Fuzzy number conjoint method to analyse students’ perceptions on the learning of calculus

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Abstract: The fuzzy conjoint method (FCM) based on fuzzy set has been applied in many areas such as education, management and business. However, the FCM uses the fuzzy set to define the membership function of the linguistic values, which the score of weight and overall attribute for different degrees of confidence that cannot be obtained. Besides, the fuzzy set which is in discrete form does not clearly represent human judgement. Thus, in this study, a fuzzy number conjoint method (FNCM) based on triangular fuzzy number is developed. The fuzzy similarity measure based on distance, height and area was used in the procedure. The FNCM was implemented to analyse students’ perception in the learning of calculus at one selected government institution in Selangor, Malaysia. The study involved a set of 5-options Likert scale questionnaire which is in linguistic values of strongly disagree, disagree, indifferent, agree and strongly agree. All the questions were on various items related to the learning of calculus. The findings showed that overall, students agreed at above 0.85 degree of similarity that they perceived positively in the learning of calculus. The developed FNCM with a degree of agreement for each linguistic value can successfully evaluate the students’ perceptions in the learning of calculus. This study will be as assistance and guidance to academicians and mathematics educators to enhance students’ achievement in the learning of calculus.

Keywords: calculus; fuzzy conjoint; perceptions; triangular fuzzy number; undergraduates

1. Introduction
Calculus is the basic entry point for anyone studying physics, chemistry, biology, economics, finance, or actuarial science. Because of its importance in such a wide range of discipline and its size of undergraduate’s enrolment, there are many studies conducted by researchers in mathematics education to investigate students’ attitudes, beliefs and perceptions towards the learning of calculus (Carlson & Madison, 2015; Mohanty & Parida, 2016; Rajagukguk, 2017; Sahin, Cavlazoglu & Zeytuncu, 2015). Some of the findings in previous research indicated that students enrolled in calculus classes have a very superficial and incomplete understanding of many basic concepts in calculus. Also, studies have found that students’ perceptions of the utility of what they have learned in calculus have affected their motivation, interest, and achievement (Liang, 2009).

Conjoint analysis is a technique used to measure preferences or relative importance given to various attributes of a product. Conjoint analysis method was first developed by Luce and Tukey (1964)
who is a mathematical psychologist (Caruso et al., 2009). The ability to capture and quantify the relative importance of the real world preferences issue has led conjoint analysis to be one of the widely used techniques for measuring and predicting consumer preference. However, human judgment is subjective, vague and imprecise in nature. Perceptions, opinion or satisfaction level depends on individual’s feeling. Fuzzy set theory proposed by Zadeh (1965) provides an excellent framework for describing preferences. Thus, Turksen and Willson (1994) proposed the fuzzy conjoint model (FCM) for measuring preference under fuzzy environment.

The FCM analysis provides each attribute with its degree of similarity to reflect the level of agreement (Abdullah et al., 2011). Due to the successfulness in representing the preferences in uncertain environment, the FCM has been applied in various areas such as in education, management and business. Lazim and Osman (2009) has applied the FCM in measuring teachers’ beliefs in Mathematics and in their study, they found that the attribute ‘drills and practice is one the best way in the learning of Mathematics’ has the highest degree of similarity with level of strongly agree. Abdullah et al. (2011) has applied the FCM in analysing students’ perceptions in the learning of algebra using computer algebra system. The study found that students viewed a certain level of agreement in order to provide greater opportunities for learning algebra using technology environment.

