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Discover Teacher's Knowledge on Neuroscience and Mathematics Learning Relevancy via Fuzzy Conjoint Analysis: Study Case in Southern Malaysia

Bakar, M. A. A.*[1], Ghani, A. T. A.[1], and Abdullah, M. L.[1]

[1]*Faculty of Computer Science and Mathematics, Universiti Malaysia Terengganu, 21030 Kuala Nerus, Terengganu, Malaysia*

E-mail: mohamadariffin6299@gmail.com
**Corresponding author*

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Abstract

This paper aims to obtain and analyze teachers' knowledge and perspectives on neuroscience and mathematics learning relevancy by using the fuzzy conjoint analysis (FCA) method. Due to a wealth of study in the neuroscience discipline but limited exposure to its application in teaching, teachers have a limited understanding of how neuroscience relates to mathematics learning. Therefore, this study employs a survey to investigate and narrow down this problem using a more precise analysis method. The FCA methodology serves as an alternative to perception surveys that utilize a quantitative approach through purposive convenience sampling. The study involved 53 mathematics teachers from a district in the southern state of Johor, Malaysia. The findings of the similarity degree analysis reveal a gap in knowledge regarding neuroscience among teachers but embrace a supportive stance towards neuroscience aspects and its integration into mathematics learning. The study's results emphasize the need for teachers to enhance their understanding of literacy and neuroscience practices to improve teaching and learning, particularly in mathematics. According to teachers' perspectives, neuroscience factors such as activation, metacognition, executive function, and working memory impact students' learning abilities. Additionally, to further advance the educational system, the curriculum and pedagogy should be transformed by incorporating principles from neuroscience.

Keywords: fuzzy conjoint analysis; triangular fuzzy number; neuroscience; mathematics learning.

1 Introduction

The discovery of neuroscience forms a new dimension in the field of research [30]. This development can be seen in various fields such as medicine [5], technology, engineering [28] and so on including in the field of education [30]. However, research in the field of education is very limited [14]. In fact, according to Hohnen and Murphy [21], not many educators are involved with neuroscience studies in the field of education. Neuroscience describes the functionality of parts of the brain and nerves and their relationships form mechanisms and networks that affect cognitive structure [14] and behaviour [30]. Indirectly, it is related to the individual learning process [24]. Many neuroscience studies are carried out to show the relationship between neuroscience and individual learning ability [28].

According to researchers, brain mechanisms play a crucial role in mathematics learning by influencing students' emotions [9], behavioral [18, 24], and cognitive coordination [37, 38]. However, there is a lack of understanding regarding neuroscience [4] and its impact on students' learning and capabilities [15, 36]. Researcher [21] point out that teachers struggle to produce effective interventions due to a lack of understanding of how the brain functions, its nature, and the potential involvement of specific components and regions in the learning process. Currently, there is a shortage of neuroscience research related to learning in practice [4]. Research in neuroscience is mostly concerned with problems related to brain development, learning illnesses such anxiety, number literacy difficulty and dyslexia, and autism spectrum disorder (ASD) [3]. Functional magnetic resonance imaging (fMRI), positron emission topography (PET), and Electroencephalography (EEG) are technologically assisted diagnostic studies that predate the establishment of neuroscience studies on typical learning issues [30]. This situation highlights the missed opportunity for education researchers to explore neuroscience mechanisms that have a stronger connection to effective learning, particularly in evaluating the potential cognitive [14] and behavioral functions [28] associated with specific brain regions.

A neuro mechanism is defined as a biological regulating mechanism based on the anatomy and function of the brain and nervous system [10]. As a result, it is ideal for consumption as a measurement component and data source while evaluating a student's mathematics learning circumstance. Typically, it will include behavioural and cognitive processes before, during, and afterwards the learning activity. The above statement is based on observations from research and debates by several researchers, who demonstrate the effectiveness of neuroscience theory [12], knowledge [21], methods [24], practices, and medications on the learning process [41]. According to Mahmood et al. [25], Malaysia is still behind in its research of neuroscience, particularly in terms of learning in the classroom.

