Malaysian Journal of Mathematical Sciences 15(2): 283–291 (2021)

Malaysian Journal of Mathematical Sciences

Journal homepage: https://einspem.upm.edu.my/journal

Triangular Fuzzy Number-Based Conjoint Analysis Method and its Application in Analyzing Factors Influencing Postgraduates Program Selection

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Received: 30 March 2020
Accepted: 18 April 2021

Abstract

Fuzzy conjoint analysis model is widely used in measuring the level of preferences in various decision making processes. The method is gaining increasing popularity particularly due to its ability in analyzing questionnaire items in surveys that require respondents to rate their preferences by means of linguistic terms. Existing fuzzy conjoint analysis procedures commonly employs discrete fuzzy sets in representing preference levels and ratings of respondents towards attributes. While discrete-type of fuzzy sets are able to handle discrete forms of preference information, some preference information are more appropriate to be presented in the form of linguistic terms or linguistic values defined on a continuous scale. These types of linguistic terms can be mathematically represented in the form of fuzzy numbers. In this paper, a triangular fuzzy number-based conjoint analysis method (TFN-CAM) is proposed for the purpose of analyzing the level of preferences of a group of respondents pertaining to factors influencing their decision in making a selection, and for ranking of the selection factors. The proposed TFN-CAM is implemented in ranking and analyzing the factors that influence a group of students in selecting a postgraduate program.

Keywords: Conjoint analysis; fuzzy number; linguistic values.

1 Introduction

Fuzzy conjoint method (FCM) which is based on the fuzzy set preference model [15] is widely used in social science and educational researches particularly in analyzing human level of satisfactions, perceptions and evaluations. Amongst the areas of interests are on the market products, quality of services, job satisfactions, academic teaching and learning practices and performance evaluation. Specifically, FCM based on discrete fuzzy sets were commonly used in evaluating market product [15], service quality and customer satisfaction [6], job satisfaction among hotel employees [2] and job satisfaction among academic staffs in higher education [11]. In the context of academic teaching and learning practices, the method was also used in investigating students' perceptions on computer algebra system learning environment [1], mathematics self-efficacy and anxiety among Malaysian upper secondary school students [7], preservice mathematics teachers' beliefs [9], students' expectation and teachers' beliefs on learning mathematics [13], and in evaluating graduates' performance [17].

In the aforementioned applications, the levels of preferences are expressed in terms of linguistic terms which are represented in the form of discrete fuzzy sets. Generally, discrete fuzzy sets are used in handling the subjective elements in human valuation [16]. The membership degrees characterizing a discrete fuzzy sets indicate the degree of satisfaction or preference of a particular individual or group of individuals in evaluating the attributes or factors associated with a specific problem under study. Nevertheless, in many cases, preference ratings may need to be mathematically defined on a continuous scale rather than in discrete form. Hence, a more general representation of the linguistic ratings defined on a continuous scale are essential. In dealing with continuous nature of human ratings, fuzzy numbers are seen as an appropriate alternative representations of human linguistic preferences. Taking this factor into consideration, the discrete fuzzy set-based FCM was extended to fuzzy number environment. Fuzzy number-based FCM defined on a continuous scale were employed in analyzing perceptions of students in learning calculus [10] and in evaluating job satisfaction [14].

Depending on the problem under study, items in a particular questionnaires could be related to some attributes, criteria, or factors which require the respondents to provide the answer(s) in the form of linguistic ratings or linguistic terms. Due to the advantages of fuzzy number-based conjoint method in modelling human preferences, this paper proposes a procedure known as Triangular Fuzzy number-based Conjoint Analysis Method (TFN-CAM) particularly for analyzing questionnaire items that solicit opinions or preferences from respondents toward factors that influence them in making decisions. The applicability of TFN-CAM is illustrated by implementing it in analyzing level of preferences of a group of students towards factors that had influenced them in choosing a postgraduate program to further their studies in a public university in Shah Alam, Selangor.

2 Preliminaries

In this section, basic concepts, definitions and operations related to the study are presented. Let X be a universe of discourse of elements where the universe can be either continuous or discrete.

