A New Product Development Concept Selection Approach Based on Cumulative Prospect Theory and Hybrid-Information MADM

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Abstract. A risk HI-MADM method based on cumulative prospect theory (CPT) is proposed to select the NPD alternative concepts. Initially, decision information in various formats is normalized and the expectations of the NPDT are set as the corresponding reference points with considering the psychology of the NPDT. Subsequently, the gains and losses matrix relative to the reference points is constructed. Furthermore, the prospect values of concept attributes are calculated based on the value function of CPT. Then, by aggregating prospect values and attribute weights by a simple additive weighting (SAW) method, the comprehensive prospect values of alternative concepts are obtained, and then the ranking order of all concepts can be determined. Finally, a NPD case study of a new automatic dishwasher is used to illustrate the feasibility and validity of the proposed approach.

1. Introduction

New product development (NPD) is widely recognized as a core product strategy with high risk and one of the most challenging components of enterprise competitiveness [1]. A general NPD process usually start from the formation of a NPD team (NPDT) comprised of product R&D manager, engineers, and persons from various business sectors and then goes through several sequential stages, e.g., the CRs identification, product conceptual design, industrial design and planning, prototyping, manufacturing design, and successive launch [2].

In the real world, the selection of NPD concepts contains significant amounts of uncertainty causing factors, which confuse the NPDT to reach the optimum choice of the alternative concepts. Basically, there are two aspects of uncertainty and ambiguity confronted. On the one hand, uncertain preference during attributes evaluation exist because of individual heterogeneity. On the other hand, human judgments on attributes are subjective and imprecise [3]. In particular, the decision information of some concept attributes are difficult or impossible to be deterministic in concept selection considering the complexity and ambiguity of available information, such as performance, quality, and stability. The decision data of these attribute are often represented in a form of interval numbers or fuzzy numbers rather than crisp numbers based on the nature of diverse attributes. For example, lead time and return on investment can be expressed with an interval number, while a fuzzy number or a linguistic term can be used to characterize some qualitative information, such as quality, stability, and reliability. Thereby, the decision data are generally represented in diversiform attribute values for sake of reservation of the original decision information, thus guaranteeing the authenticity and reliability of the final decision solutions [4]. Therefore, the concept selection problem is typical MADM problem with decision data represented in hybrid information forms, i.e., hybrid-information MADM (HI-MADM) problem. Basically, this paper focuses on the concept selection problem with attribute values in formats of crisp numbers, interval numbers, and linguistic terms.

Besides, a few psychological studies have confirmed the existence of some behavioral characteristics of DM under a condition of uncertainty, e.g., loss aversion, judgmental distortion, and reference dependence, which have a non-negligible influences on the accuracy of final solution. However, most existing concept selection methods are derived from the expected utility theory (EUT) without consideration of DM's psychological behaviors, resulting in the choice of suboptimal concepts. Since concept selection is often conducted along with fuzziness and information incompleteness, there is an indispensable implication to consider human behaviors in the NPD concept selection for sake of effective decision support to the NPDT.

In a word, the NPD alternative concept selection is a HI-MADM problem where DM's psychological behaviors and high risks exist. Traditional decision-making methods cannot directly be applied to such a problem due to the multi-form attributes and the difference of the hypothesis of psychological behavior. Therefore, there is practical significance to develop an effective NPD concept selection method to address hybrid formats of decision information as well as to reflect psychological preferences of the NPDT into a final decision solution.

2. Formulation and solution procedure of concept selection problem in NPD

In view of the functional nature of the concept attributes, the attributes considered in the HI-MADM of concept selection can be grouped into two categories, i.e., cost and profit type, both of which can be described as crisp numbers, intervals, and linguistic terms. In detail, a profit attribute is the attribute for maximization whose value is always the larger the better. Oppositely, a cost attribute is the attribute for minimization whose value is the smaller the better.

