Using a Distance between Fuzzy Number-Valued Fuzzy Measures to Determine Attribute Importance: An Outcome-Oriented Perspective

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Abstract

The purpose of this paper is to introduce a new method for measuring attribute salience in decision analysis. Fuzzy measures have been widely used to determine the degrees of subjective importance of evaluation items. We consider the value of fuzzy measures as a linguistic value and then convert linguistic terms to fuzzy numbers. The grades of attribute importance are correspondingly expressed by fuzzy number-valued fuzzy measures. However, the leniency error may exist when most attributes are assigned unduly high ratings. To reduce positive leniency in fuzzy measure ratings, we develop an importance-assessing method by comparison of fuzzy number-valued fuzzy measures using a fuzzy distance measure. An outcome-oriented approach is adopted to validate the proposed method. Several multiattribute evaluation cases in consumer decision-making reality are addressed to examine the feasibility and applicability of the current method.

Keywords: Fuzzy measure, attribute importance, positive leniency, fuzzy distance measure.

1. Introduction

A fuzzy measure, introduced by Sugeno [1], is a subjective scale for the degrees of fuzziness. Fuzzy measures are suitable in analyzing human subjective evaluation processes. When fuzzy measures are used to real world problems, the candidate sets generally correspond to the evaluation items and the values of fuzzy measures stand for the grades of importance of corresponding evaluation items. Fuzzy measures have been so far used to determine the degrees of subjective importance of evaluation items in numerous studies [2-9]. In this study, we also use fuzzy measures to express and deal with human subjective importance of evaluation items for multiple attribute decision-making analysis.

According to the principle of incompatibility [10], people's ability to make precise and yet significant statements about their behavior diminishes as the complexity of a decision system increases. As a corollary, the data of human subjective judgment are usually fuzzy in nature. Fuzzy data can be expressed in linguistic terms or in fuzzy numbers [11]. Thus, we consider the value of fuzzy measures as a linguistic value and then convert linguistic terms to fuzzy numbers. A fuzzy number-valued fuzzy measure, proposed by Zhang [12], is correspondingly used to identify the grade of importance for evaluation attributes.

Numerous methods can be used to construct membership functions that adequately capture the meanings of linguistic terms. These methods are almost invariably based on people's judgment. However, a critical issue may emerge from the investigation process of respondents' judgment concerning linguistic terms: the error of positive leniency [13, 14]. The leniency bias is an error commonly found in merit ratings [15]. Positive leniency, usually resulting from acquiescence, belongs to one type of response bias. Acquiescence bias results because some respondents tend to give positive connotations to most attribute importance. That is, these "yea-sayers" are very agreeable; they accept that all statements they are asked about. Using Likert-type ratings as an example, some respondents always provide high ratings of attribute importance on a scale such as "important" or "very important." Positive leniency in attribute importance leads to strong subadditivity of fuzzy measures. In addition, the degrees of importance for all attributes have no discrimination power in the decision making process. Researchers should recognize the high likelihood of acquiescence bias when conducting an investigation concerning attribute importance.

To control the spurious influence of positive leniency response bias, we use a fuzzy distance measure [16] to adjust overestimated ratings of attribute importance. The alternative approach is concentration or dilation of fuzzy measure values; nevertheless, the modified version of original fuzzy measure values is difficultly interpreted because of indefinite meanings of the exponential modifier in human thinking. As a word, we are concerned with the problems of vague subjective judgment and positive leniency. By taking them into

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account, a simple importance-assessing method is developed using comparison of fuzzy number-valued fuzzy measures based on a fuzzy distance measure.

Finally, we conduct an outcome-oriented approach to test the accuracy of our proposed method. The outcome-oriented approach is based on the view of the decision outcome and its correct prediction [17]. If we can correctly predict the outcome of the decision process, then we obviously understands the decision process. Therefore, we shall show several examples on consumer decision- making problems to illustrate the new importance-assessing method and compare it with three widely used methods, the weighted least square method, Saaty's eigenvector method, and typical fuzzy measures.

2. Fuzzy Number-Valued Fuzzy Measures

Zhang [12, 18, 19] developed the elementary concepts and theorems of a fuzzy number-valued fuzzy measure and a fuzzy number-valued fuzzy integral on the fuzzy set. Continuing his work, Zhang [20] discussed a series of structural characteristics for the fuzzy number-valued fuzzy measure on the fuzzy σ-algebra. Zhang [21] also gave some definitions of the convergence of a sequence of fuzzy number-valued fuzzy measurable functions.

Let X be a nonempty set and $F(X)=\{T;\ T: X\rightarrow[0,1]\}$. Let $F^*(X)\subset F(X)$ be a fuzzy σ-algebra. Let F^* be the set of all fuzzy numbers and $A\in F^*$. An α-level interval of fuzzy number A is denoted as $[{}^{\alpha}A^-,{}^{\alpha}A^+]$. Let $F_+^* = \{A;\ A\geq 0,\ A\in F^*\}$. A fuzzy distance of fuzzy numbers A and B is denoted as $D(A,B)$, where $D(A,B)=$ $\bigcup_{\alpha\in[0,1]}\alpha\left[\left|{}^1A^- - {}^1B^-\right|,\ \sup_{\alpha\leq\eta\leq 1}\left|{}^{\eta}A^- - {}^{\eta}B^-\right|\vee\left|{}^{\eta}A^+ - {}^{\eta}B^+\right|\right]$ for $A,B\in F^*$.

A fuzzy number-valued fuzzy measure (i.e., a (z)fuzzy measure) on $F^*(X)$ is a fuzzy number-valued fuzzy set function μ: $F^*(X)\rightarrow F_+^*$. $(X,F^*(X),\mu)$ is a fuzzy number-valued fuzzy measure space (i.e., a (z)fuzzy measure space). Since we apply (z)fuzzy measures to characterize attribute salience, the set X is designated a discrete and finite set, $\{x_1, x_2,\cdots, x_n\}$, throughout this paper.