In another study conducted by Tawil et al. (2011), also used the FCM in measuring the perceptions of residents on service charge in Malaysian high-rise residential management. The findings of the study showed the residents highly agree that the payment counter should be open on weekends as the highest rank. Abiyev et al. (2016) has used the FCM in measuring the job satisfaction of hotel employees. The study ranked the feeling of accomplishment of the job as the best. Sarala and Kavitha (2017) has also applied the FCM in measuring students’ expectation and teachers’ belief in the learning of Mathematics. The study found that students ranked the conceptual understanding while teachers ranked drills and practice in the learning of Mathematics as the first priority. The teachers’ beliefs in the learning of Mathematics are consistent with Sarala and Kavitha’s (2017) and Lazim and Osman’s (2009) studies. Similarly, Yaakub et al. (2018) also used the FCM in measuring consumers’ opinion on cycling transport. The study shows that consumers preferred the bicycle routes located nearby to their workplace, schools, higher education and recreational areas.

However, the above-mentioned FCM used the fuzzy sets to define the membership function of the linguistic values, in which the $\alpha$-cut of the fuzzy numbers for different values of $\alpha \in [0, 1]$ cannot be obtained. This means that the score of weight and overall attribute for different degree of confidence cannot be obtained. Besides, the fuzzy set which is in discrete form does not represent well in handling human judgement. The fuzzy numbers with continuous membership function can explain the fuzzy nature of human abstract perceptions and language semantic representation (Wang, 2014). Thus, in this paper, the FNCM based on triangular fuzzy number is developed. The FNCM is implemented in analysing undergraduate students’ perceptions in the learning of calculus at a higher institution in Selangor, Malaysia. The rest of the paper is organised as follows: preliminaries on triangular fuzzy numbers are presented in Section 2 and followed by the procedure of FNCM in Section 3. Next, Section 4 presents the implementation of FNCM in analysing students’ perceptions in the learning of calculus. Section 5 compares the ranking of FNCM with fuzzy set conjoint method (Turksen & Willson, 1994) and finally, Section 6 concludes the paper.

2. Preliminaries
This section review some basic definitions of triangular fuzzy numbers and the $\alpha$-cut of the fuzzy numbers.

A triangular fuzzy number (TFN) as shown in Figure 1, denotes as $\tilde{P} = (p, q, r)$ has a membership function defined as
\[ \mu_{\tilde{P}}(x) = \begin{cases} \frac{x-p}{q-p}, & p \leq x \leq q \\ \frac{r-x}{r-q}, & q \leq x \leq r \\ 0, & \text{otherwise} \end{cases} \]

Figure 1. Triangular fuzzy number, P

The \( \alpha \)-cut of a fuzzy number \( \tilde{P} \) in the universe of discourse \( X \) and denotes as \( \tilde{P}_\alpha \) is defined as

\[ \tilde{P}_\alpha = \{ x \in X : \mu_{\tilde{P}}(x) \geq \alpha \} = [\alpha_1^{(0)}, \alpha_2^{(0)}] \]

whereby \( \alpha \in [0,1] \).

3. The Procedure of FNCM

This section presents the procedure of fuzzy number conjoint method (FNCM). The FNCM considers a questionnaire with \( N \) attributes, \( s \) linguistic values of preferences and \( V_j (j = 1, 2, 3, \ldots, s) \) denotes as the \( j \)-th linguistic values of preferences. For \( s = 5 \), the linguistic values are denoted as \( V_1, V_2, V_3, V_4 \) and \( V_5 \), which represent values of preferences such as strongly disagree, disagree, indifferent, agree and strongly agree respectively. While for \( s = 7 \), the linguistic values are denoted as \( V_1, V_2, V_3, V_4, V_5, V_6 \) and \( V_7 \), which represent values of preference such as very strongly disagree, strongly disagree, disagree, indifferent, agree, strongly agree and very strongly agree respectively. The membership function of the linguistic values is defined in the form of triangular fuzzy numbers.

The procedure of FNCM consists of several steps as follows:

Step 1: Collect respondents’ opinions for \( N \) attributes based on \( s \) linguistic values.

Step 2: Calculate the number of respondents’ opinion denotes as \( f_{ij} \) whereby \( f_{ij} \) represents the number of respondents’ opinion for attribute \( i \) with linguistic values \( V_j \).

