

Consumer Choice in the Presence of Incomplete Information with MCDM Method under Crisp Data

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ABSTRACT

Missing data (also often called incomplete information) is a common problem in consumer choice. While some authors claim that a tendency to give more weight to attributes on which all considered options have values relative to attributes for which not all options have values. Therefore, choosing from sets with missing information can affect buyers' taste and purchase decisions. Moreover, it can lead to poor decision making by marketers and policymakers. In the present paper, to resolve this limitation, a new hybrid Multi Criteria Decision Making (MCDM/ particularly, TOPSIS method) and mathematical approach (for finding the missing data) is proposed. Tamaddon, Jahanshahloo, Lotfi, Mozaffaari, and Gholami (2009) developed the mathematical formulations for finding the missing data in the Data Envelopment Analysis (DEA) environment. In this paper, we focus our attention on the innovative combination of TOPSIS and proposed method initiated by Tamaddon et al. (2009) and its uses in the consumer choice problem in the presence of incomplete information. In the proposed method, input and output factors play the role of cost and benefit respectively. In addition, comparative analysis has been performed, and the proposed method seems to be more satisfactory than the traditional method (ignoring and discarding missing data) in solving decision problem. The paper concludes with limitations and further research directions.

Keywords: MCDM, TOPSIS, Consumer Choice, Incomplete Information

INTRODUCTION

Generally, most real life purchases involve choices among options with incomplete attribute information (Gunasti & Ross, 2009). In addition, consumers typically do not know how to interpret statements of missing data (American Institutes Research Report, 2012). However, these decisions are of great importance not only for the consumers themselves, but also for marketers and policymakers (Bettman, Johnson, & Payne, 1991). So that, manipulating consumer decision choices can help businesses as well as policymakers by maximising their profit under the same amount of investment. Moreover, understanding these processes will help with developing marketing strategies targeted to the consumer. Because one of the most important aspects of marketing is to have a complete understanding of the buyer's journey (Narang & Mishra, 2014).

Many companies and organisations spend vast amounts of money and time collecting and analysing the lifestyle, demographic and transaction data they hold about their customers. The amount of data held is increasing rapidly; but one very important aspect of the data that has received and continues to receive very little attention

is the problem of missing data (Winkler, 2004). Missing data are questions without answers or variables without observations. Therefore, in surveys, missing data can be caused by many things. Respondents may refuse to answer a question because of privacy issues or, the person taking the survey does not understand the question. Perhaps, the respondent would have answered, but the answer he or she might have given was not one of the options presented. Or, perhaps there wasn't enough time to complete the questionnaire or the respondent just lost interest. Every survey question without an answer is a missing data point. Besides survey data, research data are also prone to missing data. Missed observations may occur due to human error. For example, a researcher may forget to take a measurement such as the patients pulse. Or, a test tube can be broken which eliminates a measurement (SPSS Inc. Report, 2009). On the other side, according to the viewpoint proposed by Eliashberg (1980) many judgments made by consumers involve outcomes characterised by several attributes. Remarkable results of Slovic and Macphillamy (1974) and Kivetz and Simonson (2000), show the tendency to give more weight to attributes on which all considered options have values (common attributes) relative to attributes for which not all options have values (unique attributes). Since, consumer

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choice can be regarded as a MCDM problem. Multi Criteria Decision Making (MCDM) refers to making preference decision (e.g., evaluation, prioritisation, and selection) over the available alternatives that are characterised by multiple, usually conflicting, criteria (Yucenur & Demirel, 2012). The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) has become a popular MCDM technique, since it has a comprehensible theoretical structure and is able to provide an exact model for decision-making (Huang & Li, 2012). The underlying logic of TOPSIS is to define an ideal solution and negative ideal solution. The ideal solution is the solution that maximises the benefit attributes and minimises the cost attributes, whereas the negative ideal solution is the solution that maximises the cost attributes and minimises the benefit attributes. In short, the ideal solution consists of all best attribute values, whereas the negative ideal solution is composed of all worst attribute values. The optimal alternative is the one, which has the shortest distance from the ideal solution and the farthest distance from the negative ideal solution (Yue, 2013). On the other side, in 2009, Tamaddon *et al.* developed the mathematical formulations for finding the missing data in the Data Envelopment Analysis (DEA) environment. In this method, firstly, the missing amounts via the sum of other DMUs (Decision Maker Units) inputs and outputs in the crisp data are determined. And by using convex combination of the interval beginnings and endings, we can obtain a linear function of an analogous variable with each one of the inputs and outputs components; so that we can obtain a function for the missing data via crisp processes. In this paper, we focus on the innovative combination of TOPSIS and proposed method initiated by Tamaddon *et al.*, and its uses in the consumer choice problem under incomplete information. In the proposed method, input and output factors play the role of cost and benefit respectively. The main goal of this study is to use the combination methods (TOPSIS + mathematical formulations for finding the missing data) in consumer choice problems with incomplete information under crisp data.

