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Teaching Effectiveness Analysis of Educational Technology in Vocational Colleges: SuperHyperSoft Set Integrated with Decision-Making Approach for Increased Effectiveness

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Abstract: The integration of educational technology in vocational colleges has revolutionized teaching methodologies, improving instructional quality and student engagement. However, ensuring its effectiveness requires a structured assessment framework. This study evaluates teaching effectiveness by analyzing key criteria such as instructional quality, student engagement, technology integration, assessment effectiveness, skill development, and industry adaptability. Using a multi-criteria decision-making (MCDM) approach, this study computes the criteria weights by the LBWA and the MOORA methodology to rank the alternatives. Six criteria and seven alternatives are used in this study. We use the SuperHyperSoft Set to deal with criteria and sub criteria. This study proposes four pools of HyperSoft sets. Then we ranked the alternatives in each pool. The results show the ranks of alternatives in each pool are stable.

Keywords: Decision Making Methodology; SuperHyperSoft Set; Teaching Effectiveness; Educational Technology.

1. Introduction

In the rapidly evolving educational landscape, educational technology plays a crucial role in enhancing teaching effectiveness, particularly in vocational colleges, where practical skills and industry alignment are essential. The integration of digital learning platforms, artificial intelligence (AI), virtual simulations, and interactive tools has transformed traditional teaching methods, offering students more engaging and adaptive learning experiences[1], [2].

However, while these technologies provide new opportunities for improving education, their effectiveness must be systematically assessed to ensure they align with the desired learning outcomes. Evaluating the effective teaching of educational technology in vocational colleges requires a comprehensive framework that considers instructional quality, student engagement, industry relevance, and overall learning efficiency.

One of the fundamental aspects of teaching effectiveness in vocational education is how digital tools support practical skill development and hands-on learning experiences. Unlike traditional academic programs, vocational education is industry-oriented, requiring students to gain competencies that are directly applicable in real-world work environments. Educational technology, such as simulations, gamified learning experiences, and AI-driven assessments, can enhance the learning process by offering interactive and adaptive content[3], [4]. However, if not implemented effectively, these technologies can lead to disengagement or fail to provide the necessary depth of learning required for vocational training.

Another key factor in assessing educational technology effectiveness is student engagement and learning outcomes. Modern educational tools claim to offer personalized learning paths, real-time feedback, and collaborative learning experiences, but their actual impact on student motivation and knowledge retention needs critical evaluation. Blended learning models, which combine online and face-to-face instruction, have gained popularity in vocational education, but their success depends on student adaptability, accessibility of digital resources, and instructor proficiency in using technology effectively. Therefore, assessing the role of technology in fostering active student participation, skill acquisition, and competency-based learning is vital.

Furthermore, the alignment of educational technology with industry demands is a crucial dimension of assessment. Vocational education serves as a direct pipeline to employment, and the tools used in teaching must prepare students for real-world technological advancements and workplace requirements. Many vocational institutions adopt learning management systems (LMS), online certification programs, and industry-specific digital tools, but a mismatch between curriculum design and industry expectations can diminish the value of these technologies[5], [6]. Evaluating whether educational technology effectively bridges the gap between academia and industry is essential for ensuring that vocational graduates possess the skills needed in their respective fields.

Given these complexities, a structured, multi-criteria decision-making (MCDM) approach is necessary to assess the effectiveness of educational technology in vocational colleges. This research proposes an evaluation framework based on key performance indicators such as instructional quality, student engagement, technology integration, assessment effectiveness, skill development, and adaptability to industry needs[7], [8]. By systematically analyzing these factors, stakeholders, including educators, administrators, and policymakers, can make informed decisions about which technologies enhance learning experiences and which require further improvement[9], [10]. This assessment will contribute to the ongoing efforts to optimize vocational education and ensure its alignment with modern workforce demands.

The study of finding and selecting options in accordance with one's own beliefs and preferences is known as decision making. When a decision is made, it means that there are options to think about. In this situation, not only are as many options as possible found, but the best option is also selected to satisfy the decision maker's aims, objectives, preferences, and values. As a result, every decision-making process results in a conclusion. Making decisions and addressing problems are critical to life and business skills. Making decisions is a common part of problem resolution, and it's crucial for management and leadership[11], [12].