Meanwhile, Hamid et al. [1] proposed that academics, industry, and educators prioritise the use of neuroscience in their respective fields of study. This demonstrates an impediment in the implementation of neuroscience and educational study in Malaysia, particularly in the study of learning abilities. As reported by Hamid et al. [1], the Malaysian Academic of Science report from 2017 identified only 150 professionals in diverse sectors of neuroscience. This amount is insufficient to meet the demands of the rapidly evolving fields of neurotechnology and neuroscience, including neuroeducation. As a result, the applicability and significance of neuroscience for educational purposes must be discovered and conveyed [14]. This situation necessitates a preliminary examination of the teachers' knowledge and perspectives on neuroscience practice. What is the level of understanding among teachers, and do they hold differing perspectives and views on the relevance of neuroscience and mathematics learning? Bakar and Ab Ghani [6] found that teachers had limited exposure to neuroscience literacy and lacked practice in neuroscience-based teaching and learning. As a result, empirical research and unambiguous evidence are required to support this notion.

This study deployed a fuzzy conjoint model for collecting and evaluating teachers' perspectives and level of knowledge on neuroscience and the relevance of mathematics education as a way to address and narrow the gap. In order to go over the circumstances and make analyses and decisions, the present research offers more reliable data method of analysis. This paper's primary contributions include:

1. Reviewing teachers' perceptions based on the level of teachers' knowledge and perspectives on neuroscience and mathematics learning relevancy.
2. Illustrates how the triangular fuzzy number-based conjoint algorithm can be implemented and is appropriate for interpreting perception survey data.

As a result, the next section will clarify some of the mentioned concepts. The methodology section will then cover the study's design and procedure, as well as provide an overview of the FCA procedure and explain its use in analyzing perception survey data. The predicted results of the data analysis will be presented in the results section, followed by the discussion section, which will address the conclusions, results, and efficacy.

2 Preliminaries

The most important terms, definitions, and procedures pertaining to the investigation are provided in this section.

2.1 Neuroscience and mathematics learning

Researchers identify various factors that affect students' cognitive [14], psychological [32], and behavioral learning [27] in mathematics. These factors include belief, perception [2], motivation, retention [4], cognitive functions, metacognitive skills, thinking abilities, problem-solving ability [8], curriculum, delivery, syllabus [11], physical education activities [25], and learning methods [16]. De Smedt et al. [14] suggest that a greater understanding of neuroscience can help with the specific treatment of mathematics learning activities. Furthermore, researchers argue that understanding how the brain works [12], its anatomy [21], functioning [33], and mechanisms [35] specific to learning needs can help students develop positive self-esteem, reduce mathematics anxiety and boost confidence. This, in turn, can help teachers create a conducive atmosphere for learning, where students feel a sense of belonging and authority over their mathematics learning. Researchers have reported that teachers exposed to neuroscience literacy can improve students' attributes such as motivation [11] , self-determination [12] , efficacy [14] , goal setting [19] , thinking skills [24] and self-regulation [35] .

Moreover, neuroscience can enhance the effectiveness of students' understanding of mathematics. Teachers can provide resources, content, materials, and delivery techniques that are tailored to their students' brain plasticity capacities, memory, and thought processes. Researchers describe how executive function of brain is develops when content [2, 35] and delivery techniques [11, 14] focus on student neural activity. Organizational [21] and classroom settings [32, 34] that incorporate neuroscience information can significantly impact mathematics learning. Additionally, curriculum [11] and learning resources [42] that are suitable and effective for brain development can also influence outcomes. In this regard, Fathiazar et al. [16] and Cherrier et al. [11] demonstrate that using technology can further enhance its impact on students. By implementing neuroscience-based improvements to classroom settings, techniques, and learning materials, scaffolding, networking, and cooperation can be improved, as well as aspects related to social thinking and the learning environment [25].

