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A Hybrid Multi-Attribute Decision-Making Approach Considering Correlations Among Indicators

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Abstract

Considering the fuzzy and uncertainty of the evaluation information of the evaluation object, the type of indicators are expanded into five types of mixed evaluation information, namely, exact number, interval number, triangular fuzzy number, hesitant fuzzy number, and probabilistic linguistic term sets, and different types of evaluation information are adopted according to the different characteristics and types of indicators, respectively. When the evaluation information is hybrid information, the generalized Shapley function based on fuzzy measurement is used to analyze the interaction between indicators and determine the weights of indicators, considering that the interaction between indicators is more complicated. In view of the fact that the conversion of mixed information into the same kind of information will lead to the problem of complicated calculation and missing information, the VIKOR method is used to comprehensively evaluate the evaluation objects and select the best ones. Finally, the validity and feasibility of the proposed method is verified by taking the assessment of data literacy level and competence of teachers in a university in a western province of China as an example.

Keywords: hybrid multi-attribute decision making; inter-indicator correlation; generalized shapley function; VIKOR method; data literacy evaluation.

1 Introduction

Designers in the process of designing solutions, such as encountering the uncertainty of the needs of customers, due to the diversity of customer needs, and involves the designer's knowledge, design inspiration, imagination and experience, it is usually more difficult to accurately comprehend the needs of customers. Therefore, the designer will design a number of programs to meet the conditions, to select the best design solutions, to avoid the risk of late design changes, professional program design will make the customer more recognized. The main goal of the design program is to meet customer needs. In the process of evaluating the design solutions need to consider the customer needs, so the evaluation index of the design solutions comprehensively consider the correlation between all the indicators is very necessary.

The main goal of our evaluation is to meet the needs of our clients. In the process of evaluating design solutions, customer needs need to be taken into account, so the evaluation indicators of design solutions are very necessary to synthesize the correlation between all indicators. In fact, there are inherent characteristics of information complementarity and redundancy between evaluation indicators. The correlation between indicators will have an impact on the ranking results of design schemes have a significant impact. The ANP and DEMATEL methods are commonly used to analyze the correlation relationships between system elements. Reference [1] uses the ANP method to analyze the mutual influence relationship among various decision-making levels, and proposes a bank wealth management performance evaluation method that combines balanced scorecard and ANP. Reference [2] proposes a method based on trapezoidal straightness The DEMATEL method for improving perceptual fuzzy numbers uses linguistic variables of trapezoidal intuitionistic fuzzy numbers to express the mutual influence relationship between experts and complex system factors. The ANP and DEMATEL methods are both methods used by experts to judge the strength of the mutual influence relationship between indicators based on subjective experience, and then calculate the final matrix of the mutual influence relationship. However, there are two problems: (1) in the case of bounded rationality, due to the different subjective experiences of decision-makers, it is difficult to grasp the accuracy of the correlation relationship between indicators, which can easily lead to inconsistent evaluation results; (2) Existing literature research has shown that currently these two methods can only analyze the mutual influence relationship between adjacent indicators, and cannot analyze the mutual influence relationship between a single indicator and the remaining indicators, which has certain limitations. Fuzzy measures can analyze the mutual influence relationship between any indicator [3]. Reference [4] uses the generalized Choquet integral of hesitant fuzzy measure to analyze the mutual influence relationship between indicators and calculate indicator weights. This article adopts a method based on λ The generalized Shapley function of fuzzy measure [5] analyzes the correlation between indicators, which can not only analyze the mutual influence relationship between a single indicator and any remaining indicator set, but also analyze the mutual influence relationship between any indicator set and any remaining indicator set, making the analysis results more accurate and practical.

The evaluation metrics of the program should take into account both the needs of the client and the satisfaction of functional requirements, which vary from client to client. Indicator evaluation information is usually characterized by complexity, vagueness, uncertainty and diversity of information. Indicator information is usually expressed in the form of interval numbers, semantic values, fuzzy numbers, etc., so it is meaningful to study the appearance of indicators in the form of multiple types in the decision matrix. Different types of information are usually transformed into the same type of information to facilitate the ranking before obtaining the final ranking result. Reference [6] used triangular fuzzy numbers to deal with the mixed decision-making information generated by realistic decision-making problems, and improved the ranking ability under mixed information by considering the relationship and relative balance between alternative performances under multiple criteria. Reference [7] proposed a new method for solving mixed multi-attribute decision problems with multiple attribute values by introducing the decision maker's closeness to the positive ideal solution and the eclectic variable-weight decision-making method. Due to the complexity and uncertainty of the real problem and the diversity of various types of information, this paper expands the indicator types of the design scheme to five types: exact number, interval number, triangular fuzzy number, hesitant fuzzy number, and probabilistic linguistic term set. Mixed information produces missing information in the process of transforming into the same information, and the calculation process is complicated. Reference [8] proposed the idea of modular processing, which categorizes the indicators, and different types of indicators are processed informationally according to their characteristics, which avoids the information loss in the process of information transformation. Reference [9] proposed a modular stochastic VIKOR method to sort the programs, without the need to transform the various types of mixed information.