Some personalities are better at making decisions than others, thus such individuals should concentrate more on making better judgments. Individuals who struggle with decision-making frequently can make good judgments, but they must then act more decisively on those judgments. Effective decision-making necessitates a variety of abilities, including innovative ideation and option discovery, judgmental clarity, decision firmness, and efficient execution[13], [14].

Simple, methodical, and logical methods or mathematical tools that can consider a wide range of selection criteria and candidate alternatives are required to support and direct the decision makers. Finding the right selection criteria and arriving at the optimal choice while considering the demands of the present moment are the goals of every choosing process. While many MCDM techniques are currently available to address various evaluation and selection issues, this study aims to investigate the suitability of a relatively new MCDM technique, namely the multi-objective optimization based on ratio analysis (MOORA) method, to ranking the alternatives[15], [16].

2. The LBWA with MOORA Method

This section shows the steps of the LBWA method to compute the criteria weights and the MOORA Method to rank the alternatives. These methods are used with the SuperHyperSoft set to deal with criteria and sub criteria.

The steps of the LBWA are organized as follows:

Decision makers can identify the highest importance criterion.

Then the criteria are identified at different levels.

Level 1 k_1: The criteria are greater twice importance or equal to other criteria.

Level 2 k_2: The criteria are twice or three times lower than the highest importance criterion.

Level 3 k_3: The criteria are y or y+1 times less than the highest importance criterion are put in the level 3.

$$K = K_1 \cup K_2 \dots \cap K_y \tag{1}$$

Each attribute are assigned into integral value.

$$f = \max\{|K_1|, |K_2|, \dots, |K_y|\} \tag{2}$$

$$f_0 < f \tag{3}$$

We compute the influence function as:

$$f(C_{ip}) = \frac{f_0}{i(f_0)+I_{ip}} \tag{4}$$

Where i presents the number of levels.

Determine the criteria weights.

$$w_j = \frac{1}{1+f(C_j)+\cdots+f(C_n)} \tag{5}$$

The act of concurrently maximizing two or more competing qualities (objectives) under certain restrictions is called multi-objective optimization (or programming), often referred to as multi-criteria or multi-attribute optimization. Product and process design, finance, the oil and gas industry, the manufacturing sector, automobile design, and any other area where the best course of action must be chosen in the face of trade-offs between two or more competing objectives are examples of multi-objective optimization problems. Typical examples of Mult objective optimization issues include optimizing performance and limiting fuel consumption of a vehicle, maximizing profit and lowering the cost of a product, and minimizing weight while maximizing the strength of a certain technical component[17], [18].

Steps of the MOORA method are shown as:

Build the decision matrix

Experts and decision makers are evaluated the set of different alternatives with respect to different criteria such as:

$$U = \begin{bmatrix} u_{11} & \cdots & u_{1n} \\ \vdots & \ddots & \vdots \\ u_{m1} & \cdots & u_{mn} \end{bmatrix} \tag{6}$$

Next, a system of ratios is created where each alternative's performance on an attribute is contrasted with a denominator that represents all the options pertaining to that attribute. After examining several ratio systems, including the total ratio, Schärlig ratio, Weitendorf ratio, Jüttler ratio, Stopp ratio, Körth ratio, and others, Brauers et al. concluded that the optimum option for this denominator is the square root of the sum of squares of each possibility for each characteristic. The following is an expression for this ratio:

$$q_{ij} = u_{ij} / \sqrt{\sum_{i=1}^{m} q_{ij}^2} \,; i = 1,2,\ldots,m; j = 1,2,\ldots,n; \tag{7}$$