Additionally, incorporating neuroscience practices into the mathematics learning setting, has the potential to promote reasoning [25], questioning [16], computational abilities [26] and critical thinking [34]. When students employ neuroscience to coordinate their thinking, they can process learning or mathematical content logically and analytically, as well as have immediate implications on emotion, attention, generation, and spacing. This logical recognition of flaws and strengths [14], faults, and inaccuracies [34] can help students overcome mathematics tasks.

2.2 Triangular Fuzzy Number and Similarity Degree

Triangular fuzzy numbers are fuzzy sets composed of three parameters: lower bound, upper bound, and mode. These parameters establish a range of values using a triangular membership function that measures the degree of membership based on the value closest to the mode. Triangular fuzzy numbers can be used in survey analysis to represent uncertain or imprecise perceptions, preferences, or opinions of respondents. This effectively models uncertainty. The similarity degree value, which compares the degree of overlap between membership functions, is utilized to enhance efficiency and assist in identifying patterns in survey data analysis.

Definition 2.1. [43] *A fuzzy set M within X is a collection of ordered pairs with a value of, $M = \{(x, \mu(x)); x \in X\}$ in which $\mu(x)$ denotes the component x's degree of membership in the universe X.*

Remark 2.1. *Variables with linguistic values use language to convey what they stand for. It's commonly referred to as a linguistic term and shows an example of a fuzzy set constructed in the linguistics context where the variable is defined.*

Remark 2.2. *Fuzzy numbers are generalised fixed real numbers. Each value in the set has a weight between 0 and 1, denoting that they are in a connected state. Fuzzy numbers are then a subset of the real line's normalised fuzzy set.*

Definition 2.2. [43] *The membership function generates a triangular fuzzy number (TFN), which is a fuzzy numerical representation expressed as, $M = (m_1, m_2, m_3)$,*

$$\mu_m(x) = \begin{cases} \dfrac{x - m_1}{m_2 - m_1}, & x \in |m_1, m_2|, \\ \dfrac{x - m_3}{m_2 - m_3}, & x \in |m_2, m_3|, \\ 0, & \textit{otherwise}. \end{cases} \tag{1}$$

Give p being a scalar and notify that, $M = (m_1, m_2, m_3)$ and $N = (n_1, n_2, n_3)$ be a pair of triangular fuzzy numbers. The following is our definition of fuzzy number equality functions and arithmetic operations:

Definition 2.3. [39] *For triangular fuzzy numbers $M = (m_1, m_2, m_3)$ and $N = (n_1, n_2, n_3)$, the arithmetic operations on the triangular fuzzy numbers are defined as follows:*

(*i*) *Addition*(+):

$$M + N = (m_1 + n_1, m_2 + n_2, m_3 + n_3). \tag{2}$$

(*ii*) *Subtraction*(−):

$$M - N = (m_1 - n_1, m_2 - n_2, m_3 - n_3). \tag{3}$$

(*iii*) *Multiplication*(×):

$$p \times M = (pm_1, pm_2, pm_3), \qquad p \in \mathbb{R}, \qquad p \geq 0, \tag{4}$$

$$M \times N = (m_1 n_1, m_2 n_2, m_3 n_3). \tag{5}$$

(*iv*) *Division*(÷):

$$M^{-1} = (m_1, m_2, m_3)^{-1} \cong \left(\frac{1}{m_3}, \frac{1}{m_2}, \frac{1}{m_1}\right), \qquad m_1 > 0, \qquad m_2 > 0, \qquad m_3 > 0,$$

$$M \div N \cong \left(\frac{m_1}{n_3}, \frac{m_2}{n_2}, \frac{m_3}{n_1}\right), \qquad m_1 \geq 0, \qquad n_1 \geq 0. \tag{6}$$

Definition 2.4. [22] *We can determine the degree of similarity between M and N by utilising the resulting formula:*

$$Sim(M, N) = \frac{1}{1 + d(M, N)}, \tag{7}$$

where $d(M, N) = |P(M) - P(N)|$ *with* $P(M) = \dfrac{m_1 + 4m_2 + m_3}{6}$ *and* $P(N) = \dfrac{n_1 + 4n_2 + n_3}{6}$.

