propose an integrated methodology composed of fuzzy AHP and fuzzy TOPSIS to select the best health insurance option. The considered option types, Health Savings Account (HSA), Flexible Spending Accounts (FSA), and Health Reimbursement Arrangement (HRA) are evaluated using eight different criteria under fuzziness. A sensitivity analysis is also realized.

Keywords: health insurance, options, fuzzy sets, AHP, TOPSIS, multiattribute.

JEL Classification: I13, P46.

Introduction

Health insurance is a type of insurance coverage that pays for medical and surgical expenses those are incurred by the insured. Health insurance can either reimburse the insured for expenses incurred from illness or injury or pay the care provider directly. Health insurance has been an important issue and its applications differ among countries: Australia (Connelly *et al.* 2010), Africa Countries (Carapinha *et al.* 2011), Uganda (Basaza *et al.* 2008), South Korea and Taiwan (Lee *et al.* 2008), Ireland (Armstrong 2010), Canada (Devlin *et al.* 2011),

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Bulgaria (Atanasova et al. 2011), India (Dror et al. 2007), Holland (Bartholomée, Maarse 2007), China (Wagstaff, Lindelow 2008), Mexico (Gameren 2010), etc.

With competition increasing among health care plans, employees of large firms typically are faced with more opportunities for choice and more complex options than in the past. Most people understand that an insurance choice may be important for them, but their decision making also appears very limited. The dominant model of choice assumes careful examination and weighing of alternatives, but as the number of choices grows, this becomes an increasingly complex and difficult task.

The selection of health plans and providers is, in part, an iterative process in which individuals better learn to make informed choices responsive to their needs. The instability in initial choices, however, suggests considerable failure to understand important differences among plans in access, cost, and freedom to select providers or to be reimbursed for services outside the plan. This is particularly true as populations select plans with which they have had little prior experience. Some preferences seem much more central to people's decisions than others. The primary preferences are related to the character of established doctor/patient relationships, cost, and special needs (Mechanic 1989).

There are numerous different health insurance plans available in any country today. Because every person has their own unique situation, determining "the best" health insurance plan will vary from person to person. Situations vary and health insurance plans that are right for one person's situation may not be right for someone else's. This is why we propose a methodology for the selection among health insurance options in this paper.

Individual choice over health insurance policies may result in risk-based sorting across plans. People are generally unsuccessful in selecting an alternative with more than four criteria. In approaching choice situations, people immediately make efforts to narrow the number of operative choices to a psychologically manageable set. Typically, individuals consider very few alternatives and focus the comparison only on a subset of the many relevant dimensions. People are more likely to select familiar options. Familiarity may be assessed by prior experience with a particular type of health plan arrangement (Mechanic 1989).

The selection among health insurance options is a multiattribute decision making problem with many conflicting criteria like eligibility, portability, catch up contribution, and tax treatment. This problem is difficult to solve since people usually assign linguistic expressions rather than numerical ones. The research question of this paper is how this problem can be solved under vague and linguistic data.

Since human reasoning is vague, these linguistic evaluations involve some degree of uncertainty. The fuzzy sets theory was introduced by Zadeh (1965) to express the linguistic terms in decision making process in order to resolve the vagueness, ambiguity and subjectivity of human judgment. Fuzzy methods are purposely designed for complex and ill defined problems. Hence, many researchers have attempted to use fuzzy MCDM methods like analytic hierarchy process (AHP), analytic network process (ANP), outranking methods, multiple objective linear programming (MOLP) and goal programming.

The aim of this paper is to assess health insurance options considering multiple and conflicting criteria under incomplete and vague information using the fuzzy set theory. To the best knowledge of the authors, this is the first multiattribute fuzzy decision making study in

the health insurance literature. Two multiattribute methods are used in the evaluation of health insurance options. Since a decision-maker bases judgments on knowledge and experience, then makes decision accordingly, the AHP approach agrees well with the behavior of a decision maker. The strength of this approach is that it organizes tangible and intangible factors in a systematic way, and provides a structured yet relatively simple solution to the decision making problems. TOPSIS is preferred since it includes simple, rationally comprehensible concept, good computational efficiency, and ability to measure the relative performance for each alternative in a simple mathematical form.

To obtain the criteria weights, the most used method in the literature is AHP. The obtained weights are used as an input to TOPSIS method, which needs the criteria weights to be determined by the decision maker. Both methods are handled under fuzziness in our paper.

The rest of the paper is organized as follows. Section 1 gives a literature review on health insurance. Section 2 presents the health insurance options, which are Health Savings Account (HSA), Health Reimbursement Arrangement (HRA), and Flexible Spending Account (FSA). In Section 3, the selection criteria for health insurance options are given. In Section 4, a multiattribute selection using an integrated Fuzzy AHP-TOPSIS methodology is proposed. In the last section an application of the proposed methodology is realized together with a sensitivity analysis.

1. Literature review on health insurance

Recent works on health insurance are summarized in the following. These works are usually on risk evaluation and choice of health insurance systems.

