

RESEARCH ARTICLE



New Pythagorean Fuzzification Based on Survey Responses to Rank Learning Approach

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Abstract

Objectives: Students' progress is determined by their learning style. The goal of this research is to use survey data to develop a new framework for the Pythagorean fuzzy number in order to establish the best learning strategy. **Methods:** An inventive method for translating the questionnaire's crisp results to Pythagorean Fuzzy numbers. A new MATLAB algorithm for converting Crisp data to Pythagorean Fuzzy data was also created. The Pythagorean Fuzzy WSM is used to determine the most effective learning approach. It is also opposed with the Intuitionistic Fuzzy WSM approach. **Findings:** The procedure for evaluating and prioritizing strategies, as well as selecting the most efficient method. PFWSM received a score of 0.84254. According to the findings of this study, the most effective technique is activity-based learning. Except for two learning techniques, the rank determined in PFWSM will vary in all comparisons IFWSM (S), IFWSM (ES) to the rank of score. **Novelty:** This research presents a novel way for assessing survey questionnaire data on a Pythagorean fuzzy background. A new MATLAB algorithm for computing Pythagorean fuzzy numbers obtained from survey replies and PFWSM Ranking. This novel approach for converting survey responses to Pythagorean fuzzy type can be applied to any sort of survey.

Keywords: Pythagorean Fuzzy; Ranking; Respondent; MATLAB; WSM; Learning approach; Fuzzification

1 Introduction

There have been several research that have explored problem in multi - criteria analysis ways. TOPSIS and WSA, two multi-criteria analysis methodologies, indicate how the eight areas of Slovakia were evaluated based on nine major characteristics of quality of life⁽¹⁾. The Gardner and Korth framework are used in our method to determine the aspects of the learners' collaborative learning styles. Using an Artificial Neural Network (ANN) and the Weighted Sum Model (WSM), proposes a system for recommending collaborative activities to learners⁽²⁾. Generalised TOPSIS, WSM, and WPM, as well as MATLAB coding approaches, are utilised to determine the optimum option to choose best laser for surgery. MCDM approaches are used in the Neutrosophic soft

set environment as a case study⁽³⁾. By using the compression transformation, all PFNs are unified into the unit triangle in the first quadrant, the distance measure of PFNs is proposed according to the traditional distance meaning, and it is proven that the distance measure meets the axiomatic condition of the traditional distance, and the score function formula of PFNs and its ranking criterion are proposed using the minimum element (0,1)⁽⁴⁾. This paper provides a unique fuzzy multi-criteria decision-making system based on an enhanced scoring function of connection numbers and the Choquet integral in a Pythagorean fuzzy environment with interval values⁽⁵⁾. A novel normalisation score function for PFN is presented that minimises information loss while accounting for uncertainty. The suggested combined weight framework is based on the MEREC and SWARA weighted extensive approaches, and it is both objective and subjective⁽⁶⁾.

The new add-on for evaluating and benchmarking COVID-19 machine learning algorithms. When we compared the results of Fermatean-FDOSM, the basic FDOSM, and TOPSIS, discovered that the Fermatean-FDOSM conclusion is more rational and consistent with expert opinion. Also, we used the validation method for the final result of Fermatean-FDOSM, and discovered that the result of Fermatean-FDOSM is more logical, going through a systematic ranking, and in accordance with decision makers' viewpoints⁽⁷⁾. Pythagorean fuzzy VIKOR (PF-VIKOR) technique for addressing EVCS site selection issues is devised, in which alternative evaluations are supplied as linguistic words characterised by Pythagorean fuzzy values (PFVs). The rating values of alternatives are considered as linguistic concepts conveyed by PFVs during the performance evaluation process⁽⁸⁾. The intuitive fuzzy TOPSIS (IF-TOPSIS) approach was used to tackle the challenge of appraising socioeconomic phenomena using survey data. This allows the phenomena to be evaluated using aggregated secondary data by translating these data into intuitionistic fuzzy values⁽⁹⁾. The notion of the IFSM is presented in the work utilising Hellwig's technique for intuitionistic fuzzy sets. The IFSM allows complicated phenomena to be measured using respondents' opinions. The IFSM requires respondents to evaluate things in terms of the specified criteria using ordinal measurement scales. The findings of the respondents' opinion measurement are afterwards turned into intuitionistic fuzzy sets⁽¹⁰⁾. Based on ordinal data survey data, IFSM as a tool for quantifying complex phenomena. In this scenario, measurement data at the individual responder level are not necessary. The proposed approach may measure complicated phenomena using aggregated ordinal data from public statistics. The suggested method transforms aggregated ordinal data into intuitionistic fuzzy sets⁽¹¹⁾.