This paper proposes a hybrid multi-attribute decision-making method considering the correlation relationship between indicators, and experts can use five hybrid representations of exact number, interval number, triangular fuzzy number, hesitant fuzzy number, and probabilistic linguistic term set to obtain the evaluation information, and adopt different types of evaluation information according to the characteristics and types of indicators, respectively. Considering that the mixed evaluation information will lead to a more complicated mutual influence relationship between indicators, the generalized Shapley function based on λ fuzzy measure is used to analyze the mutual influence relationship between indicators to determine the weights of each indicator, and combined with the VIKOR method to assess the data literacy competence of college teachers, and the proposed method is validated by taking the assessment of the data literacy level and competence of the teachers of a college in one of the western provinces of China as an example.

2 Preliminaries

2.1 Interval number

Definition 1[10] Let R is the set of real numbers, an interval number can be expressed as $\tilde{r} = [r^L, r^U] = \{r^L \le r \le r^U, r \in R\}$, where r^L and r^U are the upper and lower bounds of the interval number. When $r^L = r^U$, the interval number $\tilde{r}$ degenerates to an exact number.

Definition 2[10] If $\tilde{r}_1 = [r_1^L, r_1^U]$ and $\tilde{r}_2 = [r_2^L, r_2^U]$ are two interval numbers, then the Euclidean distance between them is:

$$d(\tilde{r}_1, \tilde{r}_2) = \sqrt{\frac{1}{2}\left[\left(r_1^L - r_2^L\right)^2 + \left(r_1^U - r_2^U\right)^2\right]} \tag{1}$$

2.2 Triangular Fuzzy Number

Definition 3[11] $\tilde{a} = (a^L, a^M, a^U)and\tilde{b} = (b^L, b^M, b^U)$are two triangular fuzzy numbers, and the addition operation of triangular fuzzy numbers is defined as:

$$\tilde{a} \oplus \tilde{b} = (a^L, a^M, a^U) \oplus (b^L, b^M, b^U) = (a^L + b^L, a^M + b^M, a^U + b^U) \tag{2}$$

Definition 4[11] The multiplication operation of triangular fuzzy numbers are defined as:

$$t \otimes \tilde{a} = t \otimes (a^L, a^M, a^U) = (ta^L, ta^M, ta^U) \tag{3}$$

Usually, when calculating the distance between two triangular fuzzy numbers, the traditional Euclidean distance is used to calculate the distance of the triangular fuzzy number. However, relative preference relationship analysis can also calculate the distance of the triangular fuzzy number. Compared with deblurring, using relative preference relationship analysis to calculate the distance of the triangular fuzzy number can better reduce the lack of evaluation information[26−27].

Definition 5[12] Let $\tilde{a} = (a^L, a^M, a^U)$ and $\tilde{b} = (b^L, b^M, b^U)$are two triangular fuzzy numbers, the relative preference relationship between $\tilde{a}$ and $\tilde{b}$ are defined as:

$$\mu_p(\tilde{a}, \tilde{b}) = \frac{1}{2}\left(\frac{(a^L - b^U) + 2(a^M - b^M) + (a^U - b^L)}{2\,\|T\|} + 1\right) \tag{4}$$

Where:

$$\|T\| = \begin{cases} \frac{(t_L^+ - t_U^-) + 2(t_M^+ - t_M^-) + (t_U^+ - t_L^-)}{2}, & t_L^+ - t_U^- \ge 0 \\ \frac{(t_L^+ - t_U^-) + 2(t_M^+ - t_M^-) + (t_U^+ - t_L^-)}{2} + 2(t_U^- - t_L^+), & t_L^+ - t_U^- < 0 \end{cases}$$

$$t_L^+ = \max\{a^L, b^L\}, t_M^+ = \max\{a^M, b^M\}, t_U^+ = \max\{a^U, b^U\}$$

$$t_L^- = \min\{a^L, b^L\}, t_M^- = \min\{a^M, b^M\}, t_U^- = \min\{a^U, b^U\}$$

2.3 Hesitant Fuzzy Number

Definition 6[13] Let T is a set sorted from smallest to largest, and the hesitant fuzzy set H is a mapping function of the set T defined in the interval [0, 1], and H is denoted as:

$$H = \{(t, h_H(t)) \, | t \in T\} \tag{5}$$

Where, $h_H(t)$ is the set of different real numbers in [0,1], and is the t possible degree of $t \in T$ in the hesitant fuzzy set H. $h_H(t)$ is the fundamental element in the hesitant fuzzy set H. $h = h_H(t) = \{\gamma \, | \gamma \in h_H(t)\} = H\{\gamma^1, \gamma^2, \cdots, \gamma^l\}$ is a hesitant fuzzy number, $\gamma^\lambda \in [0, 1], \lambda = 1, 2, \cdots, l$, l represent the number of elements in the hesitant fuzzy number h.

Definition 7[14] For the hesitant fuzzy number $h = H\{\gamma_1^\lambda \, | \lambda = 1, 2, \cdots, l\}$, let λ^+ is the largest element and λ^- is the smallest element. $\bar{\lambda} = \eta\lambda^+ + (1 - \eta)\lambda^-$ is a defined number, η is a parameter, $0 < \eta < 1$. The value of the parameter η is chosen by the decision maker from risk appetite, risk aversion and risk neutrality.

(1) When decision-makers choose risk preferences, $\eta = 1, \bar{\lambda} = \lambda^+$.Need to increase the maximum value of elements in h.