Jack (2001) examines the nature of health insurance contracts when insurance companies pool high- and low-risk individuals. In a spatial product differentiation model, the normal forces of competition induce quality provision, but selection incentives induce insurers to under-provide quality. To offset selection incentives, the government can reimburse some of the insurers' costs. Iarossi and Helms (2002) assess group health insurance for fully-insured vs. self-insured employers. Sapelli and Vial (2003) study the existence of self-selection and moral hazard in the Chilean health insurance industry. Dependent workers must purchase health insurance either from one public or several private insurance providers. They analyze the relationship between health care services utilization and the choice of either private or public insurance. In the case of independent workers, they analyze the relationship between utilization and the decision to voluntarily purchase health insurance. The results show self-selection against insurance companies for independent workers, and against public insurance for dependent workers. Hussey and Anderson (2003) compare single-payer and multi-payer models in the areas of revenue collection, risk pooling, purchasing, and social solidarity. Single-payer and multi-payer systems each have advantages which may meet countries' priorities for their health insurance system.

Simon (2005) test predictions about the effect of reforms on the employer-provided health insurance market using both individual-level and employer-level data. He estimates these effects for small firms and their workers using large firms and their workers in the same states, as well as large and small firms and their workers in non-reform states, as comparison groups. Wang *et al.* (2006) examine adverse selection in a subsidized voluntary health insurance scheme, the Rural Mutual Health Care (RMHC) scheme, in a poor rural

area of China. Logistic regression is employed for the data analysis. Castano and Zambrano (2006) test the hypothesis that market failures would lead to biased selection favoring new entrants. Two household surveys are analyzed using Self-Reported Health Status and the presence of chronic conditions as prospective indicators of individual risk. Biased selection is found to take place, leading to adverse selection among incumbents, and favorable selection among new entrants.

Gao et al. (2009) study the problem of information asymmetry using data from China's individual health-insurance market. Their preliminary results appear to contradict standard-model predictions, showing that higher-risk buyers are more likely to purchase "additional" insurance than lower-risk buyers, but that they also tend to purchase lower limits of "basic" insurance coverage. They develop a theoretical model to capture the effects of buyers' wealth levels and loss amounts, and show empirically that these effects lead to the coexistence of adverse selection and advantageous selection in China's health-insurance market. Lin (2011) selects and establishes a new, proper Health Technology Assessment system in Taiwan National Health Insurance. Based on analytic hierarch process (AHP) methods, he makes interviews with health officials, health care providers and customers by using the AHP questionnaire. Fuzzy multiple criteria decision making (Fuzzy MCDM) is adopted to proceed the empirical evidence analysis and evaluation on the schemes of HTA systems. Schram and Sonnemans (2011) study decisions and decision strategies in a laboratory experiment where they create a controlled environment that closely mirrors this setting. They use an electronic information board that allows to carefully monitor the individual's decision strategy. The number of alternatives, switching costs, and the speed at which health deteriorates are varied across treatments. They find that most subjects' search is based more on attributes than on policies.

As a result of the literature review it is seen that there is a gap in the multicriteria evaluation of health insurance options under uncertainty conditions. Evaluation criteria for these options are usually expressed in linguistic terms by experts such that "with respect to criterion X, option A is fairly more important than option B". Multicriteria methods under vagueness are needed to capture these linguistic expressions in the evaluation process.

2. Health insurance options

Most countries feel constant pressure because expenditure is increasing and resources are scarce. Policy-makers have three options: containing costs, increasing funding for health services or both. Concern about an expenditure crisis in health care has led to the introduction of major changes in how health care is organized and financed. The provision and financing of health care can be simplified as an exchange or transfer of resources: the providers transfer health care resources to patients and patients or third parties transfer financial resources to the providers. Private health insurance premiums are paid by an individual, shared between the employees and the employer or paid wholly by the employer. Government may subsidize the cost of private health insurance using tax credits or tax relief (Mossialos, Dixon 2002).

In today's world, health insurance costs have risen significantly. There are many health insurance options available to the consumers. The resulting financial strain has affected

corporate and personal budgets alike, and as a result, many people have had to make some hard choices.

Because of the rising costs of traditional insurance plans, consumers are looking for new health insurance options. With Health Savings Accounts (HSAs), a special account owned by an individual in which contributions to the account is to pay for current and future medical expenses. It must be owned and used in conjunction with a high deductible health plan. It can create a platform for asset accumulation over a lifetime. With an HSA, traditionally money may be taken from your paycheck before taxes or you can open up an individual HSA account and contribute money on your own. Your employer or a family member can also contribute to your HSA. The other alternative option that may offer reduced employer costs or more control over health spending is health reimbursement arrangements (HRAs). They let employees and/or employers set aside pre-tax income to cover medical expenses. HRAs allow the employee to use the employer's money solely for medical expenses. The funds are owned by the employer, not by the employee, and they may not be withdrawn for nonmedical expenditures (CAHI.org 2004).