Definition 2.1. *[19] A fuzzy set A in X is a set of ordered pair, $A = \{(x, \mu(x)) \mid x \in X\}$ where $\mu(x)$ denotes the degree of membership of the element x in the universe X.*

Specifically, a discrete fuzzy set defined on a discrete universal set, $X = \{x_i, i = 1, 2, ..., n\}$, can be represented as $A = \{\frac{\mu(x_i)}{x_i}, x_i \in X\}$ or $A = \sum_{K} \frac{\mu(x_i)}{x_i}$, while a fuzzy set defined on continuous universal set X can be written as $A = \int_X \frac{\mu(x_i)}{x_i} dx$.

Definition 2.2. *[16] Linguistic variable is a variable that can take words as its values. These words which is known as linguistic values or linguistic terms are characterized by fuzzy sets defined in the universe of discourse upon which the variable is defined.*

Definition 2.3. *[16] A triangular fuzzy number (TFN) denoted as $A = (a_1, a_2, a_3)$ is a fuzzy number defined by the membership function,*

$$\mu_A(x) = \begin{cases} \frac{x-a_1}{a_2-a_1} & , \quad x \in [a_1, a_2], \\ \frac{x-a_3}{a_2-a_3} & , \quad x \in [a_2, a_3], \\ 0 & , \quad otherwise. \end{cases} \tag{1}$$

Let $A = (a_1, a_2, a_3)$ and $B = (b_1, b_2, b_3)$ be two triangular fuzzy numbers, and k be a scalar. The arithmetic operations and the similarity function of the fuzzy numbers are given by the following definitions:

Definition 2.4. *[5] The arithmetic operation of fuzzy numbers A and B are given as follows:*

$$A(+)B = (a_1 + b_1, a_2 + b_2, a_3 + b_3), \tag{2}$$

$$A(-)B = (a_1 - b_3, a_2 - b_2, a_3 - b_1), \tag{3}$$

$$kA = (ka_1, ka_2, ka_3). \tag{4}$$

Definition 2.5. *[8] The similarity degree between A and B can be calculated as,*

$$SIM(A, B) = \frac{1}{1 + d(A, B)}, \tag{5}$$

where $d(A, B) =\mid P(A) - P(B) \mid$ with $P(A) = \frac{a_1+4a_2+a_3}{6}$ and $P(B) = \frac{b_1+4b_2+b_3}{6}$.

3 Methodology

In this section, the procedure of the Triangular Fuzzy Number Conjoint Method (TFN-CAM) is laid out. Existing procedure of discrete fuzzy conjoint method is extended to triangular fuzzy number (TFN) environment. The predefined linguistic terms and ratings are presented in the form of TFNs. The TFN-CAM procedure is specifically tailored in analyzing and ranking of factors that influence respondents in making some decisions or selections. Generally, the procedure involve three main processes namely the aggregation of individual ratings, determining the overall group preference ratings and finally ranking of factors. In particular, the aggregation process takes into consideration all the individual respondents' linguistic ratings in the calculation. For each factor, the proportion of contribution of each linguistic rating in the aggregation process is determined by the corresponding ratio of the occurrence, that is, the number of responses associated with the k-th linguistic terms over total number of responses across all the k linguistic terms. The group preference ratings are then determined using similarity function. Various similarity measures for fuzzy numbers have been proposed in literature. These includes the distance and set theoretic-based similarity measure [3], centroid-based similarity measure [4], similarity measure based on graded mean integration [8], similarity function integrating distances and geometric shape representation [12], and vector similarity measure [18]. In the following procedure of TFN-CAM, the similarity function by [8] is adopted in the calculation due to its simplicity in formulation and its suitability with the standard type of triangular fuzzy numbers used in this paper. Ranking of factors is performed based the ordering of group preference ratings and their associated similarity degrees.

3.1 Triangular Fuzzy Number-Based Conjoint Analysis Method (TFN-CAM)

The general procedure of the TFN-CAM in the context of analyzing factors is presented as follows:

Step 1: Identify the set of factors, $F = \{F_i\}, i = 1, 2, ..., m$.

Step 2: Set the predefined linguistic terms for ratings defined by TFNs, $L_k = (a_1^k, a_2^k, a_3^k)$ with $k = 1, 2, ..., t$.

Step 3: Obtain the number of responses, r_{ik}, with respect to the linguistic term, L_k, $k = \{1, 2, ..., t\}$ on factor F_i.