Supposing that there are *m* alternative product concepts to be evaluated against *n* attributes based on the identification of competing CRs in the concept selection stage of NPD. Let $M=\{1,2,...,m\}$ and $N=\{1,2,...,n\}$. Let $S=\{s_1,s_2,...,s_m\}$ be a finite concept set, where s_i denotes the i th alternative product concept; and let $A=\{a_1,a_2,...,a_n\}$ be a finite attribute set, where a_j denotes the j th attribute. Let the subscript sets of the profit and cost attributes be denoted by N_p and N_c, respectively, which must satisfy $N_p \cup N_c = N$ as well as $N_p \cap N_c = \varnothing$. Let $\boldsymbol{w}=(w_1,w_2,...w_n)^{\mathrm{T}}$ be the vector of attribute weights, where w_j denotes the importance degree of the attribute a_j, which satisfies $1 \ge w_j \ge 0 (j \in N)$ and $\sum_{j=1}^{n} w_j = 1$. Generally, w_j can be given by the NPDT directly. Let $\boldsymbol{Q}=(q_1,q_2,...q_n)^T$ be the expectation vector of attributes, where q_j is the expectation or goal of the NPDT concerning the *j*th attribute, which can be selected as the corresponding reference point concerning a_j. Let d_{ij} denote the evaluation value of the NPDT for product concept s_i with regard to the attribute a_j, $i \in M$, $j \in N$. Then the decision matrix for the HI-MADM of alternative product concepts can be defined as

$$\boldsymbol{D}=\left[d_{ij}\right]_{m\times n}=\begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{bmatrix}.$$

In this paper, the decision data involved in the concept selection are represented in three various formats, i.e., crisp numbers, interval numbers, and linguistic terms for reflecting the nature of the attributes. Notably, the attribute value d_{ij} and expectation q_j with respect to the same attribute $a_j, j \in N$ should be described in the unified mathematical form for sake of information consistency and comparability between them. Therefore, the attributes set A can be further divided into three subsets as $A^{\mathrm{cn}} = \left\{A_1, A_2, ..., A_{k_1}\right\}$, $A^{\mathrm{in}} = \left\{A_{k_1+1}, A_{k_1+2}, ..., A_{k_2}\right\}$, and $A^{\mathrm{lt}} = \left\{A_{k_2+1}, A_{k_2+2}, ..., A_n\right\}$, where $1 \le k_1 \le k_2 \le n$, such that $A^{\mathrm{cn}} \bigcup A^{\mathrm{in}} \bigcup A^{\mathrm{lt}} = A$. The attributes in A^{cn}, A^{in}, and A^{lt} are described as crisp numbers, numerical intervals, and linguistic terms, respectively. Correspondingly, let $N_{\mathrm{cn}} = \left\{1, 2, ..., k_1\right\}$, $N_{\mathrm{in}} = \left\{k_1+1, k_1+2, ..., k_2\right\}$, and $N_{\mathrm{lt}} = \left\{k_2+1, k_2+2, ..., n\right\}$ denote the subscript set of A^{cn} , A^{in} and A^{lt} respectively, such that $N_{\mathrm{cn}} \bigcup N_{\mathrm{in}} \bigcup N_{\mathrm{lt}} = N$ obviously. Moreover, the descriptions of different formats of attribute values are further detailed as follows:

(1) **Crisp number.** If d_{ij} and q_j are crisp numbers, indicating that precise prospective expectation and evaluation with regard to attribute a_j are provided based on sufficient production information, then $q_j = q'_j$, $d_{ij} = d'_{ij}$, $j \in N_{\mathrm{cn}}$, $i \in M$. Without loss of generality, we assume $q'_j \ge 0$, $d'_{ij} \ge 0$.