Let R denote the set of all real numbers. For $\beta\in R$, let $F_\beta = \{x;\ f(x)\geq\beta\}$. A mapping f: $X\rightarrow R$ is called a fuzzy measurable function, if $\chi_{F_\beta}\in F^*(X)$ and

$$\chi_{F_\beta}(x)=\begin{cases}1 & \text{iff } x\in F_\beta,\\ 0 & \text{iff } x\notin F_\beta.\end{cases} \tag{1}$$

The set of all fuzzy measurable functions is denoted by M^*. In addition, let M_+^* denote the set of all non-negative fuzzy measurable functions.

For $T\in F^*(X)$, $f\in M_+^*$, the fuzzy number-valued fuzzy integral (i.e., (z)fuzzy integral) of f on T with respect to μ is defined by

$$\int_T f\,\mathrm{d}\mu = \bigcup_{\alpha\in[0,1]}\alpha\left[\sup_{\beta\in[0,\infty)}\beta\wedge{}^{\alpha}\big(\mu(T\cap\chi_{F_\beta})\big)^-,\ \sup_{\beta\in[0,\infty)}\beta\wedge{}^{\alpha}\big(\mu(T\cap\chi_{F_\beta})\big)^+\right], \tag{2}$$

where $F_\beta = \{x;\ f(x)\geq\beta\},\ \beta\in[0,\infty)$.

In this study, we apply (z)fuzzy measures to determine the salience of decision attributes. We use linguistic terms to collect the data of respondents' subjective judgments concerning attribute importance in the investigation stage. The linguistic terms are further transformed into fuzzy numbers, so we can subsequently construct (z)fuzzy measures to develop an importance-assessing method. Moreover, a synthetic evaluation can be derived using (z)fuzzy integrals. Next, we test the validity of the importance-assessing method by comparing the predicted and actual evaluation results. What has to be noticed is that our proposed method uses a fuzzy distance measure to overcome the problem of positive leniency. In the next section, we introduce the fuzzy distance measure used in this study.

3. Fuzzy Distance Measure in (z)Fuzzy Measures

Tran and Duckstein [16] introduced an approach for ranking fuzzy numbers based on a distance measure. By taking into account every point in both intervals, they developed a new class of distance measures for interval numbers and then used it to form a distance measure for fuzzy numbers. In this study, we apply Tran and Duckstein's distance measure for fuzzy numbers to adjust overestimated ratings of attribute importance.

Considering two generalized left right fuzzy numbers (GLRFNs) A and B, their α-level intervals are $[{}^{\alpha}A^-,{}^{\alpha}A^+]$ and $[{}^{\alpha}B^-,{}^{\alpha}B^+]$ respectively. Let w be a weighting function towards the distance between two intervals at different α levels. According to Tran and Duckstein's definition, a distance between A and B is as follows:

$$D_{\mathrm{GLRFN}}(A,B,w)=\left\langle\int_0^1\left\{\left[\left(\frac{{}^{\alpha}A^- + {}^{\alpha}A^+}{2}\right)-\left(\frac{{}^{\alpha}B^- + {}^{\alpha}B^+}{2}\right)\right]^2 + \frac{1}{3}\left[\left(\frac{{}^{\alpha}A^+ - {}^{\alpha}A^-}{2}\right)^2+\left(\frac{{}^{\alpha}B^+ - {}^{\alpha}B^-}{2}\right)^2\right]\right\}\times w(\alpha)\mathrm{d}\alpha\right\rangle\Big/\int_0^1 w(\alpha)\mathrm{d}\alpha. \tag{3}$$

Notice that $w(\alpha)$ is a continuous positive function defined on [0,1]. When $w(\alpha)=1$, the distances have equal weights at different α levels. When $w(\alpha)=\alpha$, the distances have more weights at higher α levels.

Tran and Duckstein [16] gave the equations to compute distances for triangular fuzzy numbers with two different weighting functions: $w(\alpha)=1$ and $w(\alpha)=\alpha$. Since triangular fuzzy numbers (TFNs) are the most widely-used fuzzy numbers, this study assumes that a fuzzy number-valued fuzzy set function μ on (z)fuzzy measure space $(X,F^*(X),\mu)$ is a TFN for simplicity. Given two TFNs that $A=(a_1,a_2,a_3)$ and $B=(b_1,b_2,b_3)$. When $w(\alpha)=1$, the distance between A and B is as follows:

$$\begin{aligned} D_{\mathrm{TFN}}(A,B,1) &= (a_2-b_2)^2+\frac{1}{2}(a_2-b_2)\left[(a_3+a_1)-(b_3+b_1)\right] \\ &+\frac{1}{9}\left[(a_3-a_2)^2+(a_2-a_1)^2+(b_3-b_2)^2+(b_2-b_1)^2\right] \\ &-\frac{1}{9}\left[(a_2-a_1)(a_3-a_2)+(b_2-b_1)(b_3-b_2)\right] \\ &+\frac{1}{6}(2a_2-a_1-a_3)(2b_2-b_1-b_3). \end{aligned} \tag{4}$$

When $w(\alpha)=\alpha$, the distance is as follows:

$$\begin{aligned} D_{\mathrm{TFN}}(A,B,\alpha) &= (a_2-b_2)^2+\frac{1}{3}(a_2-b_2)\left[(a_3+a_1)-(b_3+b_1)\right] \\ &+\frac{1}{18}\left[(a_3-a_2)^2+(a_2-a_1)^2+(b_3-b_2)^2+(b_2-b_1)^2\right] \\ &-\frac{1}{18}\left[(a_2-a_1)(a_3-a_2)+(b_2-b_1)(b_3-b_2)\right] \\ &-\frac{1}{12}(2a_2-a_1-a_3)(2b_2-b_1-b_3). \end{aligned} \tag{5}$$

In the following, we shall fix the (z)fuzzy measure of the most important attribute in order to identify other (z)fuzzy measures through distance equations.

4. An Importance-Assessing Method Using (z)Fuzzy Measures

This study develops an importance-assessing method by comparison of (z)fuzzy measures using a fuzzy distance measure. In the light of the positive leniency problem of investigation data, we do not ask respondents their direct explication on attribute importance, but investigate the relative importance instead. That is, respondents are asked for performing the psychological importance distance of an attribute to the most important one. For example, we can apply a comparative rating scale to require a respondent to rate attribute salience in comparison with the highest degree of importance explicitly used as a frame of reference. The longer the psychological distance is, the less important the attribute becomes. Through a simple approach using fuzzy distance measures, the fuzzy number for each attribute will be explicated and attribute importance, expressed in terms of (z)fuzzy measures, can then be ascertained. Before measuring the salience of decision attributes, we develop an approach for identifying fuzzy numbers using Tran and Duckstein's distance measures.