The paper is organised as follows. In the second section, the literature and in the third section, the proposed approach is discussed. Numerical examples are provided in the next section. The paper is concluded in the fifth and the last section.

LITERATURE REVIEW

In the current MCDM literature, many studies exist on missing data; however, most of them are limited to

Analytic Hierarchy Process (AHP) method. Studies by Harker (1987), Wedley (1993, 2006), Wedley, Schoner, and Tang (1993), Fedrizzi and Giove (2006), Gao and Zhang (2010), Carmo, Marins, Salomon, and Mello (2013), and Srdjevic, Srdjevic, and Blagojevic (2014) could be referred to as examples. Moreover, according to the viewpoint proposed by Gunasti and Ross (2015), consumer almost always faces decisions that involve making choices among options, some of which have missing information. In continuation, among various papers, which are available for consumer choice problem, we assessed just those which were based on missing values (including MCDM models and other methods that are mainly statistical). Eliashberg (1980) proposed several preference models and measurement techniques (in order to predict the consumers preferences for multi attribute alternatives) that have been used mainly by decision analysts and which are applicable in the consumer preference judgment context. Fan and Ma (1999) proposed a new approach to solve the MCDM problem with incomplete preference information on alternatives. The approach is based on an optimisation model which can be used to assess attribute weight and then to select the most desirable alternative. Kivetz and Simonson (2000) evaluated the effects of incomplete information on consumer choice. Their findings indicate that choosing from sets with missing information can affect buyer tastes and purchase decisions made subsequently. Chernev and Carpenter (2001) examined consumer inferences about product attributes that are unobservable (i.e. durability) at the time of the decision. Winkler (2004) described the problem of missing values and then discusses some of the statistical methods used to impute missing values (especially, in customer data's), particularly those that are suitable for the huge data sets held by many company's and organisations. Lu and Yang (2005) explored the impacts of incomplete travel information on airline passenger's choice behaviour in practically. They employed three different kinds of utility function to incorporate the effects on incomplete information into choice model and used binary logit model and random coefficient logit model (RCL) to estimate, based on the data collected from a stated choice experiment. Gunasti and Ross (2008) conducted three experimental studies to investigate the effects of multiple inferences in multi attribute, multi product choice environments. Their results showed that encouraging consumers to make explicit inferences about missing attributes leads to significantly different choices compared to choices made without being asked to make inferences. Gunasti and Ross (2009) examined the effect of prompted and unprompted inferences (about missing attributes) on choice outcomes and the tendency

to choose versus not to choose. Schrift, Netzer, and Kivetz (2011) demonstrated that in consumer decision making, whereby consumers complicate their decisions, consumers increase choice conflict by overweighting small disadvantages of superior alternatives, converging overall evaluations of alternatives, reversing preference ordering, and even choosing less preferred alternatives. Chuang, Kao, Cheng, and Chou (2012) investigated the statistical relationship between the incomplete information and the compromise effect in different choice scenarios. The main findings were that consumer is more likely to choose the middle option when they have incomplete information than when they have complete information. Strykowska (2013) conducted an experimental survey study to discover the likely available sources that consumers infer the information from when cues such as product price are not explicitly given at the point of purchase. Narang and Mishra (2014) analysed various modes of decision making and applied statistical models to predict consumer behaviour in various situations (i.e. in the presence of incomplete and inaccurate information) and areas of application. Gunasti and Ross (2015) focused on what happens to choices for incomplete options when consumers make compensatory inferences in an attempt to balance rival products attributes.