HSAs are similar to flexible spending accounts (FSAs), which also allow the use of pre-tax income for medical expenses. FSAs are typically used as a supplement to traditional insurance rather than an alternative. With an FSA, money is taken from your paycheck before taxes and put into an account. You can then use that money to pay for medical expenses throughout the year. It's important to understand that FSAs have a "use it or lose it" provision – meaning that you must use the dollars in the year in which they are saved or you will lose them at the end of the year. FSAs allow employees to contribute some of their own salary to an account to pay for health care expenses or their share of health insurance premiums. Like HSAs, contributions to an FSA are exempt from both income and payroll taxes. HSA and HRA funds can be rolled over to the following year so that employees can accumulate savings for unexpected health problems. In contrast, FSAs cannot be rolled over and unused funds must revert to the employer. Contributions to an HSA can be funded by the employer and/or employees. An employer with limited funds could purchase a high-deductible plan and encourage employees to make regular tax-free contributions to an HSA to fund their medical expenses up to the deductible. An HRA can be funded only by employers. HSAs and HRAs are fairly new to the health insurance market. They can help reduce spending by giving employees more direct control over funds spent on their coverage (CAHI.org 2004):

Cardon and Showalter (2007) develop an infinite horizon utility maximization model of the interaction between insurance choice and tax-preferred health savings accounts. The model can be used to examine a wide range of policy options, including flexible spending accounts, health savings accounts, and health reimbursement accounts. They create an analytic framework that is sufficiently flexible to analyze a wide range of policy proposals-HSAs, FSAs, rollover FSAs, HRAs, etc.

3. Selection criteria for health insurance options

In the literature many criteria exist for the evaluation of health insurance options. The following selection criteria are obtained from the Council for Affordable Health Insurance (CAHI.org 2004):

1. Eligibility (C1)

All insurance policies have age limits and minimum standards of health for an individual to obtain coverage. Most insurers will not cover someone with a serious or terminal disease, such as AIDS or cancer. Each insurance company, no matter whether they offer health, dental, or life insurance has ways to verify your insurance eligibility and coverage.

In Health Savings Account (HSA), individuals must be below medicare eligibility age and not covered by any other health plan which duplicates any benefits in the qualified high-deductible plan. In Flexible Spending Accounts (FSA) and Health Reimbursement Arrangements (HRAs), individuals must work for an employer who offers one.

2. Portability (C2)

Health insurance portability protects workers' access to health insurance when they change or lose their jobs by making sure that pre-existing conditions do not inhibit someone's access to health insurance.

In HSA, rollover is allowed. Individuals own HSA and take it when leaving employment. In FSA, unused funds must be spent by year's end (or by termination of employment before year's end), otherwise individual loses money. HRAs cannot be rolled over to a new employer. An employer is under no obligation to continue the arrangement after employee departure, however an employer may chose to continue reimbursing a former employee's expenses from HRA.

3. Catch up contribution (C3)

It is a type of retirement savings contribution that allows people over 50 to make additional contributions to their individual retirement accounts. The catch-up contribution provision was created by the Economic Growth and Tax Relief Reconciliation Act of 2001 (EGTRRA), so that older individuals would be able to set aside enough savings for retirement.

In HSA, individuals age 55 or older may contribute more to the account per year. Starting in 2004, an additional \$500 contribution is allowed, increasing \$100 per year, up to \$1,000 per year in 2009 and thereafter. Married couples may both contribute a catch up contribution to HSA. In FSA and HRA, it is not available.

4. Ownership (C4)

HSA and FSA options present individual/employee ownership while HRA does only employer ownership.

5. Funding (who and how) (C5)

HSA requires money to be deposited directly into the account. In FSA, a set amount of pretax wages designated by the employee is deposited directly into an account. In HRA, employer reimburses employee when presented with a valid receipt.

6. Health plan arrangement (C6)

In HSA, minimum \$1,000 for individual and \$2,000 for family coverage are needed. No maximum deductible. Total costs to the insured cannot exceed \$5,000 for an individual and \$10,000 for a family, including both the deductible and copays. Thus, a plan that pays 100% of all costs above the deductible could have a deductible as high as \$5,000 for an

individual or \$10,000 for a family. In FSA and HRA, any type of health plan arrangement is allowed.

7. Tax treatment (C7)

Qualified HSAs are tax free as long as funds are spent on medical care. Contributions to FSA are tax free and so reduce annual taxable income. In HRA, reimbursements to employee are tax free as long as they are used on qualified health care purchases.

8. Usability for non-medical expenses (C8)

In HSA, funds used for non-medical expenses are taxed as income and incur a 10% penalty. After age of Medicare eligibility there is no penalty. In FSA and HRA, usability for non-medical expenses is available for only expenses defined by Insurance Research Council.

4. Multiattribute selection using an integrated fuzzy AHP-TOPSIS methodology

In the literature to obtain the criteria weights the most used multicriteria method is AHP. It has been used for the solution of various multicriteria problems in the literature (Ginevičius *et al.* 2004; Wu *et al.* 2012). The obtained weights from AHP are usually used as inputs to the other multicriteria methods. Even AHP alone or TOPSIS alone has the capability to select the best alternative, we aimed at combining the powerful aspects of these two methods. TOPSIS lets the scores in different units (money, distance, load, etc.) to be directly used in the decision matrix.

4.1. Fuzzy AHP

AHP is one of the well-known multi-criteria decision making techniques that was first proposed by Saaty (1980). The classical AHP takes into consideration the definite judgments of decision makers (Wang, Chen 2007).

Although the classical AHP includes the opinions of experts and makes a multiple criteria evaluation, it is not capable of reflecting human's vague thoughts (Seçme *et al.* 2009; Zolfani *et al.* 2012). As the uncertainty of information and the vagueness of human feeling and recognition, it is difficult to provide exact numerical values for the criteria and make evaluations which exactly convey the feeling and recognition of objects for decision makers. Therefore, most of the selection parameters cannot be given precisely. Thus experts may prefer intermediate judgments rather than certain judgments. So the fuzzy set theory makes the comparison process more flexible and capable to explain experts' preferences (Kahraman *et al.* 2003).