If attribute salience is interpreted as a linguistic variable, then its term set T represents the scale position marked by respondents. T is a mapping from X to [0,1] (i.e., T: $X\rightarrow[0,1]$), where X is a nonempty attribute set and $X=\{x_1, x_2,\cdots, x_n\}$. Note that $T(x_i)$ for a single element x_i is denoted by T^i. The (z)fuzzy measure of the most important attribute, x_k, is denoted by $\mu(T^k)$ and $\mu(T^i)$'s are the (z)fuzzy measures of other less salient attributes, where $i\neq k$. The determination of the number of conversion scales generally depends on the nature of attributes used in a decision problem. We suggest that there can be even number of categories to handling errors of central tendency [13]. Since we hope to prevent overabounding neutral or indifferent responses, a rating scale with even number of categories will be used. In this study, we conduct a reasonable expression of attribute importance by TFNs as shown in Fig. 1. The verbal term set used in 6-scale is {very unimportant, unimportant, fairly unimportant, fairly important, important, very important}. Each of the basic linguistic terms is assigned one of six TFNs by a semantic rule [11].

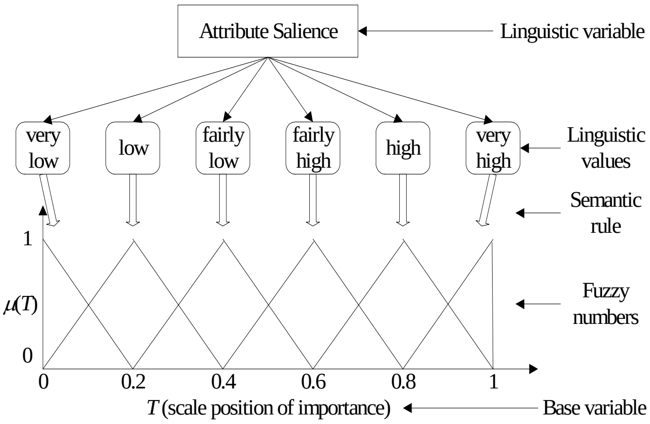

Figure 1. Six linguistic terms and their corresponding fuzzy numbers.

Assume that $\mu(T^k)=(a_{k1}, a_{k2}, a_{k3})$ and $\mu(T^i)=(a_{i1}, a_{i2}, a_{i3})$, where $a_{k_j}, a_{i_j}\in[0,1]$ for j=1,2,3. From Fig. 1, we know that the general relationship of a_{i1}, a_{i2}, and a_{i3}, except for in the cases of {very unimportant, very important}, is as follows:

$$\begin{cases} a_{i1} = a_{i3} - 0.4, \\ a_{i2} = a_{i3} - 0.2. \end{cases} \tag{6}$$

Let $w(\tau)$ be a weighting function towards the distance between $\mu(T^i)$ and $\mu(T^k)$ at different τ levels, where $\tau\in[0,1]$. When $w(\tau)=1$, applying (4) we have:

$$\begin{aligned} D_{\mathrm{TFN}}\left(\mu(T^i),\mu(T^k),1\right) &= \frac{1}{225}+(a_{i3}-a_{k2}-0.2) \\ &\quad \times(2a_{i3}-\frac{1}{2}a_{k3}-a_{k2}-\frac{1}{2}a_{k1}-0.4) \\ &\quad +\frac{1}{9}\left[(a_{k3}-a_{k2})^2+(a_{k2}-a_{k1})^2 \right. \\ &\quad \left. -(a_{k3}-a_{k2})(a_{k2}-a_{k1})\right]. \end{aligned} \tag{7}$$

When $w(\tau)=\tau$, applying (5) we have:

$$\begin{aligned} D_{\mathrm{TFN}}\left(\mu(T^i),\mu(T^k),\tau\right) &= \frac{1}{450}+\frac{1}{3}(a_{i3}-a_{k2}-0.2) \\ &\quad \times(5a_{i3}-a_{k3}-3a_{k2}-a_{k1}-1) \\ &\quad +\frac{1}{18}\left[(a_{k3}-a_{k2})^2+(a_{k2}-a_{k1})^2 \right. \\ &\quad \left. -(a_{k3}-a_{k2})(a_{k2}-a_{k1})\right]. \end{aligned} \tag{8}$$

Given a_{k1}, a_{k2}, a_{k3}, and D_{TFN}, we can derive the a_{i3} value by (7) or (8) when $w(\tau)$ equals 1 or τ respectively. The above approach supposes that the fuzzy numbers of all decision attributes have the same spread for convenience. Even though the identification result does not conform to any typical membership function of fuzzy numbers in Fig. 1, it still has the same spread, 0.4. Note that the solution of a_{i3} has to be smaller than a_{k3} because the grade of importance, (a_{k1}, a_{k2}, a_{k3}), is highest. The above approach has its exceptions in the cases of $a_{i3}<0.4$. To obtain a meaningful fuzzy number, a_{ij} must not be smaller than zero for j=1,2,3. Thus, (6) is updated as follows:

$$\begin{cases} a_{i1}=\max(a_{i3}-0.4,0), \\ a_{i2}=\max(a_{i3}-0.2,0). \end{cases} \tag{9}$$

We use the above-mentioned approach to characterize the grade of importance associating with each decision attribute, exclusive of the most important one. A simple and intuitively reasonable algorithm for modeling attribute salience is developed and the algorithm given here is suitable for a single decision maker (i.e., DM). The importance-assessing method given here is chiefly concerned with an individual’s judgment on the relative value of attributes. Therefore, an outcome-oriented approach is necessary to advance the estimation accuracy so as to obtain a more elegant method. Since the outcome-oriented approach needs to predict the result of the decision process, the decision matrix must be a part of input. The detailed implementation procedure is as follows:

IMPORTANCE-ASSESSING ALGORITHM TO A SINGLE DM

Step 0: Input data through questionnaire survey

Set the number of linguistic terms used is 6.