(2) Interval **number.** If d_{ij} and q_j are interval numbers, which means the expectation and evaluation of the NPDT concerning the attribute a_j are difficult to address exactly but probably fall in a certain numerical interval, then $q_j = \overline{q}_j$ and $d_{ij} = \overline{d}_{ij}$, where $\overline{q}_j = \left[q_j^{low}, q_j^{up}\right]$, $\overline{d}_{ij} = \left[d_{ij}^{low}, d_{ij}^{up}\right]$, $j \in N_{\mathrm{in}}$, $i \in M$. In general, we suppose that $0 \le q_j^{low} \le q_j^{up}$ and $0 \le d_{ij}^{low} \le d_{ij}^{up}$. Besides, a crisp number can appear as a special case of an interval number, e.g., $q'_j = \overline{q}_j = \left[q'_j, q'_j\right]$.

(3) **Linguistic term.** If d_{ij} and q_j are represented by linguistic terms, suggesting that the attribute value and expectation with regard to the attribute a_j are given qualitatively rather than quantitatively. Then, $q_j = \widehat{q}_j$, $d_{ij} = \widehat{d}_{ij}$, $j \in N_{\mathrm{lt}}$, $i \in M$, where $\widehat{q}_j$ and $\widehat{d}_{ij}$ are linguistic terms which must satisfy $\widehat{q}_j, \widehat{d}_{ij} \in L$. Here, $L = \left\{l_p \mid p = 0, 1, ..., E\right\}$ is a pre-defined ordered linguistic term set consisting of an odd number of linguistic terms, where E denotes the number of set elements which is usually an even number and l_p denotes the p+1th linguistic term in set L. For example, when E = 6, the set can be defined as L= {*extremely poor, very poor, poor, moderate, good, very good, extremely good*}. Besides, some operational laws for any two linguistic terms $l_a, l_b \in L$ can be expressed as follows:

(a) If $a > b$, then the set is ordered: $l_a \succ l_b$ (i.e., l_a is not inferior to l_b). Thus, a larger subscript p indicates a better attribute performance of the linguistic terms.

(b) If $a = E - b$, then a negation operator is observed: $neg\left(l_a\right) = l_b$.

(c) If $l_a \succ l_b$, then there are $\max\left(l_a, l_b\right) = l_a$ and $\min\left(l_a, l_b\right) = l_b$.

The problem considered in this paper is, in consideration of the psychological behaviors of the NPDT, how to figure out the best concept from the available alternative concepts based on the given decision information, e.g., the finite concept set $\boldsymbol{S}$, the decision matrix $\boldsymbol{D}$, the expectation vector $\boldsymbol{Q}$, and the attribute weight vector $\boldsymbol{w}$.

3. The proposed NPD concept selection approach based on CPT and HI-MADM

In this section, a detailed description of the proposed CPT-based HI-MADM approach is provided for the concept selection problem in consideration of the decision making behaviors. The proposed method can be divided into three stages, namely, transformation of three formats of decision-making information, construction of gain and loss matrix, and ranking of concept alternatives.

3.1 Transformation of Three Formats of Decision-Making Information

In the practical concept selection, heterogeneous formats of expectation and attribute values should be normalized to eliminate the influence of different physical dimensions on the accuracy of decision solutions. Let $\boldsymbol{B}=(b_1,b_2,...,b_n)^{\mathrm{T}}$ denote the normalized vector of the expectations of the NPDT, where b_j denotes the normalized value of expectation concerning *j*th attribute. Correspondingly, let $\boldsymbol{F}=\left[f_{ij}\right]_{m\times n}$ denote the normalized decision matrix, where f_{ij} denotes the normalized attribute value of the attribute a_j. Notably, diversiform values of expectation and attribute are considered to be transformed into normalized profit type data within the closed interval [0, 1]. The corresponding normalization formulas for each format of attribute are given respectively as follows:

3.1.1. Crisp number. For the $A_j\in A^{\mathrm{cn}}$, $j\in N_{cn}$, the q'_j and d'_{ij} are described as crisp numbers, then the b_j and f_{ij} are respectively defined by

$$b'_j=\begin{cases}\left(q'_j-o_j^-\right)/\left(o_j^+-o_j^-\right), j\in N_p\\ \left(o_j^+-q'_j\right)/\left(o_j^+-o_j^-\right), j\in N_c\end{cases} \tag{1}$$

$$f'_{ij}=\begin{cases}\left(f'_{ij}-o_j^-\right)/\left(o_j^+-o_j^-\right), j\in N_p, i\in M\\ \left(o_j^+-f'_{ij}\right)/\left(o_j^+-o_j^-\right), j\in N_c, i\in M\end{cases} \tag{2}$$

Where

$$\begin{cases}o_j^+=\max\left\{\max\limits_{i\in M}\left(d'_{ij}\right),q'_j\right\}, j\in N_{\mathrm{cn}}\\ o_j^-=\min\left\{\min\limits_{i\in M}\left(d'_{ij}\right),q'_j\right\}, j\in N_{\mathrm{cn}}\end{cases} \tag{3}$$

3.1.2. Interval Number. If the $\overline{d}_{ij}$ and $\overline{q}_j$ are described as interval numbers for $A_j\in A^{\mathrm{in}}$, $i\in M$, $j\in N_{in}$, then the b_j and f_{ij} are respectively given by

$$\overline{b}_{ij}=\left[b_j^{\mathrm{low}},b_j^{\mathrm{up}}\right]=\begin{cases}\left[\left(q_j^{\mathrm{low}}-o_j^{\mathrm{low}}\right)/\left(o_j^{\mathrm{up}}-o_j^{\mathrm{low}}\right),\left(q_j^{\mathrm{up}}-o_j^{\mathrm{low}}\right)/\left(o_j^{\mathrm{up}}-o_j^{\mathrm{low}}\right)\right], j\in N_p\\ \left[\left(o_j^{\mathrm{up}}-q_j^{\mathrm{up}}\right)/\left(o_j^{\mathrm{up}}-o_j^{\mathrm{low}}\right),\left(o_j^{\mathrm{up}}-q_j^{\mathrm{low}}\right)/\left(o_j^{\mathrm{up}}-o_j^{\mathrm{low}}\right)\right], j\in N_c\end{cases} \tag{4}$$

$$\overline{f}_{ij}=\left[f_{ij}^{\mathrm{low}},f_{ij}^{\mathrm{up}}\right]=\begin{cases}\left[\left(d_{ij}^{\mathrm{low}}-o_j^{\mathrm{low}}\right)/\left(o_j^{\mathrm{up}}-o_j^{\mathrm{low}}\right),\left(d_{ij}^{\mathrm{up}}-o_j^{\mathrm{low}}\right)/\left(o_j^{\mathrm{up}}-o_j^{\mathrm{low}}\right)\right], i\in M, j\in N_p\\ \left[\left(o_j^{\mathrm{up}}-d_{ij}^{\mathrm{up}}\right)/\left(o_j^{\mathrm{up}}-o_j^{\mathrm{low}}\right),\left(o_j^{\mathrm{up}}-d_{ij}^{\mathrm{low}}\right)/\left(o_j^{\mathrm{up}}-o_j^{\mathrm{low}}\right)\right], i\in M, j\in N_c\end{cases} \tag{5}$$

Where

$$\begin{cases}o_j^{\mathrm{up}}=\max\left\{\max\limits_{i\in M}\left(d_{ij}^{\mathrm{up}}\right),q_j^{\mathrm{up}}\right\}, j\in N_{\mathrm{in}}\\ o_j^{\mathrm{low}}=\min\left\{\min\limits_{i\in M}\left(d_{ij}^{\mathrm{low}}\right),q_j^{\mathrm{low}}\right\}, j\in N_{\mathrm{in}}\end{cases} \tag{6}$$