(2) When decision-makers choose risk aversion, $\eta = 0, .\bar{\lambda} = \lambda^-$.Need to increase the minimum value of elements in h.

(3) When decision-makers choose risk neutrality, $\eta = \frac{1}{2}$, $\bar{\lambda} = \frac{1}{2}(\lambda^+ + \lambda^-)$. We need to increase the average value of all elements in h.

Definition 8[15] Let $h = H\{\gamma^\lambda \, | \lambda = 1, 2, \cdots, l\}$ is a hesitant fuzzy number, then its score function is:

$$S(h) = \frac{1}{l}(\gamma^1 + \gamma^2 + \cdots + \gamma^l) \tag{6}$$

Drawing on the classical Euclidean distance measure, XU and XIA [15] proposed a distance measure due to fuzzy Euclidean distance:

$$d_E(h_1, h_2) = \sqrt{\frac{1}{l} \sum_{\lambda=1}^{l} (\gamma_1^\lambda - \gamma_2^\lambda)^2} \tag{7}$$

2.4 Probabilistic language term sets

Decision-making problems in real life, for non-quantitative attributes, it is often difficult to evaluate such attributes using precise numbers. Literature [13] proposes probabilistic linguistic term sets based on hesitant fuzzy linguistic term sets, where hesitant fuzzy linguistic term sets give the same degree of importance to the semantic term set (LTS), and probabilistic linguistic term sets are allowed to have different weights, i.e., semantic term sets have different degrees of importance in order to avoid the loss of decision maker's preference information.

Definition 9[16] Let $S = \{s_0, s_1, \cdots, s_\alpha\}$ is the semantic set, then the set of probabilistic linguistic terms is:

$$L(p) = \left\{ L^{(k)}(p^{(k)}) \middle| L^{(k)} \in S, p^{(k)} \geq 0, k = 1, 2, \cdots, \#L(p), \sum\nolimits_{k=1}^{\#L(p)} p^{(k)} \leq 1 \right\} \tag{8}$$

where$L^{(k)}(p^{(k)})$denotes the probability that the set of linguistic terms $L^{(k)}$is $p^{(k)}$ and $\#L(p)$is the number of semantic sets contained in all $L(p)$.

Definition 10[17] Let $L(p)_1$ and $L(p)_2$ are two probabilistic linguistic term sets , $L(p)_1 = \left\{L_1^{(k)}(p_1^{(k)}) \, | k = 1, 2, \cdots, \#L(p)_1\right\}$, $L(p)_2 = \left\{L_2^{(k)}(p_2^{(k)}) \, | k = 1, 2, \cdots, \#L(p)_2\right\}$, If$\#L(p)_1 > \#L(p)_2$, it is necessary to add $\#L(p)_1 - \#L(p)_2$ LTSs to $L(p)_2$, so that the number of elements in $L(p)_1$and $L(p)_2$ are the same, and increase the smallest LTS in $L(p)_2$with a weight of zero.

Definition 11[16] Let a probabilistic linguistic term set with $\sum\limits_{k=1}^{\#L(p)} p^{(k)} < 1$ that It needs to be normalized:

$$\bar{L}(p) = \left\{ L^{(k)}(\bar{p}^{(k)}) \, | k = 1, 2, \cdots, \#L(p) \right\} \tag{9}$$

where $\bar{p}^{(k)} = p^{(k)} / \sum_{k=1}^{\#L(p)} p^{(k)}$, and $L^{(k)}(\bar{p}^{(k)})$is ordered from smallest to largest.

Definition 12[16] $L_1^{(k)}$and $L_2^{(k)}$are the k-th element in $L(p)_1$ and $L(p)_2$, respectively. $p_1^{(k)}$ and $p_2^{(k)}$ denote the weights of $L_1^{(k)}$ and $L_2^{(k)}$, respectively, and their distance equations are:

$$d(L(p)_1, L(p)_2) = \sqrt{\sum_{k=1}^{\#L(p)_1} (p_1^{(k)} r_1^{(k)} - p_2^{(k)} r_2^{(k)})^2 / \#L(p)_1} \tag{10}$$

Where, $r_1^{(k)}$and $r_2^{(k)}$ denote the subscripts of $L_1^{(k)}$ and $L_2^{(k)}$, respectively.

Definition 13[17] Let $L(p) = \left\{ L^{(k)}(p^{(k)}) \,|k = 1, 2, \cdots, \#L(p) \right\}$ is a set of probabilistic linguistic terms, $r^{(k)}$is the subscript of $L^{(k)}$, and the expression of the score function of $L(p)$is that:

$$E(L(p)) = S_{\bar{\alpha}} \tag{11}$$

Where, $\bar{\alpha} = \sum_{k=1}^{\#L(p)} r^{(k)} p^{(k)} / \sum_{k=1}^{\#L(p)} p^{(k)}$.For the probabilistic semantic sets $L(p)_1$ and $L(p)_2$, if $E(L(p)_1) > E(L(p)_2)$,then $L(p)_1 > L(p)_2$.

2.5 Normalization of Evaluation Decision Matrix

In response to the evaluation information given by the decision-making experts under each criterion, the specific form of the data information is portrayed according to the different criteria, the benefit-type criterion and the cost-type criterion are differentiated, and the evaluated value of each criterion is normalized, and the methods for the normalization of a variety of different types of evaluation information are given in the following.