3 Methodology

The Fuzzy Conjoint Analysis (FCA) procedure is presented in this section. It merges a triangular fuzzy number (TFN) architecture with the current fuzzy conjoint analysis method. The TFN format is used to define and express linguistic terms. The FCA procedure is designed to acquire and analyze teachers' knowledge and perspective on the significance of neuroscience in mathematics learning. This process consists of two primary stages: consolidating the teacher's knowledge and expertise in neuroscience literacy, and evaluating the teacher's perspective on the relevance of neuroscience and mathematics learning.

3.1 Fuzzy conjoint analysis

The procedure for FCA in analyzing the aggregation of teachers' knowledge and skills about neuroscience literacy, as well as assessing their perspective on the relevance of neuroscience and mathematics learning, can be summed up as the following:

Procedure 1: Identify the attribute set, $F = \{F_i\}$, $(i = 1, 2, \ldots, n)$ that will be used as input data in the studied environment.

Procedure 2: Define appropriate linguistic values for evaluation based on the Triangular Fuzzy Number (TFN) framework, $L_j = (l_1^j, l_2^j, l_3^j)$ where $j = 1, 2, \ldots, k$.

Procedure 3: Collect the number of responses, r_{ij} for each linguistic value, $L_j, j = 1, 2, \dots, k$ assigned to the attributes, F_i.

Procedure 4: Calculate the weight of each attribute F_i with its assigned linguistic value L_j using (8):

$$w_{ij} = \frac{r_{ij}}{\sum_{j=1}^{k} r_{ij}}. \tag{8}$$

Procedure 5: Determine the overall membership function of each attribute $\widetilde{F}_i = (a_1^i, a_2^i, a_3^i)$ using (9):

$$\widetilde{F}_i = \sum_{j}^{k} w_{ij} L_j, \qquad i = 1, 2, 3, \dots, n \text{ and } j = 1, 2, 3, \dots, k. \tag{9}$$

Procedure 6: Calculate the degree of similarity between the aggregated linguistic ratings for each attribute $\widetilde{F}_i = (f_1^i, f_2^i, f_3^i), i = 1, 2, 3, \dots, n$ and the linguistic ratings, $L_j = (l_1^j, l_2^j, l_3^j)$, $j = 1, 2, 3, \dots, k$ using (10):

$$S_{ij}\left(\widetilde{F}_i, L_j\right) = \frac{1}{1 + d\left(P\left(\widetilde{F}_i\right) - P\left(L_j\right)\right)}, \quad i = 1, 2, 3, \dots, n \text{ and } j = 1, 2, 3, \dots, k, \tag{10}$$

with $P\left(\widetilde{F}_i\right) = \dfrac{f_1^i + 4f_2^i + f_3^i}{6}$ and $P\left(L_j\right) = \dfrac{l_1^j + 4l_2^j + l_3^j}{6}$.

Procedure 7: Identify the linguistic values that exhibit the highest degree of similarity. These values will reflect the group's collective evaluation of the attribute in question. Establish a priority order for the attributes based on this assessment.

3.2 Case study

A survey was carried out using a fuzzy questionnaire to gather and analyze teachers' knowledge and perspectives on neuroscience and mathematics learning relevancy. This study specifically focuses on two aspects: teachers' self-perceived knowledge level, represented by symbols $(F_1 - F_3)$, and teachers' perspectives on neuroscience and mathematics learning relevancy, represented by symbols $(F_4 - F_{11})$. Mathematics teachers in secondary schools in Pasir Gudang, Johor, Malaysia, were randomly assigned the questionnaire. A total of 53 teachers, including 20 males and 33 females, who teach mathematics and can draw upon their experiences to make choices and decisions, participated in the survey. The sampling method in this research, both random and purposive, could introduce biases, such as teachers' willingness to participate or the representation of school types or mathematics teaching experience. To address this, the researchers aimed for diversity by including teachers from various schools and backgrounds. Clear instructions were given to ensure honest responses, and anonymity was maintained to minimize social desirability bias. Table 1 below lists the attributes that were included in this survey.