Step 3: Calculate the weight of attribute \( i \) with linguistic values \( V_j \) as

\[ W_{ij} = \frac{f_{ij}}{\sum_{j=1}^{s} f_{ij}}. \quad (1) \]

Step 4: Calculate the overall membership function of attribute \( i \) as

\[ A_i = \sum_{j=1}^{s} W_{ij} V_j \quad \text{for } i = 1, 2, 3, \ldots, N \]

whereby \( V_j \) is the \( j \)-th linguistic value and \( A_i \) is in triangular fuzzy number form.

Step 5: Calculate the degree of similarity between triangular fuzzy numbers \( A_i = (a_1, a_2, a_3) \) and \( V_j = (b_1, b_2, b_3) \) using the similarity measures from Patra and Mondal (2015) defined as

\[ S(A_i, V_j) = \left[ 1 - \frac{1}{4} \{ |a_1 - b_1| + 2|a_2 - b_2| + |a_3 - b_3| \} \right] \times \left[ 1 - \frac{1}{2} |ar(A_i) - ar(V_j)| \right] \]

whereby \( ar(A) = \frac{a_3-a_1}{2} \).

Step 6: Compare the degree of similarity for attribute \( A_i \) and select the maximum degree of similarity.
of attribute \( A_i \). The maximum degree of similarity of attribute \( A_i \) represents the degree of agreement of attribute \( A_i \).

Step 7: State the linguistic values related to the maximum degree of similarity of attribute \( A_i \).

Step 8: Rank the maximum degree of similarity in Step 5 from the most preferred (highest maximum degree of similarity) to the least preferred (lowest maximum degree of similarity).

4. The Implementation of FNCM in Analysing Students’ Perceptions

The population for the study were undergraduate students majoring in Mathematics at one selected government institution in Selangor, Malaysia. Using the convenience sampling, a total of 125 undergraduate Mathematics students from various semesters participated in this study. 52 students were from the second semester, 33 students were from the fourth semester, 21 students were from the sixth semester and 19 students were from the eighth semester. A set of 5-options Likert scale questionnaire in which all the questions were on various items related to the learning of calculus were distributed to the students using the Google form. All the collected data from the Google form were composed into an Excel sheet. The data in the Excel sheet were then transferred into numerical form and were then analysed using the FNCM as presented in the following steps:

Step 1: The questionnaire consists of 14 attributes with five linguistic values such as strongly disagree \((V_1)\), disagree \((V_2)\), indifferent \((V_3)\), agree \((V_4)\) and strongly agree \((V_5)\). The linguistic values \(V_1\) to \(V_5\) in triangular fuzzy numbers form are shown in Table 1.

| Linguistic values              | Triangular fuzzy number |
|-------------------------------|-------------------------|
| Strongly Disagree \((V_1)\)   | (0,0,2)                 |
| Disagree \((V_2)\)            | (0,2,4)                 |
| Indifferent \((V_3)\)         | (3,5,7)                 |
| Agree \((V_4)\)               | (6,8,10)                |
| Strongly Agree \((V_5)\)      | (8,10,10)               |

Step 2: The frequency of respondents’ preferences \( f_{ij} \) of each attribute \( i \) for each linguistic values \( V_j \) is calculated and shown in Table 2.