When the evaluation information of attribute $C_j$is numerical, it is necessary to process the information to eliminate dimensional inconsistency. When the evaluation information is y_{ij}, standardize it to obtain $\bar{y}_{ij}$.

If C_j is a cost-type indicator:

$$\bar{y}_{ij} = \frac{1/y_{ij}}{\sqrt{\sum_{i=1}^{n} (1/y_{ij})^2}} \tag{12}$$

If C_j is a benefit-type indicator:

$$\bar{y}_{ij} = \frac{y_{ij}}{\sqrt{\sum_{i=1}^{n} (y_{ij})^2}} \tag{13}$$

When the evaluation information of attribute C_j is an interval number, the normalization method is as follows:

$$\bar{y}_{ij} = [b_{ij}^{*L}, b_{ij}^{*U}] = \begin{cases} \left[b_{ij}^L \Big/ \sqrt{\sum_{i=1}^{m} (b_{ij}^U)^2}, b_{ij}^U \Big/ \sqrt{\sum_{i=1}^{m} (b_{ij}^L)^2} \right] \\ \left[1 \Big/ \sqrt{(b_{ij}^U)^2 \sum_{i=1}^{m} (1/b_{ij}^L)^2}, 1 \Big/ \sqrt{(b_{ij}^L)^2 \sum_{i=1}^{m} (1/b_{ij}^U)^2} \right] \end{cases} \tag{14}$$

When the criterion values are described by triangular fuzzy numbers, the corresponding normalization equation is

$$\bar{y}_{ij} = (c_{ij}^{*L}, c_{ij}^{*M}, c_{ij}^{*U}) = \begin{cases} \left(c_{ij}^L \Big/ \sqrt{\sum_{i=1}^{m} (c_{ij}^U)^2}, c_{ij}^M \Big/ \sqrt{\sum_{i=1}^{m} (c_{ij}^M)^2}, c_{ij}^U \Big/ \sqrt{\sum_{i=1}^{m} (c_{ij}^L)^2}, \right) \\ \left(1 \Big/ \sqrt{(c_{ij}^U)^2 \sum_{i=1}^{m} (1/c_{ij}^L)^2}, 1 \Big/ \sqrt{(c_{ij}^M)^2 \sum_{i=1}^{m} (1/c_{ij}^M)^2}, 1 \Big/ \sqrt{(c_{ij}^L)^2 \sum_{i=1}^{m} (1/c_{ij}^U)^2}, \right) \end{cases} \tag{15}$$

When the criterion values are described by hesitant fuzzy numbers, the corresponding normalization formula is

$$\bar{y}_{ij} = \begin{cases} h_{ij} & C_j \text{ is a benefit - based indicator} \\ h_{ij} & C_j \text{ is a cost - based indicator} \end{cases} \tag{16}$$

Where, h_{ij}^cdenotes the complement of h_{ij}.

When the criterion value is described by the probabilistic linguistic term sets, the data in the original decision matrix are normalized using the normalization method proposed by Zhu [18], and the cost-type indicators are transformed into benefit-type indicators, and the corresponding normalization formula is

$$\bar{y}_{ij} = \begin{cases} r_{ij} & C_j \text{ is a benefit - based indicator} \\ -r_{ij} & C_j \text{ is a cost - based indicator} \end{cases} \tag{17}$$

2.6 λ- Fuzzy measure

Definition 15[19] Let $X = \{x_1, x_2, \cdots, x_n\}$ is a non empty set, $P(X)$ is a power set on X, $\lambda \in (-1, +\infty)$, $\mu : P(X) \to [0, 1]$. If $P(X)$ satisfies:

(1) $\mu(\varphi) = 0$, $\mu(X) = 1$;

(2) $\forall A, B \in P(X)$,if $A \subset B$, then$\mu(A) \leq \mu(B)$;

(3) $\mu(A \cup B) = \mu(A) + \mu(B) + \lambda\mu(A)\mu(B)$. Then μ is said to be aλ- fuzzy measure on X.

From the derivation of the formula$\mu(A \cup B) = \mu(A) + \mu(B) + \lambda\mu(A)\mu(B)$, we can find that (1) when $\lambda = 0$, we can get the formula$\mu(A \cup B) = \mu(A) + \mu(B)$, at this point μ is additively measurable,that is, $A$and $B$are independent of each other; (2) when $\lambda < 0$, we can get the formula$\mu(A \cup B) < \mu(A) + \mu(B)$, at this point μ is a subadditive measure ,there is a cross relationship between A and B, indicating information redundancy; (3) When $\lambda > 0$, the formula $\mu(A \cup B) > \mu(A) + \mu(B)$can be obtained, At this point $\mu$is a super-additive measure, i.e., $A$and $B$are in a mutually complementary relationship.