Step 4: Obtain the TFNs representing the aggregated linguistic ratings $\widetilde{F}_i$ with respect to the i-th factor F_i where,

$$\widetilde{F}_i = \sum_{k=1}^{t}(\beta_{ik}L_k) = (\sum_{k=1}^{t}\beta_{ik}a_1^k, \sum_{k=1}^{t}\beta_{ik}a_2^k, \sum_{k=1}^{t}\beta_{ik}a_3^k) = (a_1^i, a_2^i, a_3^i), \tag{6}$$

such that $\beta_{ik} = \frac{r_{ik}}{\sum\limits_{k=1}^{t} r_{ik}}$ represent the proportion of the k-th linguistic term.

Step 5: Calculate the degree of similarities between the aggregated linguistic ratings for the i-th factor $\widetilde{F}_i = (a_1^i, a_2^i, a_3^i)$, $i = 1, 2, ..., m$, and the linguistic ratings, $L_k = (a_1^k, a_2^k, a_3^k)$, $k = 1, 2, ..., t$ using the similarity measure $S_{ik}(\widetilde{F}_i, L_k)$ where,

$$S_{ik}(\widetilde{F}_i, L_k) = \frac{1}{1 + d(P(\widetilde{F}_i) - P(L_k))}, i = 1, 2, ..., m, k = 1, 2, ..., t, \tag{7}$$

with $P(\widetilde{F}_i) = \frac{a_1^i + 4a_2^i + a_3^i}{6}$ and $P(L_k) = \frac{a_1^k + 4a_2^k + a_3^k}{6}$.

Step 6: Identify the linguistic terms that are associated with the highest membership degrees obtained in *Step* 5. These linguistic terms will be respectively chosen to represent the overall group preference ratings towards the factors being evaluated.

Step 7: Rank the factors based on the ordering of the corresponding overall group preference ratings, followed by the associated degrees of similarities, in descending order.

3.2 Implementation of the TFN-CAM in Analyzing Factors Influencing Postgraduates Program Selection

In this section, the proposed procedure of Triangular Fuzzy Number-Based Conjoint Analysis Method (TFN-CAM) is implemented in analyzing the preference ratings of a group of postgraduate students towards 10 predetermined factors F_i, $i = 1, 2, ..., 10$ that had influenced them in selecting a postgraduate MSc program to further their study. Questionnaires were distributed to 51 students undertaking Program X, a master program by coursework offered by Faculty of Computer and Mathematical Sciences (FSKM), UiTM. The predetermined factors are: *Academic background* (F_1), *Interest towards courses offered by Program X* (F_2), *Program X reputation* (F_3), *Environment and facilities provided by the University* (F_4), *Teaching quality* (F_5), *Affordable fees* (F_6), *Scholarship availability* (F_7), *Family support* (F_8), *Peer influence* (F_9), and *Career opportunity related to Program X* (F_{10}). The respondents were asked to rate the factors using seven pre-defined fuzzy linguistic terms for ratings denoted as L_k, $k = 1, 2, ..., 7$ where the corresponding triangular fuzzy numbers (TFNs) are displayed in Table 1.

Table 1: Pre-defined Linguistic Terms and the Corresponding TFNs.

Notation, L_k	**Linguistic Term**	**TFN**
L_1	Very Strongly Disagree	$(0, 0, 0.1)$
L_2	Strongly Disagree	$(0, 0.1, 0.3)$
L_3	Disagree	$(0.1, 0.3, 0.5)$
L_4	More or Less Agree	$(0.3, 0.5, 0.7)$
L_5	Agree	$(0.5, 0.7, 0.9)$
L_6	Strongly Agree	$(0.7, 0.9, 1.0)$
L_7	Very Strongly Agree	$(0.9, 1.0, 1.0)$

The number of responses, r_{ik}, with respect to linguistic terms, L_k on the factor F_i are as presented in Table 2.

Table 2: Number of Responses on Influencing Factors.