Investigate the DM’s subjective judgment on the most important attribute x_k and its corresponding linguistic term T^k, relative importance distance of other attributes to x_k, the evaluation value of the alternative on each attribute, and the preference priority toward all alternatives.

Initialize the total number of iterations, J^{max}, as desired.

Step 1: Initialize the value of $w(\tau)$

Set the value of the weighting function in distance measures ($0\le w(\tau)\le 1$).

Set the iteration counter: J=1.

Step 2: While the stopping condition is false, do Steps 3-10.

Step 3: Convert the linguistic term T^k of x_k to a TFN

According to the pre-designated scale, convert the linguistic term T^k possessed by x_k into its corresponding fuzzy number, $\mu(T^k)$.

Step 4: Normalize the relative importance

Use linear scale transformation to normalize the importance distance between x_k and other attributes in [0,1]. An equally important attribute to x_k implies the normalized distance D_{TFN}=0; while a least important attribute to x_k implies the normalized distance D_{TFN}=1.

Step 5: Derive the fuzzy numbers by D_{TFN}

According to the normalized distance D_{TFN} and $\mu(T^k)$, identify the fuzzy number, $\mu(T^i)$'s, of other attributes. For example, apply (7) and (9) when $w(\tau)$=1 or apply (8) and (9) when $w(\tau)=\tau$.

Step 6: Obtain attribute importance expressed by (z)fuzzy measures

Construct the grades of importance for all decision attributes on (z)fuzzy measure space, $(X,F^*(X),\mu)$. That is, $\mu(T^1)$, $\mu(T^2)$,$\cdots$, and $\mu(T^n)$, respectively, represent the DM’s subjective importance on attributes x_1, x_2,$\cdots$, and x_n.

Step 7: Calculate (z)fuzzy integrals for all alternatives

Compute (z)fuzzy integrals for all of the alternatives using f and μ, as defined in (1). Here, the (z)fuzzy integral represents the synthetic evaluation of each alternative.

Step 8: Establish a priority of alternatives

Rank all of the alternatives according the values of (z)fuzzy integrals.

Step 9: Update the iteration counter

Let $J^{(new)}=J^{(old)}+1$.

Step 10: Test for the stopping condition

Compare the estimated and actual priorities toward all alternatives. If the estimated priority coincides with the DM’s preference ranking or if $J>J^{max}$, then stop; otherwise, reset the value of $w(\tau)$ and continue.

In addition, we can use Spearman rank correlation coefficient or other appropriate statistical measurements to redefine the stopping condition. On the other hand, if the DM's subjective judgment on all alternatives in Step 0 replaces ordinal preference information with cardinal preference, more precise indices, such as average error sum and average error sum of squares, can be utilized as a stopping condition.

The following example regarding hotel selection helps clarify the preceding method. The attributes a consumer uses to discriminate among the benefits offered by alternative hotels in his consideration set are room appearance, room cleanliness, friendliness of staff, and service promptness. Room cleanliness is most important among four attributes, and its linguistic term is "very important" with the corresponding fuzzy number (0.8, 1, 1). Table 1 lists the normalized distance between cleanliness and other attributes. By the importance-assessing algorithm, the (z)fuzzy measures of each attribute when $w(\tau)=1$ and $w(\tau)=\tau$ are shown in Table 1.

Table 1. (z)Fuzzy measures in the illustrative example.

Attribute	Normalized distance	(z)Fuzzy measure	
		$w(\tau)=1$	$w(\tau)=\tau$
Room appearance	0.25	(0.43, 0.63, 0.83)	(0.40, 0.60, 0.80)
Room cleanliness	0.00	(0.80, 1.00, 1.00)	(0.80, 1.00, 1.00)
Friendliness of staff	0.56	(0.25, 0.45, 0.65)	(0.20, 0.40, 0.60)
Service promptness	0.78	(0.15, 0.35, 0.55)	(0.10, 0.30, 0.50)

Furthermore, we assume that the values of (z)fuzzy measures satisfy the finite λ-rule. That is, the L function values of four attributes at each α level are λ-fuzzy measures, and so are the R function values. The λ-fuzzy measure is constrained by a parameter λ, which describes the degree of additivity between attribute importance. To illustrate the λ-value at different α levels, all relevant α-cuts of each attribute and the corresponding λ-values are revealed in Tables 2 and 3.

Table 2. α-cuts and λ-values associated with (z)fuzzy measures in the illustrative example ($w(\tau)=1$).

α level	Attribute	(z)fuzzy measure value		λ-value	
		Left side	Right side	Left side	Right side
0.0	Room appearance	0.43	0.83	-0.8711	-0.9696
	Room cleanliness	0.80	1.00		
	Friendliness of staff	0.25	0.65		
	Service promptness	0.15	0.55		
0.2	Room appearance	0.47	0.79	-0.9233	-0.9999
	Room cleanliness	0.84	1.00		
	Friendliness of staff	0.29	0.61		
	Service promptness	0.19	0.51		
0.4	Room appearance	0.51	0.75	-0.9568	-0.9999
	Room cleanliness	0.88	1.00		
	Friendliness of staff	0.33	0.57		
	Service promptness	0.23	0.47		
0.6	Room appearance	0.55	0.71	-0.9783	-0.9999
	Room cleanliness	0.92	1.00		
	Friendliness of staff	0.37	0.53		
	Service promptness	0.27	0.43		
0.8	Room appearance	0.59	0.67	-0.9918	-0.9999
	Room cleanliness	0.96	1.00		
	Friendliness of staff	0.41	0.49		
	Service promptness	0.31	0.39		
1.0	Room appearance	0.63	0.63	-0.9999	-0.9999
	Room cleanliness	1.00	1.00		
	Friendliness of staff	0.45	0.45		
	Service promptness	0.35	0.35		

Table 3. α-cuts and λ-values associated with (z)fuzzy measures in the illustrative example ($w(\tau)=\tau$).