In the context of multi-objective optimization, these normalized performances are deducted for nonbeneficial qualities and added for beneficial attributes. The optimization issue then turns into:

$$y_i = \sum_{j=1}^{g} q_{ij} - \sum_{j=g+1}^{n} q_{ij} \tag{8}$$

where y_i is the normalized assessment value of ith option about all the qualities, g is the number of attributes to be maximized, and (n−g) is the number of attributes to be reduced. It is sometimes noted that certain qualities are more significant than others. A property might be increased by its matching weight (significance coefficient) to increase its importance. After accounting for these attribute weights:

$$y_i = \sum_{j=1}^{g} w_j q_{ij} - \sum_{j=g+1}^{n} w_j q_{ij} \tag{10}$$

Depending on the sums of the decision matrix's maxima (useful characteristics) and minima (non-beneficial attributes), the y_i value may be positive or negative. The ultimate choice is shown by an ordinal ranking of y_i. As a result, the poorest option has the lowest yi value, while the greatest option has the highest.

SuperHyperSoft Set

Smarandache presented the SuperHyperSoft set which is an extension of the HyperSoft set. SuperHyperSoft set includes different HyperSoft sets. It is used in this study to show the relations between the different criteria and sub criteria[19], [20].

Let the U be a universe of discourse and the power set of U is P(U). Different criteria are Q_1, Q_2, Q_3 and the alternatives are evaluated based on these criteria.

The power set of these criteria can be defined as $P(Q_1), P(Q_2), P(Q_3)$.

The SuperHyperSoft set can be defined as:

$P(Q_1) \times P(Q_2) \times P(Q_3) \rightarrow P(U)$

3. An application

This section shows the implementation of the proposed approach to show the criteria weights and the best alternative based on a set of criteria. Four experts are evaluated the criteria and alternatives. These experts are used the scale between 0.1 and 0.9. This study uses six criteria and seven alternatives. The criteria of this study are: Student Engagement (Active, Passive), Instructional Quality (High, Low), Assessment Effectiveness (Comprehensive, Standard, Limited), Skill Development (Strong, Moderate, Weak), Adaptability to Industry Needs (High, Medium, Low), Technology Integration (Advanced, Sufficient, Minimal). The seven alternatives of teaching effectiveness.

Decision makers can identify the highest importance criterion.

Then the criteria are identified at different levels. Three levels are defined in this study.

Then we assign each attribute into integral value using Eq. (2).

Then we compute the influence function using Eq. (4).

Then we determine the criteria weights using Eq. (5) as shown in Fig 1.

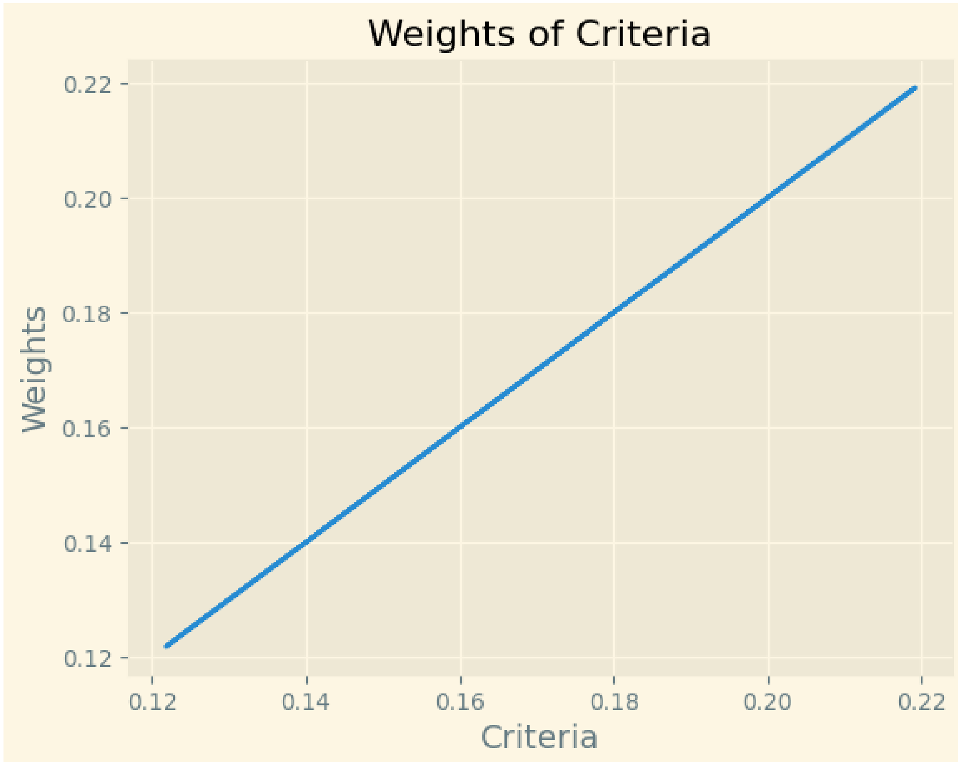

Fig 1. The criteria weights.