A literature search was carried out on the conversion of survey questionnaire responses into fuzzy, as well as MATLAB code on a fuzzy backdrop. Only a few researchers have investigated the translation of survey answer data into fuzzy data. Specifically, the Pythagorean fuzzy hunger method's translation of survey data. It was planned to do this study in New approach for translating questionnaire data to Pythagorean coupled with MATLAB to cover this research need. To close this gap, it was decided to find a new way to frame the Pythagorean fuzzy number using opinion of survey respondents. To ease the conversion of Pythagorean number, MATLAB code was created. The learning technique was rated in this study utilising Pythagorean fuzzy WSM using the MATLAB application. The outcomes were also compared in this study utilising Intuitionistic fuzzy WSM. To deal with imprecise data and confusing language, Pythagorean fuzzy set theory has been frequently used in real-world decision-making scenarios. This study's main objective is to convert survey results to Pythagorean notation. The correctness of the response notion is demonstrated by the Pythagorean Fuzzy Set (PFS). To assess survey replies, a Pythagorean WSM method and MATLAB code have been developed. In the COVID situation, studying might be quite stressful. In order to choose the best learning approach, this research applies WSM in a Pythagorean fuzzy environment. The study's findings will help decision-makers understand what the student minds require. A survey questionnaire designed for the planned study was completed by 132 students from various grade levels (6-12) and schools. The COVID-19 epidemic phase led to the adoption of several fresh policies by the Tamilnadu government to improve the way that children learn. This research will be helpful in identifying the issue and developing a solution. Future survey questions to explore respondents' attitudes might benefit from fuzzy centring analysis across a variety of categories. This innovative method for converting survey replies to Pythagorean fuzzy type may be used for all other types of surveys.

2 Methodology

2.1 Preliminaries

2.1.1 Fuzzy Set

According to Zadeh⁽¹²⁾, Let $\{x_1, x_2, \dots, x_n\}$ be a universal set, then a fuzzy subset. A of a universal set X is given by

$$A = \{ \langle x, \mu_A(x) \rangle / x \in X \} \quad (1)$$

where $0 \leq \mu_A(x) \leq 1$

In this case, $\mu_A(x)$ - Degree of membership of $x \in X$ in A.

2.1.2 Intuitionistic Fuzzy Set

As suggested by Atanassov⁽¹³⁾, IFS has various levels of membership and non-membership. A is a collection of intuitionistic fuzzy sets, and set X in the given universe follows the following pattern:

$$A = \{ \langle x, \mu_A(x), \nu_A(x) \rangle / x \in X \} \quad (2)$$

where $0 \leq \mu_A(x) + \nu_A(x) \leq 1$

In this case, $\nu_A(x)$ - Degree of non-membership. $\mu_A(x)$ - Degree of membership.

2.1.3 IF Properties

According to Xu⁽¹⁴⁾, IF properties states as follows,

$$A \oplus B = (T_A(x) + T_B(x) - T_A(x) * T_B(x), F_A(x) * F_B(x)) \quad (3)$$

$$A \otimes B = (T_A(x) * T_B(x), F_A(x) + F_B(x) - F_A(x) * F_B(x)) \quad (4)$$

$$\lambda A = (1 - (1 - T_A)^\lambda, F_A^\lambda) \quad (5)$$

2.1.4 IF Weighted Aggregation Operator

According to Liu⁽¹⁵⁾, Let $\alpha_i = (t_{\alpha i}, f_{\alpha i})$ where $i = (1, 2, \dots, n)$ be IFVs. The simply weighted intuitionistic fuzzy averaging (SWIFA) operator of dimension n

$$SWIFA = (\sum_{i=1}^n (w_i * t_{\alpha i}), \sum_{i=1}^n (w_i * f_{\alpha i})) \quad (6)$$