difficult and are important to the consumer, to marketers, and to policymakers (Bettman, Luce, & Payne, 1998). According to the viewpoint proposed by Kivetz and Simonson (2000); Chuang *et al.* (2012); Gunasti and Ross (2009); and Strykowska (2013), consumer usually lack complete information when they make a decision. In addition, typically consumers do not know how to interpret statements of missing data (American Institutes Research Report, 2012) whereas, a small percent of missing data can cause serious problems to your analysis leading to your drawing wrong conclusions (SPSS Inc. Report, 2009). Considering all above-mentioned points that the point of missing data should also be considered. In addition, as noted earlier, according to Eliashberg (1980) many judgments made by consumers involve outcomes characterised by several attributes since consumer choice can be regarded as a MCDM problem. TOPSIS proposed by Hwang and Yoon, is one of the well-known methods for classical Multiple Attribute (often called Criteria) Decision Making (Yue, 2013). Here, a major drawback in applying this method is that TOPSIS is not applicable to incomplete data. Therefore, to overcome this limitation, this paper has introduced a new framework for avoiding the incomplete information in the decision makers (DMs) preference judgment on alternatives in decision process (Fig. 1).

THE CONCEPTUAL FRAMEWORK AND PROPOSED APPROACH

Conceptual framework

Consumer choices concerning the selection, consumption, and disposal of products and services can often be

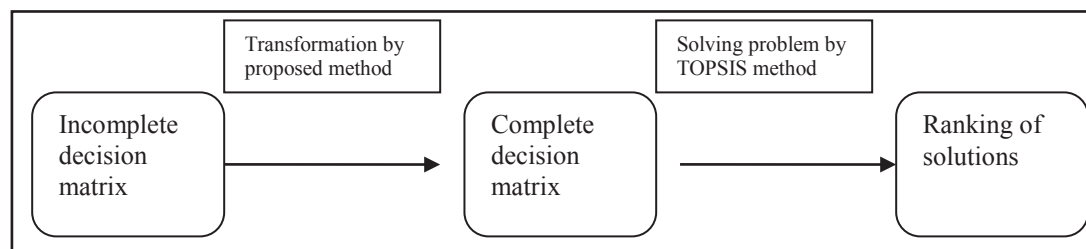


Fig. 1: The Proposed Framework

Proposed Approach

TOPSIS Method

TOPSIS assumes that we have m alternatives (options) and n attributes/criteria and we have the score of each option with respect to each criterion. Let x_{ij} be the score

of option i with respect to criterion j . we have a matrix $X = (x_{ij})_{m,n}$ matrix. Let J be the set of benefit attributes or criteria (more is better). Let J' be the set of negative attributes or criteria (less is better). The idea of TOPSIS can be expressed through a series of steps (Tayeb, Ahcene, Omar, & Mouloud, 2007):

Step 1: Obtain performance data for n alternatives over k criteria. Raw measurements are usually standardised; converting raw measures x_{ij} into standardised measures s_{ij} . Construct normalised decision matrix. This step transforms various attribute dimensions into non-dimensional attributes, which allows comparisons across criteria. Normalised scores or data as follows:

$$r_{ij} = X_{ij} / \sqrt{\sum_i X_{ij}^2} \text{ for } i = 1, \dots, m; j = 1, \dots, n. \quad (1)$$

Step 2: Develop a set of importance weights w_k , for each of the criteria. The basis for these weights can be anything, but usually, is ad hoc reflective of relative importance. Scale is not an issue if standardising was accomplished in Step 1. Construct the weighted normalised decision matrix. Assume we have a set of weights for each criteria w_j for $j = 1, \dots, n$. multiplies each column of the normalised decision matrix by its associated weight. An element of the new matrix is:

$$V_{ij} = w_j r_{ij} \quad (2)$$

Step 3: Determine the ideal and negative ideal solutions.