Various types of extensions based on λ- Fuzzy measures have been applied to the problem of analyzing the correlation relationship between indicators in multi-attribute decision making[28], let $\mu(x_i)$ denote the fuzzy measure, then the fuzzy measure formula of A is:

$$\mu(A) = \begin{cases} \frac{1}{\lambda}(\prod\limits_{x_j \in A} [1 + \lambda\mu(x_j) - 1]), \lambda \neq 0 \\ \sum\limits_{x_j \in A} \mu(x_j), \qquad \lambda = 0 \end{cases} \tag{18}$$

Let $A = X$, then $\mu(A) = \mu(X) = 1$. can be obtained:

$$\lambda + 1 = \prod_{j=1}^{m} [1 + \lambda\mu(x_j)], \lambda > -1 \text{and} \lambda \neq 0 \tag{19}$$

Definition 16[20] Let the function f is non-negative on the set X, μ is a fuzzy measure, then the Choquet integration formula based on the λ- fuzzy measure f is:

$$\int f d\mu = \sum_{i=1}^{n} f(x_{(i)})[\mu(A_{(i)}) - \mu(A_{(i+1)})] \tag{20}$$

The formula for the Shapley function based on the λ- fuzzy measure is:

$$g_s(g, X) = \sum_{T \subseteq X \backslash S} \frac{(n - s - t)!\, t!}{(n - s + 1)\,!} [\mu(S \cup T) - \mu(T)] \tag{21}$$

where X denotes the full set of indicators, S denotes a subset in X, $X \backslash S$denotes the difference set between the set X and the set S, T denotes a subset in$X \backslash S$, and n, t, and s denote the cardinality of X, T, and S, respectively.

A comparison of the formulas for the Choquet integral and the Shapley function shows that Choquet can only analyze the correlation between neighboring indicators, but not the correlation between any set of indicators, while the Shapley function can analyze the correlation between any set of indicators.

3 Evaluation model construction

Let the object to be evaluated as $A_i(i = 1, 2, \cdots, m)$ and the evaluation index as $C_j(j = 1, 2, \cdots, n)$ All the indexes are categorized, and the expert $E_k(k = 1, 2, \cdots, t)$ evaluates the assessment indexes of each object according to the indexes' own attributes by using the exact number, the interval number, the triangular fuzzy number, the hesitant fuzzy number, and the probabilistic linguistic term set, respectively. Where, x_{ij} is the evaluation information of object A_i on indicator C_j; m modules M_j, $M_j = (x_{1j}, x_{2j}, \cdots, x_{mj})^T$;$M^N$is the exact number type information; $M^I$is the interval type information; $M^T$is the triangular fuzzy number type information; $M^F$is the hesitation fuzzy number type information; $M^P$is the probabilistic linguistic term set type information. The matrix X obtained by normalizing the above information:

$$X = (x_{ij})_{n\times m} = (M_1, M_2, \cdots, M_j) = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{pmatrix} \tag{22}$$

Where, when the evaluation information is of the exact numerical type, $x_{ij} = y_{ij}$; When the evaluation information is an interval number, $x_{ij} = \tilde{r}_{ij}$; When the evaluation information is a triangular fuzzy number, $x_{ij} = \tilde{a}_{ij}$; When the evaluation information is a hesitant fuzzy number, $x_{ij} = h_{ij}$; When the evaluation information is a set of probabilistic language terms, $x_{ij} = L(P)_{ij}$. Considering the correlation between the indicators and combining the VIKOR method, the evaluation method is shown below:

Step 1: Based on the decision matrix provided by the evaluation expert, identify the positive ideal solution $P^* = \max\limits_{1\leq i\leq n}(x_{ij})$and negative ideal solution $P^- = \min\limits_{1\leq i\leq n}(x_{ij})$ for each requirement indicator.

Step 2: Determine the group benefit S_i and maximum individual regret R_i for each evaluation object.

$$S_i = \sum_{j=1}^{m} w_i \frac{P^* - x_{ij}}{P^* - P^-} \tag{23}$$

$$R_i = \max_{1\leq j\leq m} w_i \frac{P^* - x_{ij}}{P^* - P^-} \tag{24}$$

where w_i is the weight of each indicator, and the generalized Shapley function is used to analyze the mutual influence relationship between indicators to obtain the weight $w_i = \{w_1, w_2, \cdots, w_n\} = \{g_1(g, X), g_2(g, X), \cdots, g_n(g, X)\}$of each indicator.

Step 3: Calculate the comprehensive indicator $Q_i$for each evaluation object.

$$Q_i = v\frac{S_i - S^-}{S^* - S^-} + (1 - v)\frac{R_i - R^-}{R^* - R^-} \tag{25}$$

Where, $S^* = \max\limits_{1\leq i\leq m}\{S_i\}$,$S^- = \min\limits_{1\leq i\leq m}\{S_i\}$;$R^* = \max\limits_{1\leq i\leq m}\{R_i\}$,$R^- = \min\limits_{1\leq i\leq m}\{R_i\}$; v is the decision mechanism coefficient. When $v > 0.5$, it indicates that the decision maker pays more attention to the whole for decision making; when $v = 0.5$, it indicates that the decision maker is decision neutral; when $v < 0.5$, it indicates that the decision maker pays more attention to the individual regrets and thus makes decisions.

Step 4: Sort the results according to the ascending order of the composite indicator Q_i.

Step 5: Test the compromise solution, $A^{(1)}$ is the compromise solution, which needs to satisfy both condition I and condition II. $A^{(1)}$is the object that is sorted in the first place according to the composite indicatorQ_1.

Condition I: $Q(A^{(2)} - A^{(1)}) \geq DQ, DQ = \frac{1}{n-1}$.

Condition II: Solution $A^{(1)}$remains in the first place when it is sorted according to group benefit S_i and maximum individual regret R_i.