| Attribute | Strongly Disagree \((V_1)\) | Disagree \((V_2)\) | Indifferent \((V_3)\) | Agree \((V_4)\) | Strongly Agree \((V_5)\) | Total |
|-----------|-------------------------------|--------------------|-----------------------|-----------------|--------------------------|-------|
| \( Q_1 \) | 1                             | 3                  | 26                    | 59              | 36                       | 125   |
| \( Q_2 \) | 2                             | 1                  | 15                    | 72              | 35                       | 125   |
| \( Q_3 \) | 0                             | 3                  | 30                    | 55              | 37                       | 125   |
| \( Q_4 \) | 1                             | 1                  | 17                    | 71              | 35                       | 125   |
| \( Q_5 \) | 2                             | 5                  | 27                    | 69              | 22                       | 125   |
| \( Q_6 \) | 3                             | 2                  | 31                    | 61              | 28                       | 125   |
| \( Q_7 \) | 1                             | 5                  | 33                    | 65              | 21                       | 125   |
| \( Q_8 \) | 1                             | 3                  | 24                    | 69              | 28                       | 125   |
| \( Q_9 \) | 2                             | 7                  | 31                    | 69              | 17                       | 125   |
| \( Q_{10} \) | 3                             | 6                  | 45                    | 56              | 15                       | 125   |
| \( Q_{11} \) | 1                             | 1                  | 17                    | 66              | 40                       | 125   |
| \( Q_{12} \) | 2                             | 2                  | 30                    | 68              | 23                       | 125   |
| \( Q_{13} \) | 1                             | 1                  | 34                    | 68              | 21                       | 125   |
| \( Q_{14} \) | 1                             | 1                  | 14                    | 76              | 33                       | 125   |
Based on Table 2, for attribute $Q_1$, one student has chosen strongly disagree ($V_1$) (0.8%), three students have chosen disagree ($V_2$) (2.4%), twenty-six students have chosen neutral ($V_3$) (20.8%), fifty-nine students have chosen agree ($V_4$) (47.2%) and thirty-six students have chosen strongly agree ($V_5$) (28.8%). Thus, $f_{11} = 0, f_{12} = 3, f_{13} = 26, f_{14} = 59$ and $f_{15} = 36$.

Step 3: The weight, $W_{ij}$ for attribute $i$ related to linguistic values, $V_j$ is calculated using Eq. (1) and is shown in Table 3.

| Attribute | Strongly Disagree ($V_1$) | Disagree ($V_2$) | Indifferent ($V_3$) | Agree ($V_4$) | Strongly Agree ($V_5$) |
|-----------|---------------------------|-----------------|-------------------|---------------|----------------------|
| $Q_1$     | 0.008                     | 0.024           | 0.208             | 0.472         | 0.288                |
| $Q_2$     | 0.016                     | 0.008           | 0.12              | 0.576         | 0.28                 |
| $Q_3$     | 0                         | 0.024           | 0.24              | 0.44          | 0.296                |
| $Q_4$     | 0.008                     | 0.008           | 0.136             | 0.568         | 0.28                 |
| $Q_5$     | 0.016                     | 0.04            | 0.216             | 0.552         | 0.176                |
| $Q_6$     | 0.024                     | 0.016           | 0.248             | 0.488         | 0.224                |
| $Q_7$     | 0.008                     | 0.04            | 0.264             | 0.52          | 0.168                |
| $Q_8$     | 0.008                     | 0.024           | 0.192             | 0.552         | 0.224                |
| $Q_9$     | 0.016                     | 0.056           | 0.248             | 0.544         | 0.136                |
| $Q_{10}$  | 0.024                     | 0.048           | 0.36              | 0.448         | 0.12                 |
| $Q_{11}$  | 0.008                     | 0.008           | 0.136             | 0.528         | 0.32                 |
| $Q_{12}$  | 0.016                     | 0.016           | 0.24              | 0.544         | 0.184                |
| $Q_{13}$  | 0.008                     | 0.008           | 0.272             | 0.544         | 0.168                |
| $Q_{14}$  | 0.008                     | 0.008           | 0.112             | 0.608         | 0.264                |

Step 4: The overall membership function of attribute $i$, $A_i$ is calculated using Eq. (2) and is shown in Table 4.