Ideal solutions:

$$A^* = \{v_1^*, \dots, v_n^*\}, \text{ where}$$

$$V_j^* = \{\max_i (v_{ij}) \text{ if } j \in J; \min_i (v_{ij}) \text{ if } j \in J'\} \quad (3)$$

Negative ideal solutions:

$$A' = \{v_1', \dots, v_n'\}, \text{ where}$$

$$V_j' = \{\min_i (v_{ij}) \text{ if } j \in J; \max_i (v_{ij}) \text{ if } j \in J'\} \quad (4)$$

Step 4: Calculate the separation measures for each alternative. The separation from the ideal alternative is:

$$S_i^* = \left[\sum_j (v_j^* - v_{ij})^2 \right]^{1/2} \text{ } i = 1, \dots, m. \quad (5)$$

Similarly, the separation from the negative ideal alternative is:

$$S_i' = \left[\sum_j (v_j' - v_{ij})^2 \right]^{1/2} \text{ } i = 1, \dots, m. \quad (6)$$

Step 5: calculate the relative closeness to the ideal solution C_i^* :

$$C_i^* = S_i' / (S_i^* + S_i') \text{ } 0 < C_i^* < 1 \quad (7)$$

Step 6: Rank order alternatives by maximising the ratio in step 5. Select the option with C_i^* closest to 1.

Mathematical formulations for finding the missing data (or Tamaddon *et al.* method)

According to the view point proposed by Tamaddon *et al.* (2009), for finding the missing data the following method is suggested. Suppose that there are n DMUs with m inputs and s outputs, which the data of inputs and outputs are crisp but the i_{th} input from DMU $_k$; that is X_{ik} , is missing (as noted earlier, in this paper, input, output, and DMUs factors play the role of cost criteria, benefit criteria, and alternative respectively). In continuation, for each one of the inputs, of DMU $_k$, the first input to m is divided on the sum of other DMU inputs of the first to m columns and we call them P_1, \dots, P_m (be careful that P_i is not obvious). We do this process for outputs, that is, we divide the first to s_{th} outputs from DMU $_k$ on the sum of the other DMU outputs of the first to s_{th} columns and we call them P'_1, \dots, P'_m .

$$P_1 = X_{1k} / \sum_{j=1, j \neq k}^n X_{1j}, P_2 = X_{2k} / \sum_{j=1, j \neq k}^n X_{2j}, \dots, P_i = ?, \dots, P_m = X_{mk} / \sum_{j=1, j \neq k}^n X_{mj} \quad (8)$$

$$P'_1 = Y_{1k} / \sum_{j=1, j \neq k}^n Y_{1j}, P'_2 = Y_{2k} / \sum_{j=1, j \neq k}^n Y_{2j}, \dots, P'_m = Y_{mk} / \sum_{j=1, j \neq k}^n Y_{mj}. \quad (9)$$

Then, we obtain their average and call it P^- , at the end; we obtain the X_{ik} by multiplying P^- in the sum of the i_{th} inputs from all the DMUs except DMU $_k$. Therefore, we have:

$$P^- = \sum_{i=1}^m P_i + \sum_{r=1}^s P'_r / (m+s-1); \quad (10)$$

$$X_{ik} / \sum_{j=1, j \neq k}^n X_{ij} = P^- \rightarrow X_{ik} = P^- \sum_{j=1, j \neq k}^n X_{ij}$$

Numerical Example

A numerical example is discussed in this section to show how to implement the proposed method. The problem is to rank alternatives by TOPSIS techniques according to the DMs' incomplete preference information on alternatives (in other words, consumer choice problem under incomplete information). Assume that there are seven alternatives (A_1, A_2, \dots, A_7) and six criteria (C_1 =price, C_2 =order cost, C_3 =quality, C_4 =product shape, C_5 =package quality, and C_6 =taste). In addition, consumer for each reason fails to make some judgments (i.e. adding new products or modifying existing ones) thus there are empty cell in the corresponding decision matrices (Table 1).

Table 1: Incomplete Decision Matrix

Criteria Alternative	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆
A ₁	10200	115	75	9	73	1
A ₂	5230	87	58	1	82	5
A ₃	11604	97	92	5	90	3
A ₄	7077	80	57	3	91	1
A ₅	7685	106	80	3	76	1
A ₆	9451	?	96	9	?	?
A ₇	11975	142	90	5	84	5

where C₁, C₂ are cost type criteria, and C₃, C₄, C₅, and C₆ benefit type criteria.

As noted earlier, there is incomplete information in the DMs preference judgment on alternatives (i.e. for a₆₂, a₆₅, and a₆₆).