Factor	**Number of Responses (r_{ik})**							**Total Responses**
F_i	L_1	L_2	L_3	L_4	L_5	L_6	L_7	
F_1	0	0	1	1	8	17	24	51
F_2	0	3	0	2	10	23	13	51
F_3	0	2	3	12	11	19	4	51
F_4	1	1	1	11	19	11	7	51
F_5	0	0	1	3	19	18	10	51
F_6	3	0	1	12	8	13	14	51
F_7	12	1	6	13	10	8	1	51
F_8	1	0	2	8	9	10	21	51
F_9	3	2	3	14	13	11	5	51
F_{10}	1	1	1	4	15	16	13	51

Based on the number of responses in Table 2, the aggregated TFN with respect to each factor is calculated. Note that for Factor F_1, the number of respondents who rated the factor as *Disagree* (L_3), *More or less Agree* (L_4), *Agree* (L_5), *Strongly Agree* (L_6), and *Very Strongly Agree* (L_7) are 1, 1, 8, 17 and 24, respectively. Hence, using (6), the calculated aggregated TFN for F_1 is obtained as,

$$\begin{aligned}\widetilde{F_i} &= \frac{0}{51}L_1 + \frac{0}{51}L_2 + \frac{1}{51}L_3 + \frac{1}{51}L_4 + \frac{8}{51}L_5 + \frac{17}{51}L_6 + \frac{24}{51}L_7 \\ &= \frac{1}{51}(0.1, 0.3, 0.5) + ... + \frac{17}{51}(0.7, 0.9, 1) + \frac{24}{51}(0.9, 1, 1) \\ &= (0.7433, 0.896, 0.969).\end{aligned}$$

The degrees of similarity between aggregated TFNs, $\widetilde{F_i}$, $i = 1, 2, ..., 10$ and predefined linguistic terms, L_k, $k = 1, 2, ..., 7$ are determined by using (7). Specifically, the similarity degree between the pair of fuzzy numbers representing the Factor F_1 and linguistic term L_1 can be derived as follows:

$$d(P(\widetilde{F_1}) - P(L_1)) = \frac{0.743 + 4(0.896) + 0.969}{6} - \frac{0 + 4(0) + 0.1}{6} = 0.8827 - 0.0167 = 0.8660,$$

$$S_{11}(\widetilde{F_1}, L_1) = \frac{1}{1 + d(P(\widetilde{F_i}) - P(L_k))} = \frac{1}{1 + 0.868} = 0.535.$$

The aggregated TFNs for the rest of the factors are obtained in similar manner, and the corresponding calculated fuzzy numbers are displayed in Table 3.

Table 3: Aggregated TFN $\widetilde{F_i}$ for Factor F_i, $i = 1, 2, ..., 10$.

$\widetilde{F_i}$	**Aggregated TFN**
$\widetilde{F_1}$	(0.743,0.896,0.969)
$\widetilde{F_2}$	(0.655,0.824,0.927)
$\widetilde{F_3}$	(0.516,0.704,0.851)
$\widetilde{F_4}$	(0.527,0.708,0.857)
$\widetilde{F_5}$	(0.629,0.810,0.935)
$\widetilde{F_6}$	(0.576,0.737,0.851)
$\widetilde{F_7}$	(0.314,0.463,0.620)
$\widetilde{F_8}$	(0.647,0.802,0.898)
$\widetilde{F_9}$	(0.455,0.629,0.782)
$\widetilde{F_{10}}$	(0.622,0.790,0.906)

The overall calculated similarity degrees are depicted in Table 4.

Comparison between the aggregated TFN of the first factor, $\widetilde{F_1}$ across L_k, $k = 1, ..., 7$ indicates that $S_{16}(\widetilde{F_1}, L_k) = 0.9993$ gives the highest degree of similarity. As such, the associated linguistic term *Strongly Agree* (L_6) is chosen to represent the overall group preference rating for F_1. In other words, it can be said that the respondents' choice of MSc program were strongly influenced by their academic background. The factors can be ranked based on the group preference ratings and their corresponding similarity degrees. This is done by ordering the group preference ratings in descending order. If there exist factors with similar group preference ratings, then the ordering is done based on the corresponding degrees of similarities. Table 5 shows the ranking position of the factors in influencing the students in choosing their MSc Program.

From Table 5, the respondents were strongly influenced by their *Academic background* (F_1), *Interest toward courses offered by Program X* (F_2), *Teaching quality* (F_5) and *Family support* (F_8). They

Table 4: Similarity Degrees between $\widetilde{F_i}$ and L_k.