| TrFN $A_i$ | Overall membership function, $A_i$ |
|------------|-----------------------------------|
| $A_1$      | (5.76, 7.774, 9.168)              |
| $A_2$      | (6.056, 8.024, 9.464)             |
| $A_3$      | (5.728, 7.728, 9.136)             |
| $A_4$      | (6.056, 8.04, 9.48)               |
| $A_5$      | (5.368, 7.336, 8.984)             |
| $A_6$      | (5.464, 7.416, 8.968)             |
| $A_7$      | (5.256, 7.24, 8.904)              |
| $A_8$      | (5.68, 7.664, 9.216)              |
| $A_9$      | (5.096, 7.064, 8.792)             |
| $A_{10}$   | (4.728, 6.68, 8.44)               |
| $A_{11}$   | (6.136, 8.12, 9.48)               |
| $A_{12}$   | (5.456, 7.424, 9.056)             |
| $A_{13}$   | (5.424, 7.408, 9.072)             |
| $A_{14}$   | (6.096, 8.08, 9.552)              |
Step 5: The degree of similarity between $A_i$ and $V_j$, $S(A_i, V_j)$ based on Patra and Mondal (2015) are shown in Table 5.

Table 5. The similarity degree $S(A_i, V_j)$

| TrFN $A_i$ | $V_1$ | $V_2$ | $V_3$ | $V_4$ | $V_5$ |
|------------|-------|-------|-------|-------|-------|
| $A_1$      | 0.279 | 0.433 | 0.729 | 0.946*| 0.782 |
| $A_2$      | 0.252 | 0.405 | 0.7   | 0.970*| 0.810 |
| $A_3$      | 0.282 | 0.435 | 0.731 | 0.943*| 0.780 |
| $A_4$      | 0.25  | 0.404 | 0.699 | 0.969*| 0.81  |
| $A_5$      | 0.311 | 0.47  | 0.77  | 0.917*| 0.744 |
| $A_6$      | 0.306 | 0.462 | 0.759 | 0.92* | 0.752 |
| $A_7$      | 0.32  | 0.48  | 0.777 | 0.908*| 0.734 |
| $A_8$      | 0.283 | 0.429 | 0.736 | 0.944*| 0.775 |
| $A_9$      | 0.335 | 0.496 | 0.793 | 0.893*| 0.719 |
| $A_{10}$   | 0.37  | 0.533 | 0.831 | 0.857*| 0.683 |
| $A_{11}$   | 0.245 | 0.397 | 0.692 | 0.962*| 0.818 |
| $A_{12}$   | 0.303 | 0.461 | 0.758 | 0.925*| 0.753 |
| $A_{13}$   | 0.304 | 0.463 | 0.76  | 0.924*| 0.75  |
| $A_{14}$   | 0.246 | 0.399 | 0.695 | 0.968*| 0.814 |

* The maximum degree of similarity

Steps 6-7: Based on Table 5, the maximum degree of similarity of $A_i$ is calculated as follows: max(0.279, 0.433, 0.729, 0.946, 0.782) = 0.946. Since 0.946 is the degree of similarity between $A_1$ and $V_4$, thus 0.946 falls under linguistic value $V_4$ (agree). In similar manner, the maximum degree of similarity and linguistic values for $A_i$ ($i = 1, 2, ..., 14$) are shown in Table 6.

Table 6. Maximum similarity of $A_i$

| TrFN $A_i$ | Maximum similarity | Linguistic Value | Ranking |
|------------|--------------------|------------------|---------|
| $A_1$      | 0.946              | Agree            | 5       |
| $A_2$      | 0.970              | Agree            | 1       |
| $A_3$      | 0.943              | Agree            | 7       |
| $A_4$      | 0.969              | Agree            | 2       |
| $A_5$      | 0.917              | Agree            | 11      |
| $A_6$      | 0.92               | Agree            | 10      |
| $A_7$      | 0.908              | Agree            | 12      |
| $A_8$      | 0.944              | Agree            | 6       |
| $A_9$      | 0.893              | Agree            | 13      |
| $A_{10}$   | 0.857              | Agree            | 14      |
| $A_{11}$   | 0.962              | Agree            | 4       |
| $A_{12}$   | 0.925              | Agree            | 8       |
| $A_{13}$   | 0.924              | Agree            | 9       |
| $A_{14}$   | 0.968              | Agree            | 3       |