It is also worth noting here that, a consumer is likely to follow one of the three possible scenarios when she or he cannot find the information on products attribute (Strykowska, 2013):

1. Consumers search for the information externally in the environment (i.e. by asking sales assistant),
2. Consumer search for the information internally (i.e. past experience with purchasing the product), and
3. Consumers infer the value of the missing attribute from the value of another attribute. The latter scenario is preferred in this paper.

In this section, the missing value for each alternative regards to formula number (10) can be find and the results is as shown in Table 2.

i.e. for a₆₂:

$$P^- = ((9451 * (1/53771)) + (96/452) + (9/26))/5 = 0.147$$

For a₆₂, we have 0.147*627=92

Similarly,

$$a_{65} = 73$$

$$a_{66} = 2$$

Table 2: Complete Decision Matrix

Criteria Alternative	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆
A ₁	10200	115	75	9	73	1
A ₂	5230	87	58	1	82	5
A ₃	11604	97	92	5	90	3
A ₄	7077	80	57	3	91	1
A ₅	7685	106	80	3	76	1

A ₆	9451	92	96	9	73	2
A ₇	11975	142	90	5	84	5

Several researchers have argued that the equal weight rule is often a highly accurate simplification of the decision making process (Birnbaum, 1998). So, we have W_j= (0.167, 0.167, 0.167, 0.167, 0.167, and 0.167). When the TOPSIS method is applied, the following values are derived (Table 3-7).

Table 3: Normalised Decision Matrix

Criteria Alternative	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆
A ₁	.414	.416	.356	.592	.328	.123
A ₂	.212	.315	.275	.066	.380	.615
A ₃	.471	.351	.437	.329	.417	.369
A ₄	.287	.289	.270	.197	.422	.123
A ₅	.312	.383	.380	.197	.352	.123
A ₆	.383	.333	.456	.592	.338	.246
A ₇	.486	.514	.427	.329	.389	.615

Table 4: Weighted Normalised Decision Matrix*

Criteria Alternative	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆
A ₁	.069	.069	.059	.099	.056	.021
A ₂	.035	.053	.046	.011	.063	.103
A ₃	.079	.059	.073	.055	.070	.062
A ₄	.048	.048	.045	.033	.070	.021
A ₅	.052	.064	.063	.033	.059	.021
A ₆	.064	.056	.076	.099	.056	.041
A ₇	.081	.086	.071	.055	.065	.103

*. W_j= (0.167, 0.167, 0.167, 0.167, 0.167, and 0.167)

Table 5: Positive and Negative Ideal Solution

A ⁺	.076	.099	.070	.103	.035	.048
A ⁻	.045	.011	.056	.021	.081	.086

Table 6: Distance of Each Alternative from the Positive and Negative Ideal Solution

d _i ⁺	.094	.093	.075	.111	.109	.070	.074
d _i ⁻	.091	.100	.073	.056	.046	.102	.097

Table 7: Closeness Coefficient

C_i^*	.493	.517	.493	.338	.297	.593	.568
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From the results shown in Tables 3-7, it can be concluded that the ranking is as follows:

$$A_6 > A_7 > A_2 > A_1 \approx A_3 > A_4 > A_5$$

Therefore, the best alternative is A_6 , since it is superior to all the other alternatives. Meanwhile, A_5 have very bad performance.

Here, more studies have been done. According to the viewpoint proposed by Batista and Monard (2003), in a general way, missing data treatment methods can be divided into the following three categories:

1. ignoring and discarding data,
2. parameter estimation, and
3. imputation.

In continuation, this paper focuses on ignoring and discarding data. In other words, what happens if we drop the alternative 6 (alternative with incomplete information) and redo our assessment of alternatives? With no intension to describe the whole procedure, we shall only point to

the final results which are shown in Table 8.

Table 8: Closeness Coefficient (without alternative 6)

A_1	A_2	A_3	A_4	A_5	A_6	A_7
0.536	0.480	0.495	0.335	0.299	0	0.557

From the above results, it can be concluded that, the ranking is as follows:

$$A_7 > A_1 > A_3 > A_2 > A_4 > A_5$$

Therefore, the best alternative is A_7 , since it is superior to all the other alternatives. Meanwhile, A_5 have very bad performance.