If the conditions I and II cannot be satisfied simultaneously, a compromise solution is obtained:

(1) If condition II is not satisfied, both $A^{(1)}$and $A^{(2)}$ are compromise solutions;

(2) If condition I is not satisfied, $A^{(1)}$, $A^{(2)}$, ..., $A^{(x)}$ are all optimal compromise solutions.x is obtained by the inequality$Q(A^{(x)} - A^{(1)}) < \frac{1}{n-1}$.

Table 1: Evaluation information

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	15	[3,4]	{7,9,10}	H{0.3,0.4,0.5}	$\{(s_4,0.3),(s_5,0.7)\}$	$\{(s_3,0.7)\}$
A_2	17.5	[3,5]	{4,7,8}	H{0.4,0.5,0.6}	$\{(s_4,0.3),(s_5,0.2)\}$	$\{(s_2,0.4),(s_4,0.5)\}$
A_3	20	[4,5]	{4,5,6}	H{0.4,0.5,0.8}	$\{(s_3,0.6),(s_4,0.4)\}$	$\{(s_3,0.2),(s_4,0.6)\}$
A_4	22	[4,5]	{5,6,7}	H{0.6,0.7}	$\{(s_3,0.5),(s_4,0.4)\}$	$\{(s_3,0.4),(s_4,0.6)\}$
A_5	26	[4,5]	{5,7,8}	H{0.7,0.8}	$\{(s_2,0.7),(s_3,0.3)\}$	$\{(s_4,0.4),(s_5,0.6)\}$

Table 2: Evaluation information after standardization

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0.568	[3,4]	{5,6,7}	H{0.3,0.4,0.5}	$\{(s_4,0.3),(s_5,0.7)\}$	$\{(s_3,0)\ ,\ (s_3,1.0)\}$
A_2	0.487	[3,5]	{4,5,6}	H{0.4,0.5,0.6}	$\{(s_4,0.6),(s_5,0.4)\}$	$\{(s_2,0.4),(s_4,0.6)\}$
A_3	0.426	[4,5]	{4,7,8}	H{0.4,0.5,0.8}	$\{(s_3,0.6),(s_4,0.4)\}$	$\{(s_3,0.25),(s_4,0.8)\}$
A_4	0.388	[2,3]	{6,7,8}	H{0.6,0.7,0.7}	$\{(s_3,0.6),(s_4,0.4)\}$	$\{(s_3,0.4),(s_4,0.6)\}$
A_5	0.328	[4,5]	{7,9,10}	H{0.7,0.8,0.8}	$\{(s_2,0.7),(s_3,0.3)\}$	$\{(s_4,0.4),(s_5,0.6)\}$

4 Case studies

4.1 Case

Considering the data literacy evaluation of college teachers, the background of the cases in this section is taken from reference [21-23]. In order to improve the level and competence of data literacy of our teachers at a university in a province in western China, the university intends to assess teachers' data literacy competence in the following six areas: data awareness, data collection and organisation, data knowledge, data analysis, data application, and data ethics and morals, denoted by C_1,C_2,C_3,C_4,C_5,C_6, respectively. According to the attribute characteristics of each evaluation index, the exact number evaluation C_1, the interval number evaluation C_2, the triangular fuzzy number evaluation C_3, the hesitant fuzzy number evaluation C_4, and the probabilistic linguistic term set evaluation C_5 and C_6, respectively, and the evaluation information obtained is shown in Table 1.

Based on equations (12)-(17), combined with the attribute characteristics of the evaluation indicators, the data of each indicator in Table 1 are normalized, and the results of indicator normalization are shown in Table 2.

According to the method for determining the importance of customer needs in reference [3], the importance of each indicator is calculated as follows: 0.72, 0.14, 0.13, 0.42, 0.31, 0.28, namely: $\mu(C_1) = 0.72$,$\mu(C_2) = 0.14$,$\mu(C_3) = 0.13$,$\mu(C_4) = 0.42$,$\mu(C_5) = 0.31$,$\mu(C_6) = 0.28$.According to equation (15), we can get $(1 + 0.72\lambda)(1 + 0.14\lambda)(1 + 0.13\lambda)(1 + 0.42\lambda)(1 + 0.31\lambda)(1 + 0.28\lambda) = \lambda + 1$,Solving the equation gives $\lambda = -0.914$. The calculated fuzzy measures are shown in Table 3:

According to equation (18), we can get that: $g_1(g, X) = 0.405$, $g_2(g, X) = 0.061$, $g_3(g, X) = 0.056$, $g_4(g, X) = 0.204$,$g_5(g, X) = 0.145$,$g_6(g, X) = 0.129$.After analysis, the weights of the indicators are: $w_1 = g_1(g, X) = 0.405$,$w_2 = g_2(g, X) = 0.061$,$w_3 = g_3(g, X) = 0.056$,$w_4 = g_4(g, X) = 0.204$,$w_5 = g_5(g, X) = 0.145$,$w_6 = g_6(g, X) = 0.129$.