Factor	Similarity Degree, $S_{ik}(\widetilde{F_i}, L_k)$							Group Preference
$\widetilde{F_i}$	L_1	L_2	L_3	L_4	L_5	L_6	L_7	Rating
$\widetilde{F_1}$	0.5359	0.5662	0.6318	0.7232	0.8455	**0.9993**	0.9086	Strongly Agree
$\widetilde{F_2}$	0.5568	0.5896	0.6610	0.7618	0.8987	**0.9341**	0.8543	Strongly Agree
$\widetilde{F_3}$	0.5951	0.6328	0.7158	0.8354	**0.9971**	0.8430	0.7774	Agree
$\widetilde{F_4}$	0.5931	0.6305	0.7130	0.8315	**0.9974**	0.8469	0.7808	Agree
$\widetilde{F_5}$	0.5605	0.5938	0.6664	0.7688	0.9086	**0.9236**	0.8455	Strongly Agree
$\widetilde{F_6}$	0.5839	0.6201	0.6996	0.8134	**0.9714**	0.8666	0.7975	Agree
$\widetilde{F_7}$	0.6909	0.7422	0.8591	**0.9653**	0.8091	0.7046	0.6582	More or less Agree
$\widetilde{F_8}$	0.5632	0.5968	0.6702	0.7739	0.9156	**0.9164**	0.8395	Strongly Agree
$\widetilde{F_9}$	0.6214	0.6626	0.7543	0.8882	**0.9309**	0.7952	0.7366	Agree
$\widetilde{F_{10}}$	0.5667	0.6007	0.6750	0.7804	**0.9248**	0.9075	0.8320	Agree

Table 5: Final Linguistic Ratings and Ranking of Influencing Factors.

Ranking Position	Influencing Factors (F_i)	Group Preference Rating	Similarity Degree
1	Academic background (F_1)	Strongly Agree	0.9993
2	Interest toward courses offered by Program X (F_2)	Strongly Agree	0.9341
3	Teaching quality (F_5)	Strongly Agree	0.9236
4	Family support (F_8)	Strongly Agree	0.9164
5	Environment and facilities provided by university (F_4)	Agree	0.9974
6	Program X reputation (F_3)	Agree	0.9971
7	Affordable fees (F_6)	Agree	0.9714
8	Peer influence (F_9)	Agree	0.9309
9	Career opportunity related to Program X (F_{10})	Agree	0.9248
10	Scholarship availability (F_7)	More or less Agree	0.9653

also agreed that factors such as *Program X reputation* (F_3), *Environment and facilities provided by the University* (F_4), *Affordable fees* (F_6), *Peer influence* (F_9) and *Career opportunity related to Program X* (F_{10}) did play a role in influencing them into choosing the MSc program. The respondents were more or less agreed that *Scholarship availability* (F_7) had also influenced them in the selection. This factor turned out to be the least influencing factor as compared to the rest of other factors. Overall, the ranking position of the factors from the most to the least influence levels can be presented as $F_1, F_2, F_5, F_8, F_4, F_3, F_6, F_9, F_{10}$ and F_7. These findings could assist the management of the faculty to set appropriate measures by taking into consideration the strength of influence of these factors in order to provide better services and to promote the program in future.

4 Conclusions

In this paper, a fuzzy conjoint analysis procedure based on triangular fuzzy numbers has been presented in which triangular fuzzy numbers are integrated in the existing discrete fuzzy based conjoint method with some modifications. This allows the preference ratings to be represented in continuous form. The procedure was implemented in analyzing the preference levels of a group of postgraduate students towards factors that influence them in choosing their postgraduate program. The academic background of the respondents seems to be the most influential factor and the least influential factor is the availability of scholarship. The TFN-CAM can be used as an alternative method for applications that involve analyzing human preference levels on factors (or attributes) as well as for ranking of factors (or attribute) defined on continuous scale. For further research, depending on the input data, other variants of fuzzy numbers such as trapezoidal or Gaussian fuzzy numbers could also be used to represent the linguistic terms. Other suitable similarity functions could also be employed in calculating the degree of similarity between compared fuzzy numbers depending on the type of fuzzy numbers being used.

Acknowledgement The authors would like to acknowledge the Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Shah Alam, Selangor for the financial support received.

Conflicts of Interest The authors declare no conflict of interest.

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