Different methods for the fuzzification of AHP have been proposed in the literature. AHP is firstly fuzzified by Laarhoven and Pedrycz (1983), and in this study, fuzzy ratios which were defined by triangular membership functions were compared. Buckley (1985) used the comparison ratios based on trapezoidal membership functions. Chang (1996) introduced a new approach for handling fuzzy AHP, with the use of triangular fuzzy numbers for pair-wise comparison scale of fuzzy AHP, and the use of the extent analysis method for the synthetic extent values of the pair-wise comparisons. Kulak and Kahraman (2005) made a selection among the transportation companies by using fuzzy axiomatic design and fuzzy AHP. They developed fuzzy multi-attribute axiomatic design approach and compared it with fuzzy AHP.

Buckley (1985) uses the geometric mean method to derive fuzzy weights and performance scores. This method is used because it is easy to extend to the fuzzy case and guarantees a unique solution to the reciprocal comparison matrix. The weight assessing method by geometric mean is chosen for its simplicity and ease in its application to the fuzzy case. The positive reciprocal comparison matrix of criteria weights is given as:

$$C = \begin{bmatrix} C_{11} & C_{12} & \cdots & C_{1n} \\ C_{21} & C_{22} & \cdots & C_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ C_{n1} & C_{n2} & \cdots & C_{nn} \end{bmatrix}. \quad (1)$$

The geometric mean of each row is calculated as:

$$z_j = \left[\prod_{k=1}^n C_{jk} \right]^{1/n} \quad \text{for } j, k = 1, 2, \dots, n. \quad (2)$$

The weight w_j is calculated as:

$$w_j = \frac{z_j}{z_1 + z_2 + \dots + z_n}, \quad \forall j. \quad (3)$$

To facilitate the calculation of fuzzy weights, the following arithmetic operations of trapezoidal fuzzy numbers are presented. A trapezoidal fuzzy number (TrFN) can be defined as $\tilde{m} = (a, b, c, d)$ where $0 \leq a \leq b \leq c \leq d$ as shown in Figure 1. The main arithmetic operations of TrFNs can be found in (Chen et al. 2006). A triangular fuzzy number (a, b, c) can be converted to a trapezoidal fuzzy number as (a, b, b, c) .

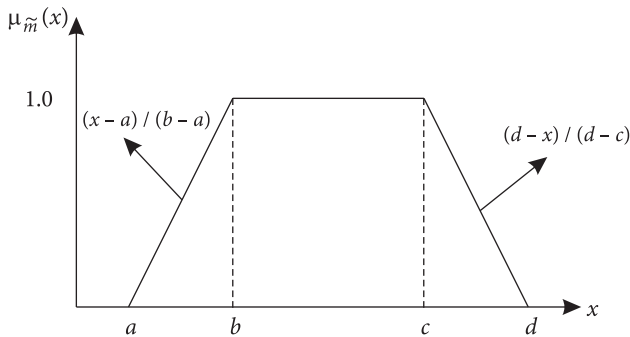


Fig. 1. Membership Function of TrFN

The steps of the fuzzy AHP algorithm can be summarized as follows:

Step 1. Evaluate the relative importance of the criteria using pairwise comparisons. The experts are required to provide their judgments on the basis of their knowledge and expertise. The experts' linguistic preferences are converted into trapezoidal fuzzy numbers using Table 1.

Table 1. Fuzzy evaluation scale for the weights

Linguistic terms	Fuzzy score
Absolutely Strong (AS)	(5/2, 3, 7/2, 4)
Very Strong (VS)	(2, 5/2, 3, 7/2)
Fairly Strong (FS)	(3/2, 2, 5/2, 3)
Slightly Strong (SS)	(1, 3/2, 2, 5/2)
Equal (E)	(1, 1, 1, 1)
Slightly Weak (SW)	(2/5, 1/2, 2/3, 1)
Fairly Weak (FW)	(1/3, 2/5, 1/2, 2/3)
Very Weak (VW)	(2/7, 1/3, 2/5, 1/2)
Absolutely Weak (AW)	(1/4, 2/7, 1/3, 2/5)

Step 2. Aggregate experts' individual preferences into group preference by applying the fuzzy trapezoidal averaging operator, which is defined by:

$$\tilde{C}_{jk} = \frac{1}{K} \left[\tilde{C}_{jk}^1 (+) \tilde{C}_{jk}^2 (+) \dots (+) \tilde{C}_{jk}^K \right], \tag{4}$$

where K is the number of experts and \tilde{C}_j^K is the evaluation of the K th decision maker on the pairwise importance comparison of j th and k th criteria.