Table 3: Fuzzy measures of demand indicator sets

fuzzy measure	**value**	**fuzzy measure**	**value**	**fuzzy measure**	**value**	**fuzzy measure**	**value**
$\mu(C_1)$	0.72	$\mu(C_3,C_5)$	0.40	$\mu(C_2,C_3,C_5)$	0.49	$\mu(C_1,C_2,C_4,C_5)$	0.95
$\mu(C_2)$	0.14	$\mu(C_3,C_6)$	0.38	$\mu(C_2,C_3,C_6)$	0.47	$\mu(C_1,C_2,C_4,C_6)$	0.95
$\mu(C_3)$	0.13	$\mu(C_4,C_5)$	0.61	$\mu(C_2,C_4,C_5)$	0.67	$\mu(C_1,C_2,C_5,C_6)$	0.92
$\mu(C_4)$	0.42	$\mu(C_4,C_6)$	0.59	$\mu(C_2,C_4,C_6)$	0.66	$\mu(C_2,C_3,C_4,C_5)$	0.72
$\mu(C_5)$	0.31	$\mu(C_5,C_6)$	0.51	$\mu(C_2,C_5,C_6)$	0.59	$\mu(C_2,C_3,C_4,C_6)$	0.71
$\mu(C_6)$	0.28	$\mu(C_1,C_2,C_3)$	0.81	$\mu(C_3,C_4,C_5)$	0.67	$\mu(C_2,C_3,C_5,C_6)$	0.65
$\mu(C_1,C_2)$	0.77	$\mu(C_1,C_2,C_4)$	0.89	$\mu(C_3,C_4,C_6)$	0.65	$\mu(C_2,C_4,C_5,C_6)$	0.78
$\mu(C_1,C_3)$	0.76	$\mu(C_1,C_2,C_5)$	0.86	$\mu(C_3,C_5,C_6)$	0.58	$\mu(C_3,C_4,C_5,C_6)$	0.78
$\mu(C_1,C_4)$	0.86	$\mu(C_1,C_2,C_6)$	0.85	$\mu(C_4,C_5,C_6)$	0.74	$\mu(C_1,C_2,C_3,C_4,C_5)$	0.97
$\mu(C_1,C_5)$	0.83	$\mu(C_1,C_3,C_4)$	0.89	$\mu(C_1,C_2,C_3,C_4)$	0.92	$\mu(C_1,C_2,C_3,C_4,C_6)$	0.96
$\mu(C_1,C_6)$	0.82	$\mu(C_1,C_3,C_5)$	0.86	$\mu(C_1,C_2,C_3,C_5)$	0.89	$\mu(C_1,C_3,C_4,C_5,C_6)$	0.99
$\mu(C_2,C_3)$	0.25	$\mu(C_1,C_3,C_6)$	0.85	$\mu(C_1,C_2,C_3,C_6)$	0.88	$\mu(C_2,C_3,C_4,C_5,C_6)$	0.82
$\mu(C_2,C_4)$	0.51	$\mu(C_1,C_4,C_5)$	0.93	$\mu(C_1,C_3,C_4,C_5)$	0.95	$\mu(C_1,C_2,C_4,C_5,C_6)$	0.99
$\mu(C_2,C_5)$	0.41	$\mu(C_1,C_4,C_6)$	0.92	$\mu(C_1,C_3,C_4,C_6)$	0.94	$\mu(C_1,C_2,C_3,C_5,C_6)$	0.94
$\mu(C_2,C_6)$	0.38	$\mu(C_1,C_5,C_6)$	0.90	$\mu(C_1,C_3,C_5,C_6)$	0.92	$\mu(C_1,C_2,C_3,C_4,C_5,C_6)$	1.00
$\mu(C_3,C_4)$	0.50	$\mu(C_2,C_3,C_4)$	0.58	$\mu(C_1,C_4,C_5,C_6)$	0.97		

Table 4: Risk Mode Assessment Table

	S_i	rank	R_i	rank	Q_i	rank
A_1	0.363	1	0.146	2	0.017	1
A_2	0.469	2	0.137	1	0.272	2
A_3	0.593	4	0.239	3	0.686	3
A_4	0.595	5	0.305	4	0.813	4
A_5	0.572	3	0.405	5	0.950	5

Table 5: ranking table without considering the mutual influence relationship between demand indicators

	S_i	rank	R_i	rank	Q_i	rank
A_1	0.391	1	0.139	2	0.092	1
A_2	0.485	2	0.122	1	0.310	2
A_3	0.603	5	0.213	3	0.836	3
A_4	0.595	4	0.271	4	0.894	4
A_5	0.551	3	0.322	5	0.827	5

Combining the weights of the indicators calculated earlier, substituting them into equations (20)-(21) to calculate the group benefit value S_i and the maximum individual regret value R_i of each evaluated teacher, the specific results are shown in Table 4, on the basis of the group benefit value $S_i$and the maximum individual regret value R_i, taking $v = 0.5$, and substituting them into equation (22) to get the comprehensive evaluation index Q_i of each evaluated teacher.

Test the compromise solution, both condition one and condition two are met. Therefore, the optimal design solution isA_1.

4.2 Comparative analysis

(1) When not considering the mutual influence relationship between indicators, i.e. not using a method based on λ The ranking results obtained from the analysis of the mutual influence relationship between indicators using the generalized Shapley function of fuzzy measures are shown in Table 5.