In the ranking of the alternatives, we use the concept of the SuperHyperSoft set to deal with the criteria and sub criteria. We use the sub criteria such as: {Active, Passive}, {High, Low}, {Comprehensive}, {Strong}, {High}, {Advanced}. Then we propose four pools.

Pool 1. {Active}, {High}, {Comprehensive}, {Strong}, {High}, {Advanced}

Pool 2. {Active,}, {Low}, {Comprehensive}, {Strong}, {High}, {Advanced}

Pool 3. {Passive}, {High}, {Comprehensive}, {Strong}, {High}, {Advanced}

Pool 4. {Passive}, {Low}, {Comprehensive}, {Strong}, {High}, {Advanced}

Then we apply the MOORA method in each pool and we rank the alternatives in each pool.

Pool 1

We build the decision matrix using Eq. (6), then we combine the decision matrix into a single matrix.

Eq. (7) is used to normalize the decision matrix as shown in Fig 2.

Then we obtain the weighted normalized decision matrix as shown in Fig 3.

Then we compute the value of y_i and then we rank the alternatives.

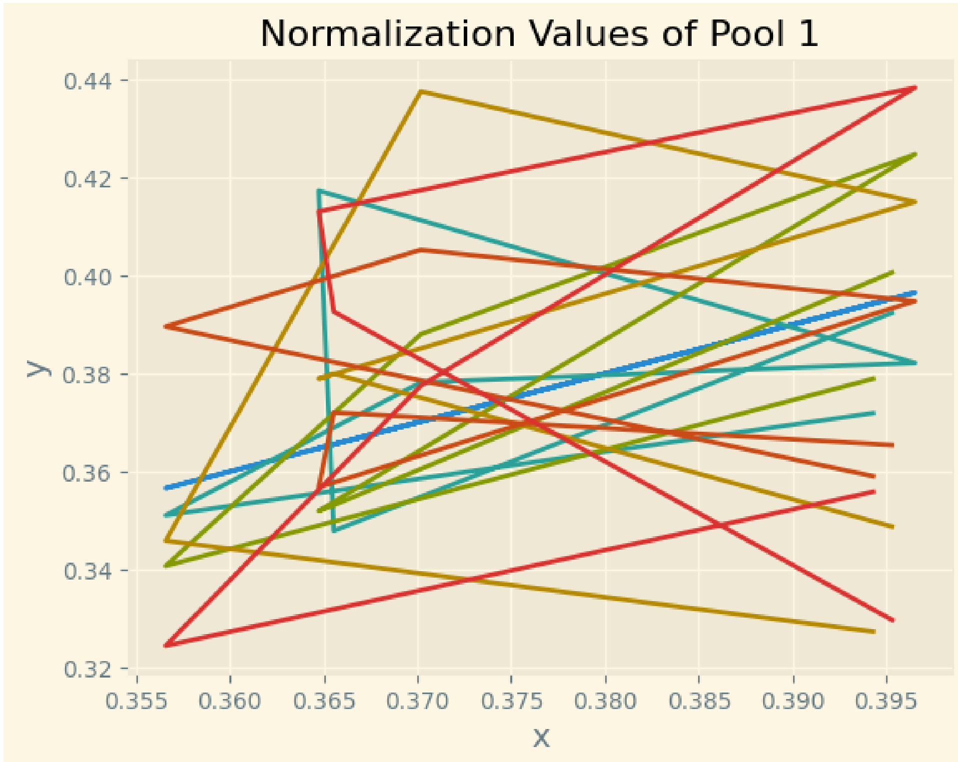

Fig 2. The normalization values.