Step 3. Obtain the fuzzy weights \tilde{w}_j . The derivation of \tilde{z}_j values (Eq. (2)) and fuzzy weights \tilde{w}_j (Eq. (3)) can be detailed as follows. Let,

$$a_j = \left[\prod_{k=1}^n a_{jk} \right]^{1/n} \text{ and } a = \sum_{j=1}^n a_j. \tag{5}$$

We can define b_j and b , c_j and c , and d_j and d . The fuzzy weight \tilde{w}_j is determined as (Chen, Hwang 1992):

$$\tilde{w}_j = \left(\frac{a_j}{d}, \frac{b_j}{c}, \frac{c_j}{b}, \frac{d_j}{a} \right), \quad \forall j. \tag{6}$$

Step 4. Defuzzify and normalize the trapezoidal fuzzy weights. To defuzzify the TrFN in Eq. (6), Eq. (7) is used:

$$w'_j = \frac{\frac{a_j}{d} + 2 \left(\frac{b_j}{c} + \frac{c_j}{b} \right) + \frac{d_j}{a}}{6}. \tag{7}$$

Now, to normalize the crisp weights Eq. (8) is used:

$$w_j = \frac{w'_j}{\sum_{j=1}^n w'_j}, \quad j = 1, 2, \dots, n. \tag{8}$$

4.2. Fuzzy TOPSIS

TOPSIS one of the classical multi-criteria decision making methods was developed by Hwang and Yoon (1981). It is based on the concept that the chosen alternative should have the shortest distance from the positive ideal solution (PIS) and the farthest from the negative ideal solution (NIS). TOPSIS also provides an easily understandable and programmable calculation procedure. It has the ability of taking various criteria with different units into account simultaneously (Ekmekçioğlu *et al.* 2010).

A number of fuzzy TOPSIS methods have been developed in recent years. Chen and Hwang (1992) first applied fuzzy numbers to establish fuzzy TOPSIS. Triantaphyllou and Lin (1996) developed a fuzzy TOPSIS method in which relative closeness for each alternative is evaluated based on fuzzy arithmetic operations. Chen (2000) extended the TOPSIS method to fuzzy group decision making situations by considering triangular fuzzy numbers and defining crisp Euclidean distance between two fuzzy numbers. Chu (2002) and Chu and Lin (2002) further improved the methodology proposed by Chen (2000). Jahanshahloo *et al.* (2006) and Chu and Lin (2009) extended the fuzzy TOPSIS method based on alpha level sets with interval arithmetic.

Fuzzy TOPSIS has been introduced for various multi-attribute decision-making problems. Yong (2006) used fuzzy TOPSIS for plant location selection and Chen *et al.* (2006) used fuzzy TOPSIS for supplier selection. Kahraman *et al.* (2007) utilized fuzzy TOPSIS for industrial robotic system selection. Ekmekçioğlu *et al.* (2010) used a modified fuzzy TOPSIS to select municipal solid waste disposal method and site. Kaya and Kahraman (2011) proposed a modified fuzzy TOPSIS for selection of the best energy technology alternative. Kim *et al.* (2011) used fuzzy TOPSIS for modeling consumer's product adoption process. Yu *et al.* (2011) proposed an evaluation model based on crisp AHP and fuzzy TOPSIS to tackle ranking e-commerce websites in e-alliance in fuzzy environment. The AHP is applied to analyze the structure of ranking problem and to determine weights of the criteria. Fuzzy TOPSIS method is used to obtain final ranking. Aydoğan (2011) proposed a conceptual performance measurement framework that takes into account company-level factors for a real world application problem. An integrated approach of analytic hierarchy process (AHP) improved by rough sets theory (Rough-AHP) and fuzzy TOPSIS method is proposed to obtain final ranking. Rostamzadeh and Sofian (2011) presented a fuzzy decision-making approach for prioritizing effective 7Ms (Management, Manpower, Marketing, Method, Machine, Material, and Money) to improve production systems performance. Linguistic values are used to assess the ratings and weights for 7Ms. A multiple criteria decision-making model based on fuzzy AHP and fuzzy TOPSIS are applied.

In the following, Chen's fuzzy TOPSIS method is explained:

Chen (2000) extended the TOPSIS method to fuzzy group decision making situations by considering triangular fuzzy numbers and defining crisp Euclidean distance between two fuzzy numbers. In Chen's fuzzy TOPSIS, linguistic preferences can easily be converted to fuzzy numbers which are allowed to be used in calculations (Önüt, Soner 2008; Ekmekçioğlu *et al.* 2010; Kutlu, Ekmekçioğlu 2010).

It is suggested that the decision makers use linguistic variables to evaluate the ratings of alternatives with respect to criteria. Table 2 gives the linguistic scale for evaluation of the alternatives. Assuming that a decision group has K people, the ratings of alternatives with respect to each criterion can be calculated as:

$$\tilde{x}_{ij} = \frac{1}{K} [\tilde{x}_{ij}^1 (+) \tilde{x}_{ij}^2 (+) \dots (+) \tilde{x}_{ij}^K], \tag{9}$$

where \tilde{x}_{ij}^K is the rating of the K th decision maker for i th alternative with respect to j th criterion (Chen 2000).

Table 2. Fuzzy evaluation scores for the alternatives

Linguistic terms	Triangular fuzzy scores	Trapezoidal fuzzy scores
Very Poor (VP)	(0, 0, 10)	(0, 0, 0, 10)
Poor (P)	(0, 10, 30)	(0, 10, 10, 30)
Medium Poor (MP)	(10, 30, 50)	(10, 30, 30, 50)
Fair (F)	(30, 50, 70)	(30, 50, 50, 70)
Medium Good (MG)	(50, 70, 90)	(50, 70, 70, 90)
Good (G)	(70, 90, 100)	(70, 90, 90, 100)
Very Good (VG)	(90, 100, 100)	(90, 100, 100, 100)