α level	Attribute	(z)fuzzy measure value		λ-value	
		Left side	Right side	Left side	Right side
0.0	Room appearance	0.40	0.80	-0.8261	-0.9999
	Room cleanliness	0.80	1.00		
	Friendliness of staff	0.20	0.60		
	Service promptness	0.10	0.50		
0.2	Room appearance	0.44	0.76	-0.8981	-0.9999
	Room cleanliness	0.84	1.00		
	Friendliness of staff	0.24	0.56		
	Service promptness	0.14	0.46		
0.4	Room appearance	0.48	0.72	-0.9431	-0.9999
	Room cleanliness	0.88	1.00		
	Friendliness of staff	0.28	0.52		
	Service promptness	0.18	0.42		
0.6	Room appearance	0.52	0.68	-0.9715	-0.9999
	Room cleanliness	0.92	1.00		
	Friendliness of staff	0.32	0.48		
	Service promptness	0.22	0.38		
0.8	Room appearance	0.56	0.64	-0.9893	-0.9999
	Room cleanliness	0.96	1.00		
	Friendliness of staff	0.36	0.44		
	Service promptness	0.26	0.34		
1.0	Room appearance	0.60	0.60	-0.9999	-0.9999
	Room cleanliness	1.00	1.00		
	Friendliness of staff	0.40	0.40		
	Service promptness	0.30	0.30		

Since the outcome-oriented approach will be used to examine the proposed method, we suppose that DMs apply a compensatory decision rule and then calculate (z)fuzzy integrals as overall evaluations. Let E_j be the overall rating of the j-th alternative, $f_j(x_i)$ be the evaluation of the j-th alternative on evaluative attribute x_i, $\mu(T^i)$ be the importance or weight attached to evaluative attribute x_i, and n be the number of evaluative attributes considered relevant. For $\beta \in R$, let $F_\beta^j = \{x; f_j(x) \geq \beta\}$. A fuzzy measurable function f_j: $X \rightarrow R$ satisfies that $\chi_{F_\beta^j} \in F^*(X)$ and

$$\chi_{F_\beta^j}(x) = \begin{cases} 1 & \text{iff } x \in F_\beta^j, \\ 0 & \text{iff } x \notin F_\beta^j. \end{cases}$$

The compensatory decision rule states that the alternative that rates highest on the sum of the DM's judgments of the relevant evaluative attributes will be chosen. This can be illustrated as:

$$
\begin{aligned}
E_j &= \int_T f_j(x)\,\mathrm{d}\mu \\
&= \underset{\alpha\in[0,1]}{\cup} \alpha\left[\sup_{\beta\in[0,\infty)} \beta \wedge^{\alpha} \left(\mu(T\cap\chi_{F_\beta^j})\right)^{-}, \sup_{\beta\in[0,\infty)} \beta \wedge^{\alpha} \left(\mu(T\cap\chi_{F_\beta^j})\right)^{+} \right],
\end{aligned}
\tag{10}
$$

where $\beta\in[0,\infty)$.

Since attribute set $X(=\{x_1, x_2,\cdots, x_n\})$ is discrete and finite, (10) can be further rewritten as follows:

$$
E_j = \underset{\alpha\in[0,1]}{\cup} \alpha\left[\bigvee_{i=1}^{n} \left[f_j(x_i) \wedge^{\alpha} \left(\mu(T)\right)^{-} \right], \bigvee_{i=1}^{n} \left[f_j(x_i) \wedge^{\alpha} \left(\mu(T)\right)^{+} \right] \right], \tag{11}
$$

where $f_j(x_i)$ is monotonically decreasing with respect to i. If the inequality $f_j(x_1)\geq f_j(x_2)\geq\cdots\geq f_j(x_n)$ does not hold initially, the elements in X must be renumbered. Since using the Choquet integral can obtain more reasonable results than using the fuzzy integral in many cases [22], we apply the Choquet integral throughout the calculation of (z)fuzzy integrals.

In the illustrative example, suppose that there are three alternatives: Hotels A, B, and C. The comparable numerical decision matrix for the hotel selection problem is shown in Table 4. In applying the Choquet integral, the results of (z)fuzzy integrals when $w(\tau)=1$ and $w(\tau)=\tau$ are presented in Fig.s 2 and 3, respectively. In addition, Tables 5 and 6 lists the detailed (z)fuzzy integral values. If the consumer indicates that his preference priority is Hotel B≻Hotel A≻Hotel C, the (z)fuzzy measures in Table 1 can approximate grades of attribute importance in this hotel selection problem.

Table 4. A hotel selection problem in the illustrative example.

Attribute	Alternative		
	Hotel A	Hotel B	Hotel C
Room appearance	0.46	0.73	0.54
Room cleanliness	0.67	0.82	0.30
Friendliness of staff	0.79	0.55	0.62
Service promptness	0.88	0.35	0.42

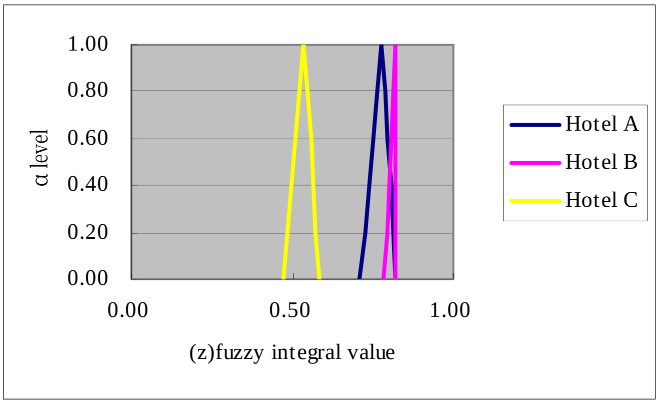

Figure 2. (z)Fuzzy integrals of three alternative hotels in the illustrative example ($w(\tau)=1$).