3.1.3. Linguistic term. The $\widehat{d}_{ij}$ and $\widehat{q}_j$ are described qualitatively as linguistic assessment terms for the $A_j\in A^{\mathrm{lt}}$, $i\in M$, $j\in N_{lt}$. Then the b_j and f_{ij} are respectively given by

$$\widehat{b}_j=\begin{cases}\widehat{q}_j, \quad j\in N_p\\ neg\left(\widehat{q}_j\right), j\in N_c\end{cases} \tag{7}$$

$$\hat{f}_{ij} = \begin{cases} \hat{d}_{ij}, & i \in M, j \in N_p \\ neg\left(\hat{d}_{ij}\right), & i \in M, j \in N_c \end{cases} \tag{8}$$

Specially, the decision information in the form of linguistic terms can be transformed into triangular fuzzy numbers for the convenience of calculations. Let $\tilde{b}_j = \left(b_j^1, b_j^2, b_j^3\right)$ and $\tilde{f}_{ij} = \left(f_{ij}^1, f_{ij}^2, f_{ij}^3\right)$, $i \in M$, $j \in N_{lt}$ denote the transformed expectation and decision matrix in the form of triangular fuzzy numbers, respectively. Further, according to the fuzzy set theory, the corresponding transformation formula is given as

$$\tilde{l} = \left(\max\left\{\left(p-1\right)/E, 0\right\}, p/E, \min\left\{\left(p+1\right)/E, 1\right\}\right) \tag{9}$$

Consequently, the normalized expectation vector $\boldsymbol{B} = (b_1, b_2, ..., b_n)^{\mathrm{T}}$ and decision matrix $\boldsymbol{F} = \left[f_{ij}\right]_{m\times n}$ are obtained by the aforementioned normalization methods by using Eqs. (1) − (9).

3.2 Gain and loss matrix construction

The type of gain or loss of a concept attribute can be determined by the order relation comparison between the attribute value and the value of the relative reference point. In view of the incommensurability of diversiform attributes, the comparison processes for three attribute types are detailed respectively in the next paragraph.

(1) For attribute $A_j \in A^{\mathrm{cn}}$, the order relation between normalized reference point b_j' and normalized attribute value f_{ij}' can be determined by the mathematical comparison within real number field.

(2) For attribute $A_j \in A^{\mathrm{in}}$, let b_i^{c} and f_{ij}^{c} denote the center of the interval number $\bar{b}_j = \left[b_j^{\mathrm{low}}, b_j^{\mathrm{up}}\right]$ and $\bar{f}_{ij} = \left[f_{ij}^{\mathrm{low}}, f_{ij}^{\mathrm{up}}\right]$ respectively. Correspondingly, let b_i^{w} and f_{ij}^{w} denote the width of $\bar{b}_j$ and $\bar{f}_{ij}$ respectively. Supposing that $b_i^{\mathrm{c}} == \frac{1}{2}\left(b_j^{\mathrm{up}} + b_j^{\mathrm{low}}\right)$, $b_i^{\mathrm{w}} = b_j^{\mathrm{up}} - b_j^{\mathrm{low}}$, $f_{ij}^{\mathrm{c}} == \frac{1}{2}\left(f_{ij}^{\mathrm{up}} + f_{ij}^{\mathrm{low}}\right)$ and $f_{ij}^{\mathrm{w}} = f_{ij}^{\mathrm{up}} - f_{ij}^{\mathrm{low}}$, then the order relation between $\bar{b}_j$ and $\bar{f}_{ij}$ is determined by the following criteria (Ishibuchi & Tanaka, 1990):

a. When $b_i^{\mathrm{c}} \neq f_{ij}^{\mathrm{c}}$, if $b_i^{\mathrm{c}} > f_{ij}^{\mathrm{c}}$, then $\bar{b}_j > \bar{f}_{ij}$; if $b_i^{\mathrm{c}} < f_{ij}^{\mathrm{c}}$, then $\bar{b}_j < \bar{f}_{ij}$.

b. When $b_i^{\mathrm{c}} = f_{ij}^{\mathrm{c}}$, if $b_i^{\mathrm{w}} < f_{ij}^{\mathrm{w}}$, then $\bar{b}_j > \bar{f}_{ij}$; if $b_i^{\mathrm{w}} > f_{ij}^{\mathrm{w}}$, then $\bar{b}_j < \bar{f}_{ij}$; if $b_i^{\mathrm{w}} = f_{ij}^{\mathrm{w}}$, then $\bar{b}_j = \bar{f}_{ij}$.