Obtaining weights of the criteria and fuzzy ratings of alternatives with respect to each criterion, the fuzzy multi-criteria decision-making problem can be expressed in matrix format as:

$$D = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1n} \\ \vdots & \vdots & \dots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \dots & \tilde{x}_{mn} \end{bmatrix}, \tag{10}$$

$$W = [w_1, w_2, \dots, w_n], \quad j = 1, 2, \dots, n, \tag{11}$$

where \tilde{x}_{ij} is the rating of the alternative A_i with respect to criterion j (i.e. C_j) and w_j denotes the importance weight of C_j . These linguistic variables can be described by triangular fuzzy numbers: $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$. To avoid the complicated normalization formula used in classical TOPSIS, the linear scale transformation is used here to transform the various criteria scales into a comparable scale. Therefore, we can obtain the normalized fuzzy decision matrix denoted by \tilde{R} :

$$\tilde{R} = [\tilde{r}_{ij}]_{m \times n}, \tag{12}$$

where B and C are the set of benefit criteria and cost criteria, respectively, and

$$\tilde{r} = \left(\frac{\tilde{a}_{ij}}{c_j^*}, \frac{\tilde{b}_{ij}}{c_j^*}, \frac{\tilde{c}_{ij}}{c_j^*} \right), \quad j \in B; \tag{13}$$

$$\tilde{r} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} \right), \quad j \in C; \tag{14}$$

$$c_j^* = \max_i c_{ij} \quad \text{if } j \in B; \quad (15)$$

$$a_j^- = \min_i a_{ij} \quad \text{if } j \in C. \quad (16)$$

The normalization method mentioned above is to preserve the property that the ranges of normalized triangular fuzzy numbers belong to $[0; 1]$.

Considering the different importance of each criterion, we can construct the weighted normalized fuzzy decision matrix as:

$$\tilde{V} = \left[\tilde{v}_{ij} \right]_{m \times n}, \quad i = 1, 2, \dots, m; j = 1, 2, \dots, n, \quad (17)$$

where

$$\tilde{v}_{ij} = \tilde{r}_{ij}(\cdot) d(C_j). \quad (18)$$

According to the weighted normalized fuzzy decision matrix, we know that the elements $\tilde{v}_{ij} \quad \forall i, j$ are normalized positive triangular fuzzy numbers and their ranges belong to the closed interval $[0, 1]$. Then, we can define the fuzzy positive-ideal solution (FPIS, A^*) and fuzzy negative-ideal solution (FNIS, A^-) as:

$$A^* = (\tilde{v}_1^*, \tilde{v}_2^*, \dots, \tilde{v}_n^*); \quad (19)$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-), \quad (20)$$

where

$$\tilde{v}_j^* = (1, 1, 1) \quad \text{and} \quad \tilde{v}_j^- = (0, 0, 0), \quad j = 1, 2, \dots, n. \quad (21)$$

The distance of each alternative from A^* and A^- can be currently calculated as:

$$d_i^* = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^*), \quad i = 1, 2, \dots, m; \quad (22)$$

$$d_i^- = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^-), \quad i = 1, 2, \dots, m, \quad (23)$$

where $d(\cdot, \cdot)$ is the distance measurement between two fuzzy numbers calculating with the following formula:

$$d(\tilde{\rho}, \tilde{\tau}) = \sqrt{\frac{1}{3} \left[(\rho_1 - \tau_1)^2 + (\rho_2 - \tau_2)^2 + (\rho_3 - \tau_3)^2 \right]}, \quad (24)$$

where $\tilde{\rho} = (\rho_1, \rho_2, \rho_3)$ and $\tilde{\tau} = (\tau_1, \tau_2, \tau_3)$ are two triangular fuzzy numbers.

A closeness coefficient is defined to determine the ranking order of all alternatives once the \tilde{d}_j^* and \tilde{d}_j^- of each alternative A_i ($i = 1, 2, \dots, m$) are calculated. The closeness coefficient of each alternative is calculated as:

$$CC_i = \frac{\tilde{d}_j^-}{\tilde{d}_j^* + \tilde{d}_j^-}, \quad i = 1, 2, \dots, m. \quad (25)$$

Obviously, an alternative A_i is closer to the (FPIS, A^*) and farther from (FNIS, A^-) as CC_i approaches to 1. Therefore, according to the closeness coefficient, we can determine the ranking order of all alternatives and select the best one from among a set of feasible alternatives.

5. Application of the methodology

5.1. Selection among health insurance options

The considered three insurance options are evaluated with respect to the following eight criteria: Eligibility (C1), Portability (C2), Catch up contribution (C3), Ownership (C4), Funding (C5), Health plan arrangement (C6), Tax treatment (C7), and Usability for non-medical expenses (C8).

Five experts from three insurance companies in Turkey determined the criteria weights by the pairwise comparison matrix in Table 3 using the fuzzy evaluation scale in Table 1. The fuzzy scores in the matrix are the compromised values.

Using Eq. (7) in Buckley’s (1985) fuzzy AHP method, the criteria weights given in Table 4 are obtained. The consistency of the defuzzified pairwise comparison matrix was measured and found to be 0.02.