2.1.5 IF Score function

According to Zeng⁽¹⁶⁾, If $\alpha = \langle \mu_\alpha(x), \nu_\alpha(x) \rangle$ is an IFN, then its IFS(S) can be expressed as follows:

$$s(\alpha) = \mu_\alpha(x) - \nu_\alpha(x) \quad (7)$$

2.1.6 IF Expectation score function

According to Feng⁽¹⁷⁾, If $s(\alpha) = \mu_\alpha(x) - \nu_\alpha(x) = \langle \mu_\alpha(x), \nu_\alpha(x) \rangle$ is an IFN, then its IFS(ES) can be expressed as follows:

$$m(\alpha) = \frac{\mu_\alpha(x) - \nu_\alpha(x) + 1}{2} \quad (8)$$

2.1.7 Pythagorean Fuzzy Set

According to Yager⁽¹⁸⁾, In the given universe Set X follows the following pattern: P is a Pythagorean fuzzy set collection,

$$P = \{ \langle x, \mu_P(x), \nu_P(x) \rangle / x \in X \} \text{ where } 0 \leq (\mu_P(x))^2 + (\nu_P(x))^2 \leq 1 \quad (9)$$

In this case, $\mu_P(x)$ - Membership degree and $\nu_P(x)$ - Non-membership degree

2.1.8 PF Properties

Consider that A and B are distinct PFS is what is stated in Pérez-Domínguez⁽¹⁹⁾,

$$A \oplus B = (\sqrt{T_A^2 + T_B^2 - T_A^2 * T_B^2}, F_A * F_B) \quad (10)$$

$$A \otimes B = (T_A * T_B, \sqrt{F_A^2 + F_B^2 - F_A^2 * F_B^2}) \quad (11)$$

$$\lambda A = \left(\sqrt{1 - (1 - T_A^2)^\lambda}, F_A^\lambda \right), \lambda > 0 \quad (12)$$

$$A^\lambda = \left(T_A^\lambda, \sqrt{1 - (1 - F_A^2)^\lambda} \right), \lambda > 0 \quad (13)$$

2.1.9 PF Weighted Sum Average

According to Zhang⁽²⁰⁾, Suppose $p_{ij} = (\mu_{ij}, v_{ij})$, is a group of PFVs. The PFWSA expression is therefore defined as follows:

$$r_i = (\mu_i, v_i) = \bigoplus_{j=1}^n w_j, \quad i = 1, 2, \dots, m \& j = 1, 2, \dots, n \quad (14)$$

$$r_i = \left(\sqrt{1 - \prod_{j=1}^n (1 - \mu_{ij}^2)^{w_j}}, \prod_{j=1}^n (v_{ij})^{w_j} \right) \quad (15)$$

Where $w = (w_1, w_2, \dots, w_n)$ be the weight vector of p_{ij} and $w_j > 0, \sum_{j=1}^n w_j = 1$.

The Pythagorean fuzzy weighted sum average value of the i -th questionnaire is denoted by r_i .

2.1.10 PF Score function

According to Wu⁽²¹⁾, If $r_i = (\mu_i, v_i)$ where $i = 1, 2, \dots, m$ is a PFN, then its PFS (S) may be expressed as follows:

$$S_i = \frac{1 + \mu_i^2 - v_i^2}{2} \quad (16)$$

2.2 Proposed Framework

By leveraging survey data, the proposed study will develop a brand-new technique for calculating the Pythagorean fuzzy number. The PF WSM approach was used to assess the learning strategy. New computations for Pythagorean fuzzy numbers and PF WSM are defined in the MATLAB code. Figure 1 displays the suggested framework's stages.

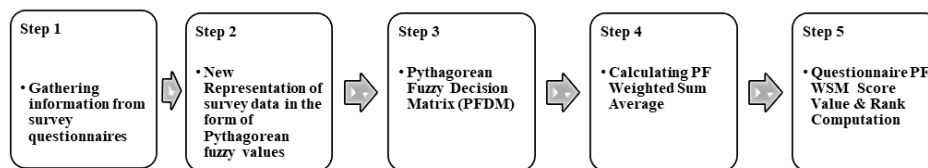


Fig 1. Proposed Framework Flow Chart

Based on the results, a questionnaire was created to gauge students' favourite learning strategies. The optimal learning technique was built with 10 questions. 6 to 12 standard Students in the Krishnagiri district were asked to respond to questionnaires. Two categories of decision makers provided a combined 132 replies. The responder choose any option from the ordinal $O = \{o_1, o_2\}$ which is denoted as $o_1 = \text{Agree}$ and $o_2 = \text{Disagree}$. For the students, learning is very essential. Every instructor uses their preferred method of instruction in the classroom, but the only way to tell if students enjoy it all is by their responses. This study uses the Pythagorean fuzzy WSA to analyse the learning approach utilising 10 questions. Each questionnaire is designed to test each learning approach. Figure 2 depicts a total of 10 Learning approach.