A comparison of the test results is given in Table 9 and Fig. 2.

Table 9: Comparison of Results

Method	priority
TOPSIS with incomplete data (with A_6)	$A_6 > A_7 > A_2 > A_1 \approx A_3 > A_4 > A_5$.593 .568 .517 .493 .493 .338 .297
TOPSIS with complete data (without A_6)	$A_7 > A_1 > A_3 > A_2 > A_4 > A_5$.557 .536 .495 .480 .335 .299

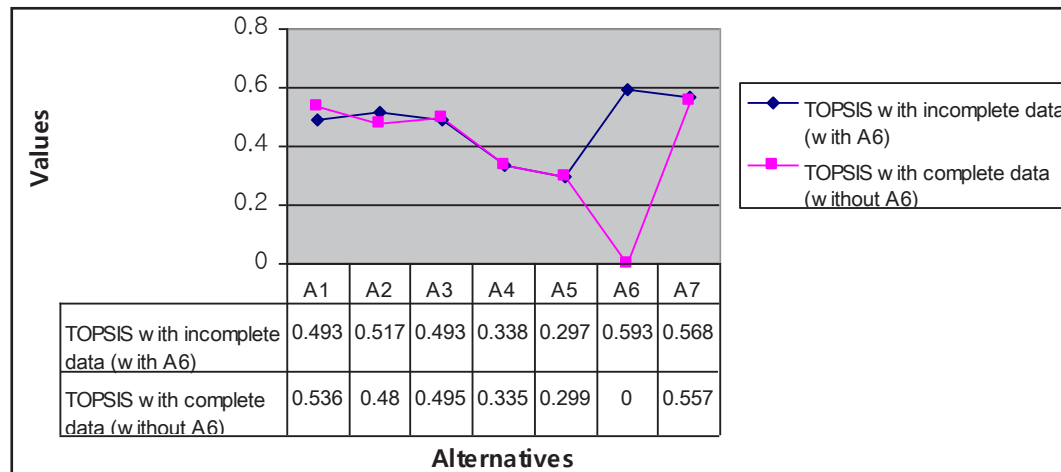


Fig. 2: Comparison of Results

As can be seen in Table 9 and Fig. 2, the differences between two models are clear. The current priority (TOPSIS with complete data) is $A_7 > A_1 > A_3 > A_2 > A_4 > A_5$. This differs from that of the TOPSIS with incomplete information ($A_6 > A_7 > A_2 > A_1 \approx A_3 > A_4 > A_5$). This difference is due to the missing value considered. In other words, missing value estimation impact could greatly improve the decision making process. So, A_6 becomes the suitable alternative instead of A_7 . Therefore, findings in this paper confirm the effectiveness of proposed method.

CONCLUDING REMARKS

In this paper, we focus on the following problem: how to help the decision maker (consumer / marketers and policymakers) to determine the optimal solution(s) from sets with incomplete information. Because consumers typically do not know how to interpret statements of missing data. On the other side, manipulating consumer decision choices can help businesses as well as policymakers by maximising their profit under the same

amount of investment. Nevertheless, in this paper, the combination of two methods (hybrid model): a TOPSIS-mathematical formulation for finding the missing data (or Tamaddon *et al.* method) was applied. The method has two stages: 1. finding the missing amount and 2. rank solution. However, ignoring and discarding missing data is the default method in many decision problems. Nevertheless, findings in this paper show that results obtained by TOPSIS-mathematical formulation for finding the missing data were significantly different from those got when TOPSIS with complete information (in other words, ignoring and discarding missing data) was used. The alternative ranking provided by TOPSIS with complete information was $A_7 > A_1 > A_3 > A_2 > A_4 > A_5$, while the TOPSIS-mathematical formulation for finding the missing data method ranked the alternatives as $A_6 > A_7, A_2, A_1, A_3$, and A_4 over A_5 . In addition, it is also worth noting that the proposed method (mathematical formulation for finding the missing data) has been developed for the DEA, nor for MCDM environment. This could cause some bias in the final result. So, more studies are needed. In addition, further research can apply this proposed approach to other managerial issues or compare it with another existing models (in other words, another statistical, mathematical or MCDM methods).

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