Table 1: The elements of the survey concerning the perspectives and knowledge of teachers on neuroscience and their relevance of mathematics learning.

Elements	Attributes	Statement
Level of teachers'	F_1	What is your level of knowledge in the field of neuroscience?
Knowledge of neuroscience	F_2	What is the importance of neuroscience in the process of learning mathematics?
	F_3	What kind of interaction exists between students' cognitive processes and neuroscience?
Teachers' perspectives about neuroscience and mathematics learning relevancy	F_4	The way and process of thinking is the neuroscience practice
	F_5	Teachers need to have knowledge about neuroscience
	F_6	The activation of the mind affects student learning
	F_7	Executive function plays a role in the learning process
	F_8	Metacognition plays a role in the learning process
	F_9	Working memory plays a role in the learning process
	F_{10}	Teachers need to increase their knowledge about the neuroscience practice
	F_{11}	Neuroscience elements are required in assessing students' learning ability

Table 2 presents two survey objectives categorized by agreement and level, using a fuzzy scale. The fuzzy set L_j, where $j = 1, 2, 3, 4, 5, 6, 7$ represents the linguistic values expressed on the fuzzy scale. In FCA, linguistic values are represented as fuzzy sets, which allow for the handling of imprecise and uncertain information. Each linguistic term is associated with a fuzzy set that captures the degree of membership of an element in that linguistic category. For example, if teachers consider the linguistic term "Good", it can be represented by a triangular fuzzy set where values close to the midpoint of the scale (i.e., neither good nor poor) have a high degree of membership, while values farther away have lower degrees of membership. Similarly, other linguistic terms are represented by fuzzy sets with varying degrees of membership across the scale.

Table 2: Illustration of the fuzzy scale.

Fuzzy Scale		Rating, L_j	TFN
Extremely poor	Very strongly disagree	1	$(0.0, 0.0, 0.1)$
Very poor	Strongly disagree	2	$(0.0, 0.1, 0.3)$
Poor	Disagree	3	$(0.1, 0.3, 0.5)$
Neither good or poor	Neutral	4	$(0.3, 0.5, 0.7)$
Good	Agree	5	$(0.5, 0.7, 0.9)$
Very good	Strongly agree	6	$(0.7, 0.9, 1.0)$
Excellent	Very strongly agree	7	$(0.9, 1.0, 1.0)$

In the case of teachers' perspectives on neuroscience and mathematics learning relevancy, linguistic values are used to capture the subjective nature of their opinions. By allowing teachers to express their perspectives using linguistic terms rather than precise numerical values, FCA enables a more nuanced analysis that considers the uncertainty and variability in their opinions. During the analysis, these linguistic values contribute by providing a framework for interpreting the responses of the teachers. FCA aggregates the linguistic values provided by each teacher to determine the overall preferences and perspectives of the group. This allows researchers to identify patterns, trends, and consensus among the participants, even when their responses may vary in terms of linguistic terms.

This study requires consideration of 11 attributes. Following is a guide to employ this method. The process starts by collecting teachers' responses for each attribute F_i and determining the weight assigned to each attribute using (8). Then, (9) is used to compute the overall membership function of the attribute, $\widetilde{F}_i$, and (10) determines the degree of similarity between two sets, $\widetilde{F}_i$ and L_j. Next, the highest degree of similarity is chosen. Finally, the rank for the specifications of each group is determined, and interpretation and justification are provided based on the teachers' knowledge and perspectives regarding the relevance of neuroscience and mathematics learning.

4 Results

Table 3 displays the number of responds, r_{ij} regarding the linguistic values, L_j on the attributes F_i.

Table 3: The frequency that respondents preferred particular linguistic values.