(3) For attribute $A_j \in A^{\mathrm{la}}$, let $l_{ij}^f\left(f = 0,1,2,...,E-1,E\right)$ and $l_j^b\left(b = 0,1,2,...,E-1,E\right)$ denote the linguistic terms concerning the normalized attribute value $\tilde{f}_{ij}$, and those concerning the reference point $\tilde{b}_j$. The method of order relation comparison between $\tilde{f}_{ij}$ and $\tilde{b}_j$ can be described as

$$\begin{cases} \tilde{f}_{ij} > \tilde{b}_j & l_{ij}^f \succ l_j^b \\ \tilde{f}_{ij} = \tilde{b}_j & l_{ij}^f = l_j^b \\ \tilde{f}_{ij} < \tilde{b}_j & l_{ij}^f \prec l_j^b \end{cases}.$$

In addition, the measurement of perceptive benefit or loss of each attribute should be determined for the construction of gain and loss matrix. The amounts of benefit and loss can be regarded as the deviation degree between the attribute values and corresponding reference point, which can be calculated by the Euclidean distance functions for advantages of convenient calculation and accurate expression of the true distance between two points. Let $\boldsymbol{R} = \left[r_{ij}\right]_{m\times n}$ denote the distance matrix, where r_{ij} is the distance measurement between the attribute value f_{ij} and its relative reference point b_j. The calculation formulas are given by:

$$r_{ij}=\begin{cases}\left|f'_{ij}-b'_j\right|, & i\in \boldsymbol{M},\ j\in \boldsymbol{N}_{\mathrm{cn}}\\ \sqrt{\frac{1}{2}\left[\left(f_{ij}^{up}-b_j^{up}\right)^2+\left(f_{ij}^{low}-b_j^{low}\right)^2\right]} & i\in \boldsymbol{M},\ j\in \boldsymbol{N}_{\mathrm{in}}\\ \sqrt{\frac{1}{3}\left[\left(f_{ij}^{1}-b_j^{1}\right)^2+\left(f_{ij}^{2}-b_j^{2}\right)^2+\left(f_{ij}^{3}-b_j^{3}\right)^2\right]} & i\in \boldsymbol{M},\ j\in \boldsymbol{N}_{\mathrm{la}}\end{cases} \tag{10}$$

After that, the prospective gains and losses can be calculated based on the determined type of gain and loss and distance measurement between each attribute and its reference point. Let $C\left(f_{ij}\right)$ denote the gain or loss of f_{ij} relative to reference point b_j, which can be given by

$$C\left(f_{ij}\right)=\begin{cases} r_{ij}, & f_{ij}\geq b_j, i\in M, j\in N\\ -r_{ij}, & f_{ij}< b_j, i\in M, j\in N\end{cases} \tag{11}$$

Here, if $C\left(f_{ij}\right)\geq 0$, it indicates the cognitive gain of the f_{ij} with respect to b_j; if $C\left(f_{ij}\right)<0$, then it means cognitive loss of the f_{ij} with respect to b_j. Then, the gain and loss matrix $\left[C(f_{ij})\right]_{m\times n}$ can be constructed as

$$\boldsymbol{C}=\left[C(f_{ij})\right]_{m\times n}=\begin{bmatrix} C(f_{11}) & C(f_{12}) & \cdots & C(f_{1n})\\ C(f_{21}) & C(f_{22}) & \cdots & C(f_{2n})\\ \vdots & \vdots & \ddots & \vdots\\ C(f_{m1}) & C(f_{m2}) & \cdots & C(f_{mn})\end{bmatrix}$$