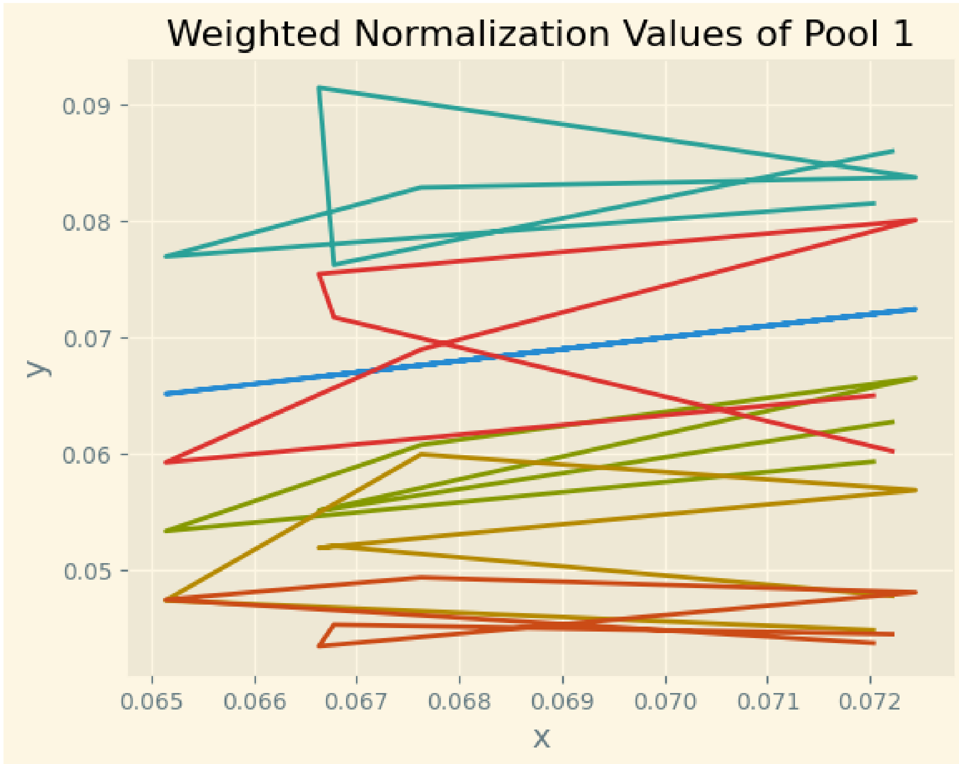

Fig 3. The weighted normalized decision matrix.

Pool 2

We normalize the decision matrix as shown in Fig 4.

Then we obtain the weighted normalized decision matrix as shown in Fig 5.

Then we compute the value of y_i and then we rank the alternatives.