Attributes	L_1	L_2	L_3	L_4	L_5	L_6	L_7	Total
F_1	9	6	14	14	8	2	0	53
F_2	2	1	6	16	18	7	3	53
F_3	2	0	10	14	14	8	5	53
F_4	0	0	0	21	15	8	9	53
F_5	0	0	2	11	17	9	14	53
F_6	0	0	2	6	4	19	22	53
F_7	0	0	5	3	10	16	19	53
F_8	0	0	5	5	12	12	19	53
F_9	0	3	5	3	7	22	13	53
F_{10}	0	0	2	8	15	11	17	53
F_{11}	0	0	0	14	17	13	9	53

The linguistic values for each attribute were decided by matching teachers' rankings with specific terms like "Strongly Agree" or "Neutral" on the questionnaire. These values help measure how much teachers agree or disagree with each attribute, making it easier to understand and analyze the data. They are important because they help assess teachers' views on neuroscience and its impact on math learning in a more organized manner. Next, Table 4 presents a comprehensive list of weights, as well as the overall membership function or aggregated Triangular Fuzzy Numbers (TFNs) for all attributes. These calculations have been made using (8) and (9).

Table 4: The weight w_{ij} and overall membership function for attribute F_i related to linguistic values, L_j.

Attributes	L_1	L_2	L_3	L_4	L_5	L_6	L_7	Overall membership function, F_i
F_1	0.1698	0.1132	0.2642	0.2642	0.1509	0.0377	0.0000	$(0.204, 0.348, 0.524)$
F_2	0.0377	0.0189	0.1132	0.3019	0.3396	0.1321	0.0566	$(0.464, 0.648, 0.804)$
F_3	0.0377	0.0000	0.1887	0.2642	0.2642	0.1509	0.0943	$(0.444, 0.628, 0.784)$
F_4	0.0000	0.0000	0.0000	0.3962	0.2830	0.1509	0.1698	$(0.492, 0.680, 0.840)$
F_5	0.0000	0.0000	0.0377	0.2075	0.3208	0.1698	0.2642	$(0.564, 0.740, 0.876)$
F_6	0.0000	0.0000	0.0377	0.1132	0.0755	0.3585	0.4151	$(0.700, 0.856, 0.936)$
F_7	0.0000	0.0000	0.0943	0.0566	0.1887	0.3019	0.3585	$(0.676, 0.836, 0.924)$
F_8	0.0000	0.0000	0.0943	0.0943	0.2264	0.2264	0.3585	$(0.660, 0.816, 0.908)$
F_9	0.0000	0.0566	0.0943	0.0566	0.1321	0.4151	0.2453	$(0.644, 0.816, 0.920)$
F_{10}	0.0000	0.0000	0.0377	0.1509	0.2830	0.2075	0.3208	$(0.628, 0.800, 0.916)$
F_{11}	0.0000	0.0000	0.0000	0.2642	0.3208	0.2453	0.1698	$(0.572, 0.752, 0.892)$

The next step is to determine the level of similarity for each element by using (10) to rank and identify each attribute. The similarity degree is indeed crucial for ranking and identifying attributes. Several factors are typically considered in this process, such as, expert opinions (refer to teachers), linguistic value, weighting factors etc. The agreements of teachers play a significant role in determining the similarity between attributes. Teachers may evaluate the attributes based on their knowledge, experience, and understanding of the neuroscience and mathematics learning domain. The resulting similarity degrees provide a measure of how closely related or similar the attributes are to each other. Attributes with higher similarity degrees are considered more closely related, while those with lower similarity degrees are less related. Table 5 displays the degree of similarity and ranking of the attributes.

Table 5: Similarity degree $S(\widetilde{F}_i, L_j)$ for teachers' knowledge and perspectives on neuroscience and mathematics learning relevancy.