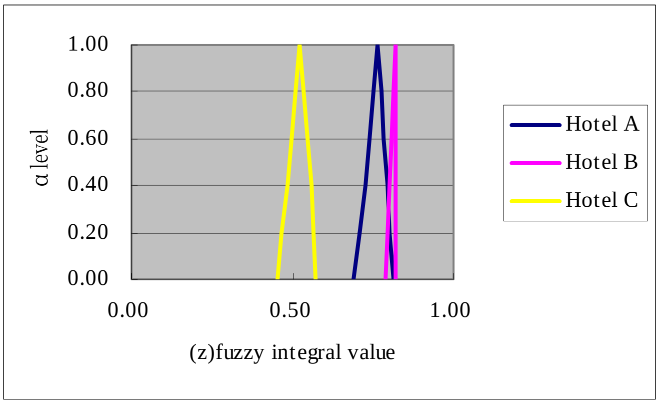

Figure 3. (z)Fuzzy integrals of three alternative hotels in the illustrative example ($w(\tau)=\tau$).

Table 5. The values of (z)fuzzy integrals in the illustrative example ($w(\tau)=1$).

α level	Hotel A		Hotel B		Hotel C	
	Left side	Right side	Left side	Right side	Left side	Right side
0.0	0.7090	0.8206	0.7850	0.8200	0.4695	0.5816
0.2	0.7252	0.8130	0.7923	0.8200	0.4848	0.5742
0.4	0.7402	0.8050	0.7996	0.8200	0.4990	0.5659
0.6	0.7540	0.7966	0.8067	0.8200	0.5122	0.5567
0.8	0.7667	0.7878	0.8136	0.8200	0.5244	0.5467
1.0	0.7786	0.7786	0.8200	0.8200	0.5357	0.5357

Table 6. The values of (z)fuzzy integrals in the illustrative example ($w(\tau)=\tau$).

α level	Hotel A		Hotel B		Hotel C	
	Left side	Right side	Left side	Right side	Left side	Right side
0.0	0.6912	0.8110	0.7866	0.8200	0.4508	0.5736
0.2	0.7090	0.8029	0.7930	0.8200	0.4676	0.5653
0.4	0.7252	0.7944	0.7998	0.8200	0.4831	0.5561
0.6	0.7401	0.7855	0.8068	0.8200	0.4974	0.5461
0.8	0.7539	0.7762	0.8135	0.8200	0.5107	0.5350
1.0	0.7666	0.7666	0.8200	0.8200	0.5230	0.5230

In the following, several multiattribute evaluation cases in consumer decision-making reality will be addressed to examine the feasibility and applicability of our importance-assessing method.

5. A Comparative Study on Consumer Choice Problems

An outcome-oriented approach is taken to verify the correct prediction. Namely, to demonstrate the effects of (z)fuzzy measures on identifying attribute salience, we compare the determination results of the current method with typical fuzzy measures [1], Saaty's eigenvector method [23], and the weighted least square method [24]. The main input data for typical fuzzy measures are linguistic values about importance of each attribute. As for the eigenvector method, the DM is supposed to judge the relative importance of two attributes, and thus the scaling ratios in the pair wise comparison matrix are the main input data. The weighted least square method is also applied to Saaty's comparison matrix.

The flowchart of the procedure to test the relative accuracy of the proposed method to other approaches is presented in Fig. 4. Here, we merely adopt the unadjusted (z)fuzzy measures (when $w(\tau)=1$ or $w(\tau)=\tau$) to draw a comparison; that is, the testing procedure includes only Steps 3-6 of our proposed importance-assessing algorithm. Moreover, the values of (z)fuzzy measures and typical fuzzy measures are supposed to satisfy the finite λ-rule. Note that the testing procedure is appropriate for multiple DMs since we intend comparing the whole performance of importance approximation.

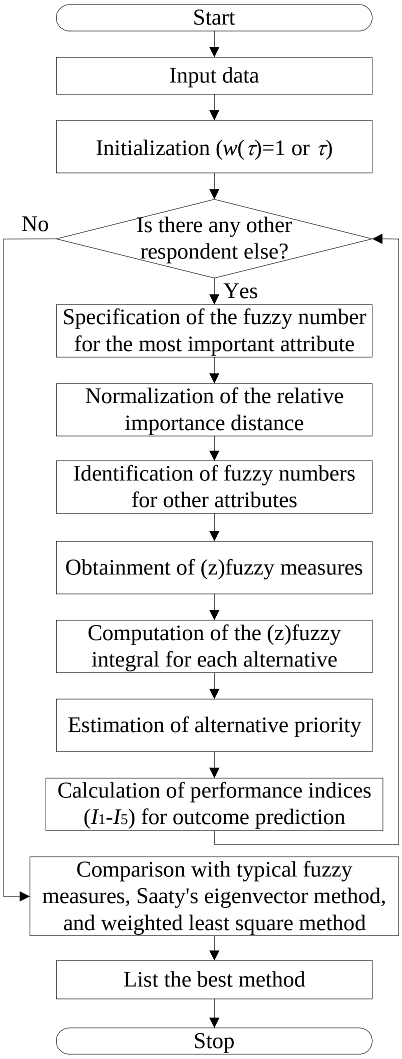

Figure 4. Flowchart of the testing procedure.

There are five kinds of performance indices for outcome prediction comparison, including total order index (I_1), partial order index (I_2), average rank correlation coefficient (I_3), average residual sum (I_4), and average error sum of squares (I_5). The first third indices are developed for the ordinal preferences of alternatives given. The last two indices treat cardinal preferences of alternatives.

The total order index measures the level of concordance of the complete preference order, whereas the partial order index measures the concordance level of the partial order between alternatives. Let m be the number of alternatives and Q be the number of respondents (i.e., sample size). I_1 is defined as the ratio of the number of concordance total order to Q. Let I_2^q be the partial order index for the q-th respondent, and I_2^q is defined as the ratio of the number of concordance partial order to C_2^m (=$m(m$-1)/2). I_2 is then given by $\sum_{q=1}^{Q} I_2^q \big/ Q$.

Let p_j^q denote the overall rank of the j-th alternative judged by the q-th respondent and $\hat{p}_j^q$ denote the estimated one. The definition of Spearman rank correlation coefficient with regard to the q-th respondent is as follows:

$$I_3^q = 1 - \frac{6 \cdot \sum_{j=1}^{m} \left(p_j^q - \hat{p}_j^q\right)^2}{m(m^2-1)} \tag{12}$$

When the estimated rank of alternatives is the same as the actual rank, all the differences (p_j^q - $\hat{p}_j^q$)'s will be equal to zero, and I_3^q will be equal to +1. When the estimated rank is the reverse of the other, $I_3^q = -1$. Then, average rank correlation coefficient I_3 is derived by $\sum_{q=1}^{Q} I_3^q \big/ Q$.