Table 3. Pairwise comparison matrix of criteria using linguistic terms

	C1	C2	C3	C4	C5	C6	C7	C8
C1	E	FS	AS	AS	SS	FS	AS	AS
C2	FW	E	SS	SS	FW	SW	SS	SS
C3	AW	SW	E	E	VW	FW	E	E
C4	AW	SW	E	E	VW	FW	E	E
C5	SW	FS	VS	VS	E	SS	AS	AS
C6	FW	SS	FS	FS	SW	E	FS	FS
C7	AW	SW	E	E	AW	FW	E	E
C8	AW	SW	E	E	AW	FW	E	E

Table 4. Criteria weights

C1	C2	C3	C4	C5	C6	C7	C8
0.25	0.11	0.07	0.07	0.21	0.15	0.07	0.07

According to the results in Table 5, the priority vector of the criteria gives us the ranking order as C1 (eligibility) > C5 (funding) > C6 (health plan arrangement) > C2 (portability) > C3 (catch up contribution) = C4 (ownership) = C7 (tax treatment) = C8 (usability for non-medical expenses).

After obtaining the criteria weights, the fuzzy decision matrix, which are composed of compromise values are generated by the five experts as in Table 5. The fuzzy normalized decision matrix is given in Table 6. To obtain the fuzzy normalized decision matrix Eqs (13–14) were used for benefits and cost criteria, respectively. The fuzzy weighted normalized decision matrix is presented in Table 7. The values in Table 7 were obtained by multiplying the values in Table 6 with the criteria weights in Table 4. The distances to the fuzzy positive ideal solution and the fuzzy negative ideal solution values are given in Table 8. The values in Table 8 were obtained by using Eq. (24). The closeness coefficients and ranking order of the three alternatives are presented in Table 9. The values in Table 9 were obtained by using Eqs (22), (23), and (25).

Table 5. Fuzzy decision matrix

OP-TIONS	CRITERIA							
	C1	C2	C3	C4	C5	C6	C7	C8
HSA	(75, 80, 85)	(90, 95, 100)	(80, 90, 100)	(90, 95, 100)	(35, 40, 45)	(35, 45, 55)	(45, 55, 65)	(65, 70, 75)
FSA	(60, 65, 70)	(75, 80, 85)	(35, 40, 45)	(90, 95, 100)	(65, 70, 75)	(80, 85, 90)	(75, 80, 85)	(35, 40, 45)
HRA	(55, 65, 75)	(50, 60, 70)	(35, 40, 45)	(45, 50, 55)	(90, 95, 100)	(80, 85, 90)	(45, 55, 65)	(35, 40, 45)
Criteria Weights	0.25	0.11	0.07	0.07	0.21	0.15	0.07	0.07

Table 6. Fuzzy normalized decision matrix

OPTIONS	CRITERIA			
	C1	C2	C3	C4
HSA	(0.8824, 0.9412, 1)	(0.9, 0.95, 1)	(0.8, 0.9, 1)	(0.9, 0.95, 1)
FSA	(0.7059, 0.7647, 0.8235)	(0.75, 0.8, 0.85)	(0.35, 0.4, 0.45)	(0.9, 0.95, 1)
HRA	(0.6471, 0.7647, 0.8824)	(0.5, 0.6, 0.7)	(0.35, 0.4, 0.45)	(0.45, 0.5, 0.55)
OPTIONS	C5	C6	C7	C8
HSA	(0.35, 0.4, 0.45)	(0.3889, 0.5, 0.6111)	(0.5294, 0.6471, 0.7647)	(0.8667, 0.9333, 1)
FSA	(0.65, 0.7, 0.75)	(0.8889, 0.9444, 1)	(0.8824, 0.9412, 1)	(0.4667, 0.5333, 0.6)
HRA	(0.9, 0.95, 1)	(0.8889, 0.9444, 1)	(0.5294, 0.6471, 0.7647)	(0.4667, 0.5333, 0.6)

Table 7. Fuzzy weighted normalized decision matrix

OPTIONS	CRITERIA			
	C1	C2	C3	C4
HSA	(0.2206, 0.2353, 0.25)	(0.0990, 0.1045, 0.11)	(0.0560, 0.0630, 0.07)	(0.0630, 0.0665, 0.07)
FSA	(0.1765, 0.1912, 0.2059)	(0.0825, 0.0880, 0.0935)	(0.0245, 0.0280, 0.0315)	(0.0630, 0.0665, 0.07)
HRA	(0.1618, 0.1912, 0.2206)	(0.0550, 0.0660, 0.0770)	(0.0245, 0.0280, 0.0315)	(0.0315, 0.0350, 0.0385)
OPTIONS	C5	C6	C7	C8
HSA	(0.0735, 0.0840, 0.0945)	(0.0583, 0.0750, 0.0917)	(0.0371, 0.0453, 0.0535)	(0.0607, 0.0653, 0.07)
FSA	(0.1365, 0.1470, 0.1575)	(0.1333, 0.1417, 0.15)	(0.0618, 0.0659, 0.07)	(0.0327, 0.0373, 0.0420)
HRA	(0.1890, 0.1995, 0.21)	(0.1333, 0.1417, 0.15)	(0.0371, 0.0453, 0.0535)	(0.0327, 0.0373, 0.0420)

Table 8. Distance measurements

OPTIONS	(FPIS)	(FNIS)
HSA	7.2614	0.7419
FSA	7.2346	0.7669
HRA	7.2565	0.7474

Table 9. Closeness coefficients and ranking order of the three alternatives

OPTIONS	CLOSENESS COEFFICIENTS	ORDER OF THE ALTERNATIVES
HSA	0.8441	3
FSA	0.8730	1
HRA	0.8504	2

5.2. Sensitivity analysis

In order to see the effects of the changes in the weights of the criteria, a sensitivity analysis has been realized. The six different cases given in Table 10 have been examined and the obtained results have been illustrated in Figure 2. In the sensitivity analysis, new weights were obtained by using slightly modified pairwise comparison matrices of AHP to see if these slight changes affected the ranking of alternatives. Accordingly the obtained weights were used as inputs to TOPSIS.