Step 8: The maximum degree of similarity in Table 6 is ranked with the highest maximum degree of similarity as the most preferred to the lowest maximum degree of similarity as the least preferred. The ranking is shown in Table 6.
Based on Table 6, the students agreed with all the attributes at more than 0.85 degree of similarity. The second attribute with ‘agree’ at 0.970 degree of similarity is the highest rank. This shows that students gave the highest ranking to agree that calculus course will be useful to them in their future profession (0.970 degree of similarity). The fourth attribute is ranked third which students agreed that calculus training is relevant to their field of study (0.969 degree of similarity). The 7th attribute is ranked third lowest which students agreed that calculus is too oriented to be much use in the future (0.908 degree of similarity). The 9th attribute is ranked second lowest which students agreed that studying calculus can fill up their leisure time (0.893 degree of similarity). The least preferred attribute is the 10th attribute which students agreed that calculus plays an important role in their daily life (0.857 degree of similarity).

5. Comparing the ranking of FNCM with Fuzzy Set Conjoint Method
This study used the Spearman’s rank correlation to compare the ranking of FNCM with fuzzy set conjoint method (Turksen & Willson, 1994). The Spearman rank correlation coefficient is calculated using Eq. (4).

\[ r_s = 1 - \frac{6 \sum_{i=1}^{n} d_i^2}{n(n^2-1)} \]  

whereby \( d_i \) is the difference in ranking and \( n \) is the sample size.

| \( A_i \) | Fuzzy set conjoint method | Proposed FNCM | Differences (\( d_i \)) |
|---|---|---|---|
| \( A_1 \) | 4 | 5 | -1 |
| \( A_2 \) | 5 | 1 | 4 |
| \( A_3 \) | 2 | 7 | -5 |
| \( A_4 \) | 3 | 2 | 1 |
| \( A_5 \) | 10 | 11 | -1 |
| \( A_6 \) | 12 | 10 | 2 |
| \( A_7 \) | 11 | 12 | -1 |
| \( A_8 \) | 7 | 6 | 1 |
| \( A_9 \) | 13 | 13 | 0 |
| \( A_{10} \) | 14 | 14 | 0 |
| \( A_{11} \) | 1 | 4 | -3 |
| \( A_{12} \) | 9 | 8 | 1 |
| \( A_{13} \) | 6 | 9 | -3 |
| \( A_{14} \) | 8 | 3 | 5 |

The null hypothesis is ‘The two rankings are not similar’. The critical values of Spearman’s rank correlation from Daniel (1990), for sample size \( n = 14 \), with level of significance \( \alpha = 0.05 \) is 0.464. Based on the differences (\( d_i \)) of ranking in Table 7 and Eq. (4), produces \( r_s = 0.7934 \). The value of \( r_s \) is greater than the critical value 0.464, which indicates that the null hypothesis is rejected. This concludes that the difference in the ranking results is statistically insignificant and thus, the ranking in degree of agreement based on FNCM is reliable.

6. Conclusion
In this paper, the developed FCM based on triangular fuzzy numbers is used to analyse students’ perceptions on the learning of calculus. The method does not only provide the conclusion of ‘agree’ but also gives a degree of similarity value to represent the strength of ‘agree’. Students seemed to agree to all the attributes with ranking \( A_2 > A_4 > A_{10} > A_{11} > A_1 > A_5 > A_3 > A_{12} > A_6 > A_5 > A_7 > A_9 > A_{10} \). The results show that students need more exposure on the usage of calculus in their daily life by contextualizing calculus with everyday examples to enhance conceptual learning. This study will be as assistance and guidance to academicians and mathematics educators to further improve the quality of calculus learning.
Further applications of FCM especially in social sciences studies could possibly be explored and perhaps would offer more viable and meaningful results.

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