Let E_j^q be the overall rating of the j-th alternative judged by the q-th respondent and $\hat{E}_j^q$ denote the estimated one (i.e., (z)fuzzy integral value). For the q-th respondent, the average residual sum between E_j^q and $\hat{E}_j^q$ is defined by I_4^q = $\sum_{j=1}^{m} | E_j^q - \hat{E}_j^q | \big/ m$. In addition, I_4 is obtained by $\sum_{q=1}^{Q} I_4^q \big/ Q$. Similarly, the average error sum of squares in regard to the q-th respondent is defined by I_5^q = $\sum_{j=1}^{m} (E_j^q - \hat{E}_j^q)^2 \big/ m$. Then, we have I_5=$\sum_{q=1}^{Q} I_5^q \big/ Q$.

The empirical study intends to inquire into consumer choice problems to examine the estimation results of different importance-assessing methods. Three kinds of consumer goods regularly used by Taiwanese college students were selected from the 2005 E-ICP (Eastern integrated consumer profile) database (http://www.eicp.com.tw/): convenience goods, electronic goods, and health foods. The product with the highest buying frequency was then chosen from the selected kind of goods. Three product categories are taken as empirical cases, including pudding in convenience goods, CD burner in electronic goods, and health tea in health foods. We investigated those who have consumption experience with three designated product categories. For each product category, we conducted a face-to-face interview on experienced college students in Taoyuan County about the data items listed in Step 0 of the proposed algorithm. The sample sizes of three product categories were designated as 40, respectively.

Table 7 summarizes the major results of performance indices using four importance-assessing methods. The detailed results are listed at http://ba.cgu.edu.tw/tychen/Empirical_Results.htm. In view of the total order index (I_1), our proposed method performs better than other methods in pudding and CD burner categories; while the weighted least square method performs best in the health tea category. In regard to the partial order index (I_2), the accuracy level of our proposed method is highest in CD burner and health tea categories. In addition, the superior methods are (z)FM and FM in the pudding category. Concerning average rank correlation coefficient (I_3), the best methods are (z)FM and FM in the pudding category, (z)FM in the CD burner category, and WLS in the health tea category. Our method performs well both in the average residual sum (I_4) and average error sum of squares (I_5). We can be fairly certain that the proposed importance-assessing method is more practical for consumer choice problems. The empirical results support the validity of using a distance between (z)fuzzy measures to determine attribute importance.

Table 7. Empirical results of performance indices using four methods.

Product category	Performance index	(z)FM[1]		FM[2]	AHP[3]	WLS[4]
		$w(\tau)=1$	$w(\tau)=\tau$			
Pudding	I_1	**0.9743**	0.9487	0.9487	0.8717	0.8717
	I_2	**0.9332**	**0.9332**	**0.9332**	0.9167	0.9167
	I_3	**0.9167**	0.8654	**0.9167**	0.8910	0.8910
	I_4	**0.0296**	0.0301	0.0315	0.0318	0.0323
	I_5	0.0074	**0.0073**	0.0083	0.0092	0.0092
CD burner	I_1	**0.8461**	0.8205	0.7948	0.6923	0.6923
	I_2	**0.8672**	0.8587	0.8631	0.7736	0.8077
	I_3	**0.7372**	0.7244	0.6538	0.5513	0.6282
	I_4	**0.0380**	0.0377	0.0419	0.0410	0.0412
	I_5	**0.0029**	**0.0029**	0.0033	0.0031	0.0110
Health tea	I_1	0.7750	0.7750	0.7750	0.7750	**0.8250**
	I_2	**0.9168**	0.9125	0.9043	0.8960	0.9128
	I_3	0.8313	0.8250	0.7688	0.8188	**0.8688**
	I_4	**0.0322**	0.0330	0.0362	0.0350	0.0345
	I_5	**0.0023**	0.0026	0.0032	0.0026	0.0025

[1] (z)FM represents the importance-assessing method with (z)fuzzy measures.
[2] FM represents the importance-assessing method with typical fuzzy measures.
[3] AHP represents the eigenvector method.
[4] WLS represents the weighted least square method.

The observation of λ-value changes between (z)fuzzy measures and typical fuzzy measures will be implemented and evaluated as a method for eliminating errors of positive leniency in rating systems. At different α levels, if the λ-value of (z)fuzzy measures is larger than one of typical fuzzy measures, the bias of positive leniency has been reduced and the comparison result is checked "+". When there is no change in λ-values, we check the result with "O". Comparing with the original λ-value of typical fuzzy measures, a decreasing λ-value (checked "–") represents a turning for the worse in leniency errors. The comparison results in λ-values are presented in Tables 8 and 9. As sketched here, most of positive leniency errors can be improved, especially in the L function values. In regard of the R function values, positive leniency gradually declines in the high α levels. We can reasonably conclude that the usage of a distance between (z)fuzzy measures can eliminate the positive leniency effect in importance ratings without loss of estimation validity.

Table 8. Improvement results of errors of positive leniency ($w(\tau)=1$).