3.3. The ranking of the alternatives

According to the CPT theory [5], the prospect value is an effective tool to reflect the intuitively perceived utility of an individual. Based on the gain or loss of the attribute A_j ($C(f_{1j}), C(f_{2j}),\ldots, C(f_{mj})$), the prospective utility, i.e., the prospect value of attribute A_j can be calculated to describe the cognitive utility of concept attributes to the NPDT. Let $V\left(f_{ij}\right)$ denote the prospect value with regard to the attribute $a_j\left(j\in N\right)$ of the concept alternative $s_i\left(i\in M\right)$, and then it is given based on the value function of CPT as

$$V\left(f_{ij}\right)=\begin{cases}\left(C\left(f_{ij}\right)\right)^{\alpha}, & C\left(f_{ij}\right)\geq 0\\ -\lambda\left(-C\left(f_{ij}\right)\right)^{\beta}, & C\left(f_{ij}\right)<0\end{cases} \tag{12}$$

where α and β denote the exponent parameters and λ denotes the loss aversion parameter, satisfying $\alpha,\beta\in[0,1], \lambda>1$. The function for $0<\alpha<1$ indicates risk aversion over gains; the function for $0<\beta<1$ exhibits risk seeking over losses. Therefore, a larger α indicates higher risk aversion in the loss domain, and a larger β indicates higher risk seeking in the gain domain. Notably, β is usually larger than α. Moreover, the loss aversion coefficient λ is widely recognized to be larger than 1 because of the psychological nature of the NPDT, i.e., high level of loss aversion in the decision making. In this paper, the values of α, β, and λ are determined based on previous studies [6-8] as α=0.89, β=0.92, and λ=2.25. Based on the gains and losses of attributes, the prospect decision matrix can be built as $\boldsymbol{V}=\left[V(f_{ij})\right]_{m\times n}$.

Finally, according to the prospect values $V\left(f_{ij}\right)$ and corresponding weight of attributes $\left(w_1, w_2,\ldots w_j\right)$, the comprehensive prospect value of the concept $s_i, i\in M$ can be calculated. To do this, the SAW method is used to aggregate $V\left(f_{ij}\right)$ and $\boldsymbol{w}$ into the overall prospect value of concept s_i. Let the comprehensive prospect value be denoted by $U\left(s_i\right)$, and then it can be calculated by

$$U\left(s_i\right)=\sum_{j=1}^{n}(V\left(f_{ij}\right)*\omega_j),i\in M \tag{13}$$

Obviously, a larger comprehensive prospect value $U\left(s_i\right)$ indicates that the product concept s_i will have a better performance. Therefore, the ranking of the finite alternative NPD concepts can be determined based on the comprehensive prospect values; moreover, the most desirable product concept for the fulfillment of CRs as well as the competitiveness improvement will be selected.

4. Conclusions

In this paper, an effective CPT-based concept selection method is developed for solving HI-MADM problem in the risk decision making environment. The most notable characteristic of the proposed method is that it can sufficiently take into account the NPDT's psychological decision behaviors (e.g., reference point, loss aversion, and diminishing sensitivity) under the context of uncertainty and incomplete information. In this method, crisp numbers, intervals, and linguistic terms are used to describe multiple types of evaluation information and expectations of NPDT for retaining objective and subjective decision information. Firstly, decision information is normalized into profit numbers within the closed interval [0, 1] and the expectation of the NPDT is chosen as the reference point. Then, the gain and loss matrix is constructed on the basis of pairwise order relation comparison and distance measure between attributes and reference points. Furthermore, the value function of CPT is applied to calculate the prospect values which can reflect the perspective utility of each attribute. Consequently, the comprehensive prospect values of all concepts are derived by aggregating prospect values and attributes weights. The ranking order of concepts is generated according to the obtained comprehensive prospect values.

5. References

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