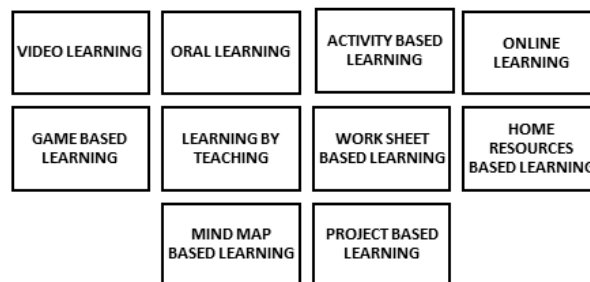


Fig 2. Determination of Learning approach

2.3 Proposed Algorithm

The survey data are represented into PFSs using innovative methods in this study, which is coded in MATLAB. The aforesaid approach was verified by PFWSM and contrasted with IFWSM. The actions this paper took are as follows:

Step :1 Gathering information from survey questionnaires

This section proposes a novel approach for generating Pythagorean Fuzzy numbers using survey data. Let $Q = \{Q_1, Q_2, Q_3, \dots, Q_m\}$ where $i=1,2,\dots,m$ be the collection of questions used to evaluate the survey, Where $j=1,2,\dots,n$ is the set of decision makers for the questions are assessed, D is defined as $D = \{D_1, D_2, \dots, D_j\}$ where $j=1,2,\dots,n$. We assume that respondents used an ordinal measurement scale to reply to questions, resulting in two possible perceptions about the questionnaire: "favourable perception of the questionnaire" and "An unfavourable perception of the questionnaire". Here, $Q = \{Q_1, Q_2, Q_3, \dots, Q_{10}\}$ is the set of ten questions utilised in the survey, where $i=1,2,\dots,10$ and there are two qualitative decision-makers. In a questionnaire survey, where $j=1,2$, the replies of the respondents are gathered, $D = \{D_1, D_2\}$. The respondent in this survey chooses one of the ordinal scale options. $O = \{o_1, o_2\}$ is denoted by the symbols $o_1 = \text{Agree}$ and $o_2 = \text{Disagree}$. Survey questionnaire response rate is shown in Table 1.

Step :2 New way of representing survey data as PFN

Step:2 (a) New configuration of PFN

This stage describes new way PFN configuration derived from survey data responses. The opinions of questionnaire respondents (Q_i) for decision maker (D_j) are expressed by

$$P(\mu_{ij}, v_{ij}) = \left(\sqrt{\frac{S_{ij}}{S_{ij} + F_{ij}}}, \sqrt{\frac{F_{ij}}{S_{ij} + F_{ij}}} \right) \quad (17)$$

where $\mu_{ij} + v_{ij} > 1$ and $(\mu_{ij})^2 + (v_{ij})^2 = 1$ (7)

In this case, μ_{ij} - Membership degree and v_{ij} - Non-membership degree.

μ_{ij} —square root of the proportion of favourable perceptions regarding the i -th questionnaire in relation to the j -th decision maker. v_{ij} — the square root of the proportion of an unfavourable perception on the i -th questionnaire with regard to the j -th decision maker. S_{ij} — the overall number of those who responded that rated the i -th questionnaire favourably in relation to the j -th decision maker. F_{ij} —the overall number of those who responded that rated the i -th questionnaire unfavourably in relation to the j -th decision maker.

Step 2(b) Numerical Example: For example, ninth questions from decision maker 1, a novel configuration of Pythagorean fuzzy is defined using survey data responses. Apply the responses in (17),

$$\begin{aligned} P(\mu_{91}, v_{91}) &= \left(\sqrt{\frac{S_{91}}{S_{91} + F_{91}}}, \sqrt{\frac{F_{91}}{S_{91} + F_{91}}} \right) = \left(\sqrt{\frac{44}{44 + 22}}, \sqrt{\frac{22}{44 + 22}} \right) \\ &= (0.81650, 0.57735) \end{aligned}$$

Step 2(c) Verification:

Utilising the PFs value $(\mu_{91}, v_{91}) = (0.81650, 0.57735)$, confirm the aforementioned two requirements in accordance with (17).