Table 10. Criteria weights of six different cases

	CRITERIA WEIGHTS							
	C1	C2	C3	C4	C5	C6	C7	C8
Case 1	0.250	0.110	0.070	0.070	0.210	0.150	0.070	0.070
Case 2	0.035	0.211	0.199	0.051	0.218	0.034	0.179	0.073
Case 3	0.199	0.059	0.018	0.132	0.237	0.066	0.189	0.100
Case 4	0.020	0.236	0.191	0.126	0.092	0.111	0.096	0.128
Case 5	0.140	0.010	0.050	0.050	0.450	0.250	0.049	0.001
Case 6	0.005	0.200	0.150	0.005	0.280	0.180	0.010	0.170

Case 1 represents the ranking order of the results obtained by the criteria weights originally assigned by the experts. According to Case 1, FSA is the best option. In the following, sensitivity results are interpreted with respect to the original criteria weights used in Case 1.

In Case 2, the weights of the criteria C2 (portability), C3 (catch up contribution), and C7 (tax treatment) are significantly increased while the weight of C6 (health plan arrangement) is significantly decreased. This caused HSA to be the best option. In Case 3, the weights of the criteria C4 (ownership) and C7 (tax treatment) are significantly increased while the weight of C1 (eligibility), C2 (portability), and C6 (health plan arrangement) are significantly decreased.

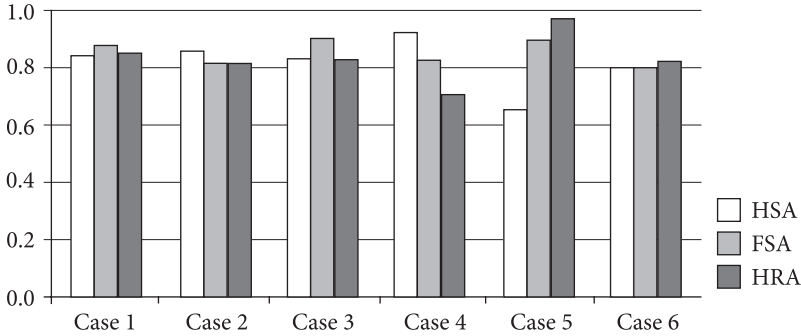


Fig. 2. Results of six different cases

This changed the ranking order of HSA and HRA. In Case 4, the weights of the criteria C2 (portability), C3 (catch up contribution), C4 (ownership), and C8 (usability for non-medical expenses) are significantly increased while the weight of C1 (eligibility) and C5 (funding) are significantly decreased. This caused HSA to be the best option. In Case 5, the weights of the criteria C5 (funding) and C6 (health plan arrangement) are significantly increased while the weights of C1 (eligibility), C2 (portability), and C8 (usability for non-medical expenses) are significantly decreased. This caused HRA to be the best option. In Case 6, the weights of the criteria C2 (portability), C3 (catch up contribution), C5 (funding), and C8 (usability for non-medical expenses) are significantly increased while the weights of C1 (eligibility), C4 (portability), and C7 (tax treatment) are significantly decreased. This caused HRA to be the best option. This changed the ranking order of HSA and FSA.

The results of Case 4 and Case 5 are remarkable. The weights of the criteria C2, C3, C4, C7, and C8 are significantly decreased while the weights of C1, C5, and C6 are significantly increased. The ranking order in Case 4 is HSA > FSA > HRA while it is HRA > FSA > HAS in Case 5. This is because of that individuals own HSA and takes it when leaving employment but HRAs cannot be rolled over to a new employer. Similar comments are valid for the others.

Sensitivity analyses show that the decision given by the expected values of criteria weights does not change unless large deviations occur in these expected values.

Conclusions

Employers may either choose to provide various insurance products from which workers can choose or could increase wages but not offer any health coverage allowing workers to decide how to spend that extra money to meet their health care needs. Employees may have a difficulty in selecting the best health insurance product to meet their needs since it is a complex problem including many dimensions.

We proposed a fuzzy integrated multiattribute decision making methodology based on AHP and TOPSIS. The criteria weights have been obtained by fuzzy AHP and health insurance options weighted by these weights have been evaluated by fuzzy TOPSIS. Our methodology has the advantage of using linguistics expressions instead of sharp numerical data.

Sensitivity analyses show that the decision given by the expected values of criteria weights does not change unless large deviations occur in these expected values.

The compromised assessments from the experts were received in our case. Some aggregation methods can be used when separate assessments come from experts. As a limitation of our methodology, if the number of criteria gets larger, the process of obtaining criteria weights become impossible with sufficient consistency.

In addition to the theoretical contributions of the proposed method, our study is expected to provide new insights for practical insurance management. In the present case insurance managers should advice FSA option to their customers. The proposed method can be used to consider new insurance options and market conditions by the management.

For further research we suggest that other multicriteria decision making methods like fuzzy VIKOR, fuzzy ELECTRE or fuzzy utility models. The obtained results by these methods can be compared by our results.

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