TFN, F_i	L_1	L_2	L_3	L_4	L_5	L_6	L_7	S_{max}	$L(S_{max})$	Rank
F_1	0.7481	0.8086	0.9494	0.8721	0.7426	0.6536	0.6135	0.9494	L_3	5
F_2	0.6148	0.6550	0.7444	0.8746	0.9464	0.8065	0.7463	0.9464	L_5	6
F_3	0.6224	0.6637	0.7557	0.8902	0.9288	0.7937	0.7353	0.9288	L_5	10
F_4	0.6029	0.6416	0.7271	0.8508	0.9759	0.8278	0.7645	0.9759	L_5	1
F_5	0.5825	0.6186	0.6977	0.8108	0.9677	0.8696	0.8000	0.9677	L_5	2
F_6	0.5474	0.5792	0.6479	0.7444	0.8746	0.9615	0.8772	0.9615	L_6	3
F_7	0.5533	0.5857	0.6562	0.7553	0.8897	0.9440	0.8626	0.9440	L_6	7
F_8	0.5591	0.5922	0.6643	0.7661	0.9047	0.9276	0.8489	0.9276	L_6	8
F_9	0.5593	0.5924	0.6646	0.7665	0.9053	0.9271	0.8484	0.9271	L_6	9
F_{10}	0.5637	0.5974	0.6708	0.7748	0.9169	0.9152	0.8385	0.9169	$L5$	11
F_{11}	0.5785	0.6140	0.6919	0.8030	0.9566	0.8787	0.8078	0.9566	L_5	4

Table 5 above displays the similarity degree values ranging from 0.9169 to 0.9759. Notably, attribute F_4 receives the highest degree of similarity while attribute F_{10} obtains the lowest. Based on these values, the ranking of attributes is as follows: F_4, F_5, F_6, F_{11}, F_1, F_2, F_7, F_8, F_9, F_3 and

F_{10}. It is worth mentioning that the ratings primarily focus on L_5 and L_6, except for attribute F_1 which is rated at L_3. Consequently, this indicates that the teacher's assessment corresponds to linguistic values of "Good" and "Very Good" in terms of measurement level, and aligns with "Agree" and "Strongly Agree" for agreement measurement.

5 Discussion

In this study, the researcher utilized Fuzzy Conjoint Analysis (FCA), which involved 53 mathematics teachers, to assess and analyze their level of knowledge and perspectives on the relevance of neuroscience to mathematics learning. This procedure follows the steps in the needs study recommended by Cuiccio and Husby-Slater [13], which include analyzing knowledge levels and gaps, reviewing perspectives, and obtaining direct feedback from the parties involved regarding the phenomenon or situation under study. In this study, the phenomenon is the assumption of a low level of teacher knowledge [4] and limited exposure to neuroscience practices [19, 21].

The purpose of attributes $F_1 - F_3$ is to assess the teacher's understanding of neuroscience, the significance of neuroscience in mathematics learning, and the connection between neuroscience and students' thinking processes. The findings reveal that the teacher's knowledge level is rated as L_3, indicating a poor understanding, with a similarity degree value of 0.9494. Previous studies by Amran and Bakar [4] and; Bakar and Ab Ghani [6] have also shown that teachers generally lack knowledge in the field of neuroscience. However, both the evaluation of the importance of neuroscience in mathematics learning (F_2) and the strength of the relationship between neuroscience and students' thinking (F_3) receive a rating of L_5, which is "Good", with similarity degree scores of 0.9464 and 0.9288, respectively. This demonstrates that teachers are aware of the significance of neuroscience for mathematics education, i.e., its role and substantial influence on student's modes of thinking. According to researchers, learning mathematics is related to cognitive [12, 21] and behavioural mechanisms [24, 41] that act to shape the regulation of learning. Neuroscience studies reveal that cognitive and individual behaviour is the result of the relationship between stimuli [2], nerves [4] and parts of the brain [28] that occur during the learning process. Significantly, there is a clear relationship between neuroscience practice and mathematics learning. The conclusion that can be made is, that teachers know about the connection between neuroscience and learning, but it is still not clear what exactly neuroscience is.