The result of the S_i ordering is$A_1 \succ A_2 \succ A_5 \succ A_3 \succ A_4$,The ranking result of the method proposed in this paper is$A_1 \succ A_2 \succ A_3 \succ A_4 \succ A_5$. Through comparison, it can be found that after analyzing the mutual influence relationship between indicators through the generalized Shapley function, the weight of the C_1 data awareness indicator has increased compared to the weight before the analysis. This is because data awareness is usually the first element that university teachers prioritize in data literacy, which is subconscious and spontaneous. Teachers with higher data awareness will also have corresponding improvements in other indicators. However, when the awareness of data is relatively low and the effectiveness of other indicators is not significantly reduced, the data literacy ability of teachers will also decrease. The data awareness indicator will have an impact on other indicators, so increasing the weight of data awareness is more in line with the actual situation. When the weight of data awareness indicators increases, the teacher A_5 has the strongest data literacy ability, which can improve their data analysis and application abilities. Therefore, after analyzing the mutual influence relationship between indicators through the generalized Shapley function, the evaluation results can be more accurate and more in line with reality.

(2) When the method proposed in this article is not used to evaluate the design scheme, it is necessary to transform the evaluation information into the same type for comparison. The standardized evaluation information table obtained is shown in Table 6.

In existing literature models, the consideration of the correlation and indicator correlation in group decision-making is not sufficient. For example, the model in reference [24] establishes a trust function

Table 6: Evaluation information converted to exact numbers

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0.568	0.400	0.717	0.321	0.678	0.394
A_2	0.487	0.457	0.533	0.401	0.635	0.409
A_3	0.426	0.514	0.410	0.454	0.490	0.493
A_4	0.388	0.514	0.492	0.521	0.497	0.473
A_5	0.328	0.514	0.553	0.601	0.332	0.605

Table 7: Ranking results of different models

Evaluate model	Ranking of teacher data literacy level and ability
Model in this paper	$A_1 \succ A_2 \succ A_3 \succ A_4 \succ A_5$
Reference [24] model	$A_1 \succ A_2 \succ A_5 \succ A_3 \succ A_4$
Reference [25] model	$A_1 \succ A_2 \succ A_3 \succ A_4 \succ A_5$

based on the principle of information entropy to determine decision weights and gather group decision-making information. The objective weight of indicators is determined through the entropy method to avoid attribute switching between indicators. Applying this method to the case study in this article, the results are shown in Table 7.

From the final ranking results, the literature [24] and this paper have a large deviation in the evaluation of A_1. On the one hand, when assembling group decision-making information, it does not take into account the preference association between experts, which makes the weight of individual experts large, resulting in a certain deviation in the assembly of subjective information. On the other hand, when determining the weights of evaluation indexes, it is mainly based on the entropy value method to calculate the objective weights of different evaluation indexes, and does not take into account the correlation between different indexes, which is also the reason for the discrepancy in the final evaluation results. In this paper, λ-Shapley fuzzy measure is used to measure the fuzzy relationship between experts, and DEMATEL is introduced into the decision-making model to evaluate the correlation between indicators and determine the weights, so that the multi-attribute group decision-making model is more in line with the decision-makers' evaluation and perception of the complexity of the actual problem.

When using the generalized Shapley function to analyze the mutual influence relationship between indicators, the ranking result of the data literacy ability and level of teachers in a certain university in a western province obtained is$A_1 \succ A_2 \succ A_4 \succ A_3 \succ A_5$.Through comparative analysis, it can be found that the positions of teachers A_3 and A_4 have swapped with the positions of the methods proposed in this article. This is because the mixed information is directly transformed into the same type of information, and all evaluation information of indicators is converted into accurate numerical values, the conversion of different semantic information in the process of information aggregation and transformation will inevitably cause information loss, thereby affecting the accuracy of the final sorting results. The modular random multi criteria compromise ranking method proposed in this article divides evaluation information into independent modules, avoiding information loss during the aggregation process, and obtaining more accurate ranking results that reflect the data literacy ability and level of teachers.

5 Conclusion

As an important role in talent cultivation, the ability of data literacy is particularly important for university teachers. This paper proposes a mixed information university teacher data literacy evaluation method that considers the mutual influence between indicators, with the following characteristics:

(1) Expand the types of indicators into five types of mixed evaluation information: precise numbers, interval numbers, triangular fuzzy numbers, hesitant fuzzy numbers, and probabilistic language terminology sets. Different types of evaluation information are used for different properties and types of indicators.

(2) Considering that the indicators are not independent of each other and the evaluation information is mixed, analyzing the correlation between indicators is also more complex. Unlike ANP and DEMATEL, which can only analyze the mutual influence relationship between adjacent indicators, this paper analyzes the mutual influence relationship between indicators through a generalized Shapley function based on fuzzy measures. Using a generalized Shapley function based on fuzzy measures can analyze the mutual influence relationship between a single indicator and other remaining arbitrary indicator sets.

(3) In the past, when hybrid evaluation information was aggregated and transformed into the same type of information, it often resulted in missing information, affecting the accuracy of evaluation

results. This article adopts a modular approach, categorizes indicators, and aggregates information using different information processing methods. Then, combined with the VIKOR method, the data literacy ability and level of teachers in a certain university in the western province were evaluated and ranked to avoid information loss during the aggregation process.

Finally, taking the evaluation of data literacy ability and level of teachers in a certain university in a western province as an example, the effectiveness and feasibility of the method proposed in this article were verified through comparative analysis.

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