Condition (I): $\mu_{ij} + v_{ij} > 1$

$\mu_{91} + v_{91} = 1.3939 > 1$ It meets condition (I).

Condition (II) $(\mu_{ij})^2 + (v_{ij})^2 = 1$ $(\mu_{91})^2 + (v_{91})^2 = (0.8165)^2 + 1$

It meets condition (II).

Step :3 Pythagorean Fuzzy Decision Matrix (PFDM)

Data respondent converted into PFDM. R has m questions and n decision makers. D - Decision makers and Q - Questions. It determined as follows,

		D_1	D_2	\dots	D_n
	Q_1	(μ_{11}, v_{11})	(μ_{12}, v_{12})	\dots	(μ_{1n}, v_{1n})
$R =$	Q_2	(μ_{21}, v_{21})	(μ_{22}, v_{22})	\dots	(μ_{2n}, v_{2n})
	\vdots	\vdots	\ddots	\ddots	\vdots
	Q_m	(μ_{m1}, v_{m1})	(μ_{m2}, v_{m2})	\dots	(μ_{mn}, v_{mn})

(18)

A crisp response was converted to Pythagorean fuzzy and the Pythagorean fuzzy decision matrix was created. It shows in the Table 1.

Step :4 Calculating PF Weighted Sum Average

We believed that the weights of decision makers were identical since the survey items had the same priority in the evaluation. As previously stated by Maggino and Ruviglioni⁽²²⁾, identical weights are employed in many applications. In this research, $w_1=0.5$ and $w_2 = 0.5$. Table 1 shows the PF WSA consolidation outcome. For instance, r_9 is computed according to (15) as follows:

$$\begin{aligned}
 r_9 &= (\mu_9, \nu_9) = \oplus_{j=1}^2 w_j * p_{9j} \\
 &= \left(\sqrt{1 - \prod_{j=1}^2 (1 - \mu_{9j}^2)^{w_j}}, \prod_{j=1}^2 (\nu_{9j})^{w_j} \right) \\
 &= \left(\sqrt{1 - [(1 - \mu_{91}^2)^{w_1} * (1 - \mu_{92}^2)^{w_2}]}, [(v_{91})^{w_1} * (v_{92})^{w_2}] \right) \\
 &= \left(\sqrt{1 - [(1 - 0.8165^2)^{0.5} * (1 - 0.90453^2)^{0.5}]}, [(0.57735)^{0.5} * (0.4264)^{0.5}] \right) \\
 r_9 &= (0.86823, 0.49617)
 \end{aligned}$$

Step :5 Questionnaire PFWSM Score Value & Rank Computation

According to (16), For example, $S_9 = \frac{1 + \mu_9^2 - \nu_9^2}{2} = \frac{1 + 0.86823^2 - 0.49617^2}{2} = 0.75382$

Table 1. Displays the PFWSM Score Value & Rank

S.No.	Learning approach (Q _i)	Survey questionnaire response rate				Pythagorean Matrix (PFDM)		Fuzzy Decision maker		PF Weighted Sum Average		PFWSM Score & Rank	
		Decision maker (D ₁)		Decision maker (D ₂)		Decision maker (D ₁)		Decision maker (D ₂)		PFWSA		PF WSM	
		Agree	Disagree	Agree	Disagree	PF Agree	PF Disagree	PF Agree	PF Disagree	μ_i	ν_i	Score	Rank
		(S _{i1})	(F _{i1})	(S _{i2})	(F _{i2})	(μ_{i1})	(ν_{i1})	(μ_{i1})	(ν_{i1})				
1	Work sheet	43	23	49	17	0.80716	0.59033	0.86164	0.50752	0.8369	0.54736	0.7004	6
2	Project	45	21	44	22	0.82572	0.56408	0.8165	0.57735	0.82118	0.57067	0.67433	7
3	Mind map	41	25	47	19	0.78817	0.61546	0.84387	0.53654	0.8184	0.57465	0.66978	8
4	Learning by teaching	53	13	56	10	0.89612	0.44381	0.92113	0.38925	0.90953	0.41564	0.82725	2
5	Online	29	37	38	28	0.66287	0.74874	0.75879	0.65134	0.71576	0.69834	0.51232	10
6	Activity	48	18	60	6	0.8528	0.52223	0.95346	0.30151	0.9179	0.39681	0.84254	1
7	Oral	39	27	45	21	0.76871	0.6396	0.82572	0.56408	0.79951	0.60065	0.63922	9
8	Video	47	19	55	11	0.84387	0.53654	0.91287	0.40825	0.88372	0.46802	0.78096	3
9	Game	44	22	54	12	0.8165	0.57735	0.90453	0.4264	0.86823	0.49617	0.75382	4
10	Home-resource	46	20	47	19	0.83485	0.55048	0.84387	0.53654	0.83943	0.54347	0.70464	5