Product category	α level	Left side			Right side		
		+	O	–	+	O	–
Pudding	0.0	40[1] (100[2])	0 (0.0)	0 (0.0)	0 (0.0)	26 (65.0)	14 (35.0)
	0.2	40 (100)	0 (0.0)	0 (0.0)	0 (0.0)	26 (65.0)	14 (35.0)
	0.4	40 (100)	0 (0.0)	0 (0.0)	5 (12.5)	27 (67.5)	8 (20.0)
	0.6	40 (100)	0 (0.0)	0 (0.0)	10 (25.0)	26 (65.0)	4 (10.0)
	0.8	40 (100)	0 (0.0)	0 (0.0)	12 (30.0)	26 (65.0)	2 (5.0)
	1.0	14 (35.0)	26 (65.0)	0 (0.0)	14 (35.0)	26 (65.0)	0 (0.0)
CD burner	0.0	40 (100)	0 (0.0)	0 (0.0)	1 (2.5)	22 (55.0)	17 (42.5)
	0.2	40 (100)	0 (0.0)	0 (0.0)	4 (10.0)	22 (55.0)	14 (35.0)
	0.4	40 (100)	0 (0.0)	0 (0.0)	7 (17.5)	22 (55.0)	11 (27.5)
	0.6	40 (100)	0 (0.0)	0 (0.0)	13 (32.5)	22 (55.0)	5 (12.5)
	0.8	40 (100)	0 (0.0)	0 (0.0)	16 (40.0)	22 (55.0)	2 (5.0)
	1.0	18 (45.0)	22 (55.0)	0 (0.0)	18 (45.0)	22 (55.0)	0 (0.0)
Health tea	0.0	40 (100)	0 (0.0)	0 (0.0)	1 (2.5)	13 (32.5)	16 (40.0)
	0.2	40 (100)	0 (0.0)	0 (0.0)	1 (2.5)	13 (32.5)	16 (40.0)
	0.4	40 (100)	0 (0.0)	0 (0.0)	7 (17.5)	13 (32.5)	10 (25.0)
	0.6	40 (100)	0 (0.0)	0 (0.0)	11 (27.5)	23 (57.5)	6 (15.0)
	0.8	40 (100)	0 (0.0)	0 (0.0)	16 (40.0)	13 (32.5)	1 (2.5)
	1.0	17 (42.5)	23 (57.5)	0 (0.0)	17 (42.5)	23 (57.5)	0 (0.0)

[1] Frequency
[2] Percent of Respondents

Table 9. Improvement results of errors of positive leniency ($w(\tau)=\tau$).

Product category	α level	Left side			Right side		
		+	O	–	+	O	–
Pudding	0.0	40[1] (100[2])	0 (0.0)	0 (0.0)	0 (0.0)	26 (65.0)	14 (35.0)
	0.2	40 (100)	0 (0.0)	0 (0.0)	3 (7.5)	26 (65.0)	7 (17.5)
	0.4	40 (100)	0 (0.0)	0 (0.0)	6 (7.5)	26 (65.0)	8 (20.0)
	0.6	40 (100)	0 (0.0)	0 (0.0)	10 (25.0)	26 (65.0)	4 (10.0)
	0.8	40 (100)	0 (0.0)	0 (0.0)	13 (32.5)	26 (65.0)	1 (2.5)
	1.0	14 (35.0)	26 (65.0)	0 (0.0)	14 (35.0)	26 (65.0)	0 (0.0)
CD burner	0.0	40 (100)	0 (0.0)	0 (0.0)	2 (5.0)	13 (32.5)	15 (37.5)
	0.2	40 (100)	0 (0.0)	0 (0.0)	5 (12.5)	23 (57.5)	12 (30.0)
	0.4	40 (100)	0 (0.0)	0 (0.0)	9 (22.5)	23 (57.5)	8 (20.0)
	0.6	40 (100)	0 (0.0)	0 (0.0)	14 (35.0)	23 (57.5)	3 (7.5)
	0.8	40 (100)	0 (0.0)	0 (0.0)	17 (42.5)	23 (57.5)	2 (5.0)
	1.0	17 (42.5)	23 (57.5)	0 (0.0)	17 (42.5)	23 (57.5)	0 (0.0)
Health tea	0.0	40 (100)	0 (0.0)	0 (0.0)	1 (2.5)	23 (57.5)	16 (40.0)
	0.2	40 (100)	0 (0.0)	0 (0.0)	2 (5.0)	23 (57.5)	15 (37.5)
	0.4	40 (100)	0 (0.0)	0 (0.0)	9 (22.5)	13 (32.5)	8 (20.0)
	0.6	40 (100)	0 (0.0)	0 (0.0)	15 (37.5)	23 (57.5)	2 (5.0)
	0.8	40 (100)	0 (0.0)	0 (0.0)	17 (42.5)	23 (57.5)	0 (0.0)
	1.0	17 (42.5)	23 (57.5)	0 (0.0)	17 (42.5)	23 (57.5)	0 (0.0)

[1] Frequency
[2] Percent of Respondents

Another area of applications is during the phase of gathering the data for a multiattribute decision-making problem, given a limited budget. The data collection procedure of the eigenvector method or weighted least square method typically requires the respondent to compare all possible pairs of the attributes. If there are n attributes to be evaluated, there will be $n(n-1)/2$ paired comparisons required in the judgment task. The geometric expansion in the number of paired comparisons limits the usefulness of the eigenvector method and weighted least square method for the evaluation of large attribute sets. On the contrary, the data requirement of (z)fuzzy measures equals n only. Our proposed method can significantly reduce the data requirement in assessing grades of importance, and markedly enhance the applicability of fuzzy measures in actual practice.

6. Conclusions

Based on the distance between (z)fuzzy measures, we developed a new importance-assessing method to determine the salience of decision attributes. From an outcome-oriented point of view, several empirical consumer decision-making problems were addressed to examine the applicability of the current method in contrast to several popular methods for assessing attribute importance. There are two comparison approaches for evaluating the performance of importance-assessing methods, including indices by priority prediction (I_1, I_2, and I_3) and indices by overall rating prediction (I_4, and I_5). The comparison results show that the proposed method makes a relatively correct prediction of decision outcomes than several existing importance-assessing approaches. Furthermore, our method deals with the matter of positive leniency and helps overcome the problem of the indiscriminative weights. Meanwhile, for each numerical case, there are only n input data required by our proposed method, and this can reduce the difficulty of data collection in practice.

The stopping condition in the importance-assessing algorithm is worth a mention in passing. When the stopping condition holds only in the case of $J>J^{max}$, we cannot approximate grades of attribute importance. Since total order coincidence is a strict requirement, we can weaken the original stopping condition and turn to partial order coincidence. That is, the stopping condition is redefined by an acceptable ratio concerning partial order index or a threshold value for Spearman rank correlation coefficient. When the overall evaluation towards alternatives is expressed by cardinal preference, a designated value regarding average residual sum or average error sum of squares can be also considered as a stopping condition. Other feasible approaches to improve the preceding problem are applying other types of fuzzy numbers (e.g., trapezoidal fuzzy numbers) or trying different patterns in fuzzy integral computation.

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