In the group of elements reflecting the teacher's perspective on the practice of neuroscience ($F_4 - F_{11}$), the attributes with the highest degree of similarity are F_4, F_5, F_6, and F_{11}. These attributes have been rated as "Agree" and "Strongly agree" (L_5 and L_6) respectively. Each is related to the way and process of thinking in the neuroscience practice, teachers need to have knowledge about neuroscience, the activation of the mind affects student learning and neuroscience elements are required in assessing students' learning ability. This finding is consistent with previous research [2], which shows that ways of thinking (cognitive and metacognitive), and the aspects of activation during the thinking process influence students' learning ability. Meanwhile, in the teacher's view, this tendency or mechanism can also be used as a parameter for measuring student intelligence in learning. The results of the analysis show that attribute F_5 obtained the similarity degree values at the rating positions of L_5 (Agree). This shows that teachers agree need to have knowledge about neuroscience and increase their knowledge about neuroscience practices.

Next, from the analysis of attributes, $F_6 - F_9$ shows the perspective of teachers towards aspects of neuroscience that influence mathematics learning. Through the similarity degree values for those attributes with 0.9615, 0.9440, 0.9276, and 0.9271 respectively, the teachers "Strongly agree" (rating of L_6) with the statement that the activation of the mind affects student learning, executive function, metacognition and working memory, plays a role in the learning process. This result is in line and significant with the study and report by researchers, which shows that activation [18], executive function [38], metacognition [9] and working memory [37] are factors that strongly influence and determine success in student mathematics learning. In summary, this study's findings echo past research, revealing teachers' limited neuroscience knowledge yet strong optimism about its application in mathematics learning. This alignment underscores the ongoing need for educational interventions to enhance teachers' grasp of neuroscience. It also highlights the increasing recognition of neuroscience's potential in education, emphasizing the importance of integrating its principles into teaching methods for better learning outcomes.

Fuzzy conjoint analysis exploits the constancy and fluctuation of the similarity degree value for a variety of purposes beyond ranking [40]. Perception surveys can be conducted and analysed using the fuzzy conjoint analysis method, as shown by the studies of Halim and Idris [20] for measuring students' satisfaction toward bus services, Kasim and Sukri [23] in measuring perception about mathematics learning, Mukhtar and Sulaiman [29] in analyzing factors influencing postgraduates program selection, Abu Bakar et al. [7] for model development justification, Osman et al. [31] to analyse students' perceptions on calculus and Gopal et al. [17] to study self-efficacy and anxiety. It starts with validating the presence of the matter (phenomena) under consideration, evaluating the perspective or criterion, and finally directly analyzing the decision. FCA allows for a granular analysis of teachers' responses by capturing the nuances in their perceptions through linguistic values. By using fuzzy scales to represent the level of understanding of neuroscience knowledge and perspectives on its influence, FCA enables a detailed examination of the data beyond simple categorical responses. FCA ranks attributes based on their importance or influence, providing a hierarchy of factors that shape teachers' perceptions. By analyzing the ranked attributes, the study can highlight which aspects of neuroscience knowledge are most salient to teachers and how these factors impact their views on mathematics learning.

6 Conclusions

The efficacy of applying the fuzzy conjoint analysis technique in the context of perception surveys is demonstrated by this study. Additionally, it demonstrates the validity of utilizing fuzzy conjoint and triangular fuzzy numbers as versatile and valuable computerized analysis tools. The purpose of the preliminary survey was to determine the truth of an assumption. The research aimed to show that teachers have insufficient neuroscience knowledge and embrace a supportive stance towards integrating neuroscience practices. However, it's essential to consider the limitations of FCA in this context, which may affect the validity of the conclusions. Subjectivity, complexity of analysis, sample representation, and limited scope are among the constraints faced.

As a result, future studies should broaden the sample size to generalise the findings. Furthermore, there is a gap between the research and the findings of this study that can be used as an argument for future studies, namely, the level of neuroscience knowledge is low, but teacher perceptions of the implications of neuroscience practice are positive and high. It's fascinating to find out how things came to be. Could it be due to a lack of fundamental understanding of the learning process or a lack of pedagogical knowledge? Perhaps it is the mentality of teachers who do not want to acquire and explore new knowledge, such as neuroscience, which seems extraneous to their profession. In addition, alternative methods of analysis might be used for debating such results from diverse methodological viewpoints.

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