Table 1 shows the PFWSM score and rank for the learning approach. It reveals that every learning approach falls between 0.5 and 0.9. It denotes a rating based on score as $Q_6 > Q_4 > Q_8 > Q_9 > Q_{10} > Q_1 > Q_2 > Q_3 > Q_7 > Q_5$. According to rank and score value, students favour activity-based learning as a preferred learning approach.

3 Results and Discussion

3.1 New MATLAB Code for representing survey respondents to Pythagorean fuzzy & PFWSM Score

The new MATLAB code was written from scratch to represent survey data as Pythagorean fuzzy numbers and to verify the conditions of the Pythagorean fuzzy number as well as to compute the PFWSM score value for the 9th Learning method. The outputs are shown below,

Output.....

Pythagorean fuzzy number from survey data frequency for DM1

$Pm91v91 = 0.8165 \ 0.5774$

Condition1: $m91+v91>1$ Satisfies

Condition2: $((m91)^2+(v91)^2)=1$ Satisfies

Pythagorean fuzzy number from survey data frequency for DM2

$Pm92v92 = 0.9045 \ 0.4264$

Condition1: $m92+v92>1$ Satisfies

Condition2: $((m92)^2+(v92)^2)=1$ Satisfies

PF Weighted Sum Average

$r9 = 0.8682 \ 0.4962$

Pythagorean fuzzy number scoring functions

$s9 = 0.7538$

3.2 PFWSM Learning approach analysis based on the score and rank:

Activity-based learning came in first place for preferred learning technique, as shown by Figure 3 and Table 1. Many students like to learn through doing. Teaching others to learn came in second. Children passionately enjoy learning through teaching-based learning. It demonstrates the eagerness of the student body to learn new topics. The students awarded third place to the video-based learning, because students of days are interested in watching movies. Game-based learning came in fourth. Students are always eager to play. It is also a crucial component of students successful learning strategies. Home-based learning options for students came in sixth.

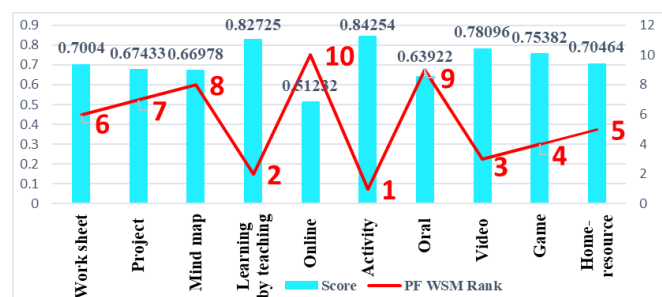


Fig 3. PFWSM Learning approach analysis based on the score and rank

The video-based learning was given to third place by the students. Because now a days students are the interested to see videos. Game based learning got fourth place. Always students are interested to play. It is also a key to success learning approach among the students. Home based resources on students' learning approach came in fifth. However, parents should actively encourage their children to use these tools at home. Worksheet, project, mind map, oral presentation, and online learning also received respectable rankings from sixth to tenth. This finding indicates that students are not motivated to pursue online or oral learning. Every learning technique was developed with consideration for a child's whole development.

3.3 Preferred & Unpreferred learning approach

By assembling 10 learning approaches and categorising them into two groups, such as Preferred learning approaches and Unpreferred learning approaches, the suggested research offers an overview. The top five learning approaches have been determined as the recommended standards by the students' replies. It was shown in Figure 4 (a). The most harmful five learning

strategies are those that were shown to be unfavourable in this study's situation. They are shown in Figure 4 (b). It contends that policymakers had to develop a strategy for motivating teachers as well as one for giving them training .

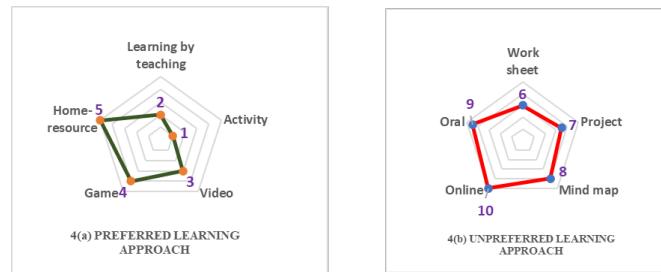


Fig 4. Preferred & Unpreferred learning approach

3.4 Graphic analysis Score comparison of PF WSM, IF WSM (S) and IF WSM (ES)

Use the formulas 16, 7, and 8 to calculate the PF WSM, IF WSM (S) and IF WSM (ES) score values. The score value is contrasted with PFWSM, IFWSM(S), and IFWSM(ES) in the graph. For each learning strategy, the PFWSM and IFWSM (ES) score values are almost the same visually. The IFWSM (S) score value, however, rarely changes. It illustrates that the rank identified in PFWSM will vary in all comparisons to the rank of score, except for two learning approaches. The PFWSM is listed in the same order in every other learning strategy. The Figure 5 shows the rank as follows,

PFWSM Rank of Score is as $Q_6 > Q_4 > Q_8 > Q_9 > Q_{10} > Q_1 > Q_2 > Q_3 > Q_7 > Q_5$.

IFWSM (S) Rank of score is $Q_4 > Q_6 > Q_8 > Q_9 > Q_{10} > Q_1 > Q_2 > Q_3 > Q_7 > Q_5$.

IFWSM (ES) Rank of score is $Q_4 > Q_6 > Q_8 > Q_9 > Q_{10} > Q_1 > Q_2 > Q_3 > Q_7 > Q_5$

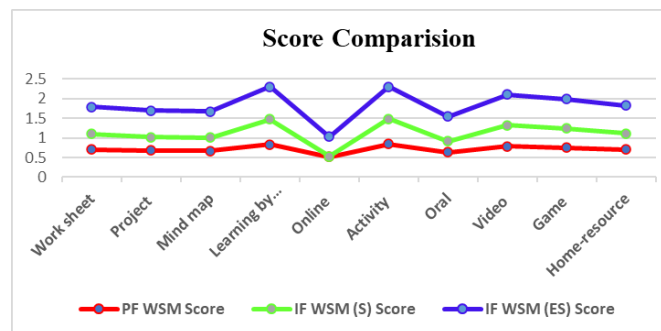


Fig 5. Graphic analysis Score comparison of PF WSM, IF WSM (S) and IF WSM (ES)

4 Conclusion

This study explains how to turn survey data into Pythagorean fuzzy using a novel approach and new MATLAB code. In this study, we presented the Pythagorean fuzzy WSM (PFWSM) method for analysing learning approaches using survey data. For starters, the suggested method does not require raw data and takes ambiguity in respondents' opinions into account. This permits the phenomena to be evaluated using aggregated secondary data by translating these data into Pythagorean fuzzy values. The degree of participation in the Pythagorean fuzzy value is equal to the square root of the proportion of positive views of the questionnaire in connection to the decision maker. The degree of non-membership to Pythagorean fuzzy value is the square root of the proportion of respondents who had an adverse view of the decision maker on the questionnaire.

Second, the suggested method for transforming aggregate secondary data into Pythagorean fuzzy values does not contradict the assumptions about the measurement level of ordinal scales, as well as the acceptable relations and transformations of their values. Following data transformation, the PF-WSM technique evaluates the complicated phenomena using arithmetic operations, comparisons, and transformations that are permitted for Pythagorean fuzzy values. Typically, researchers are unable to specify the ideal values of the criterion. This is because, among other things, to the fact that adding another object to the

study sample may affect the coordinates of the Pythagorean fuzzy good and unfavourable objects, hence changing their ranking position. The parameters of Pythagorean fuzzy values are used in the article's technique of calculating coordinates. This method has the added benefit of allowing the findings to be compared. Comparing the PFWSM technique against the standard IFWSM (S) and IFWSM (ES) methods allowed the study to highlight the proposed approach's strengths and drawbacks.

The next research challenge will be to propose a change to the PFWSM approach that will allow for the consideration of the distribution of ratings into distinct categories on the positive and negative side. Future study will also concentrate on applying the proposed technique to various challenges. The usage of MATLAB code in future problem-solving will be advantageous. Transform the replies into numerous fuzzy types in the future, such as Neutrosophic Pythagorean. Using multiple ranking systems, use the survey replies to address a variety of challenges in the future.

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