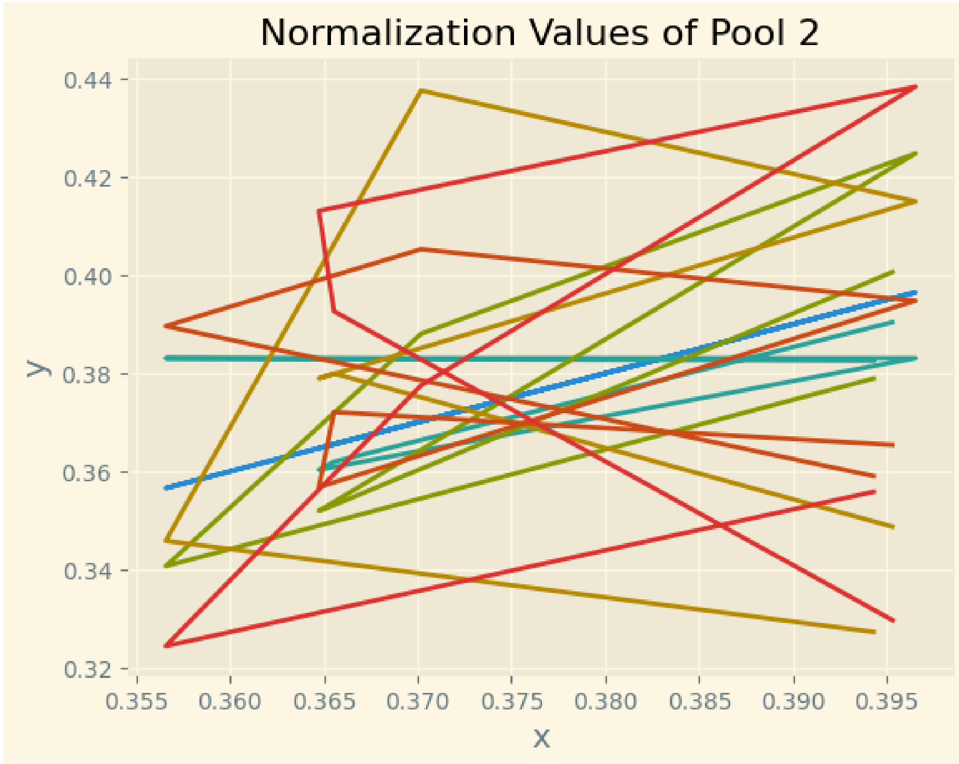

Fig 4. The normalization values.

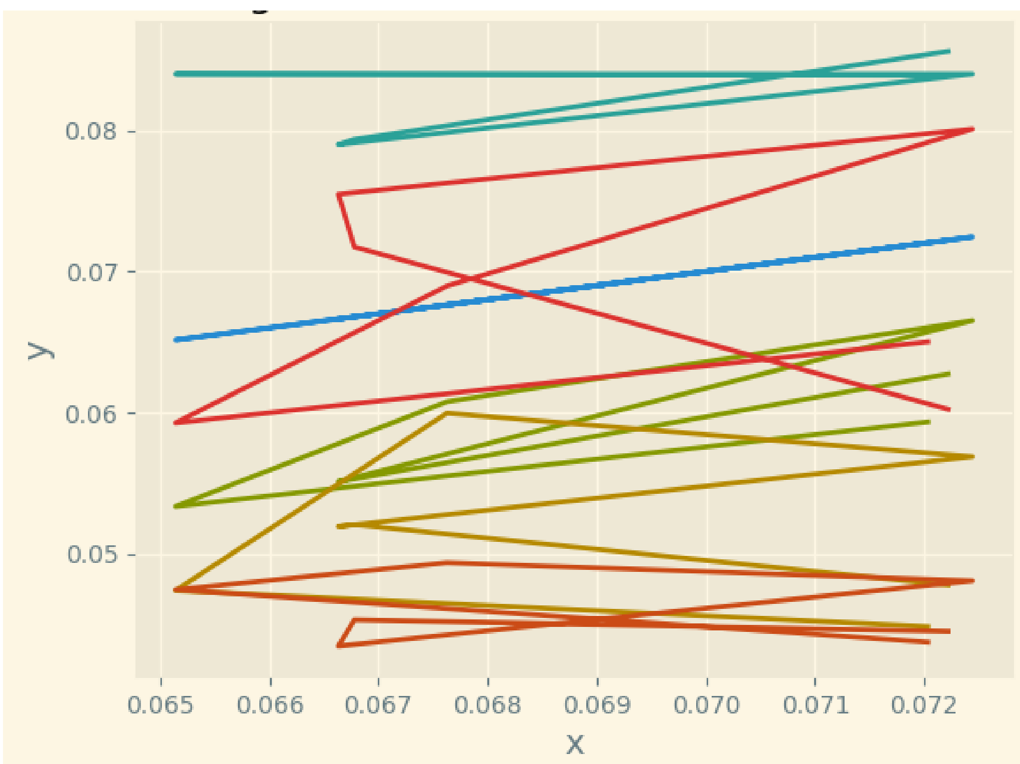

Fig 5. The weighted normalized decision matrix.

Pool 3

We normalize the decision matrix as shown in Fig 6.

Then we obtain the weighted normalized decision matrix as shown in Fig 7.

Then we compute the value of y_i and then we rank the alternatives.

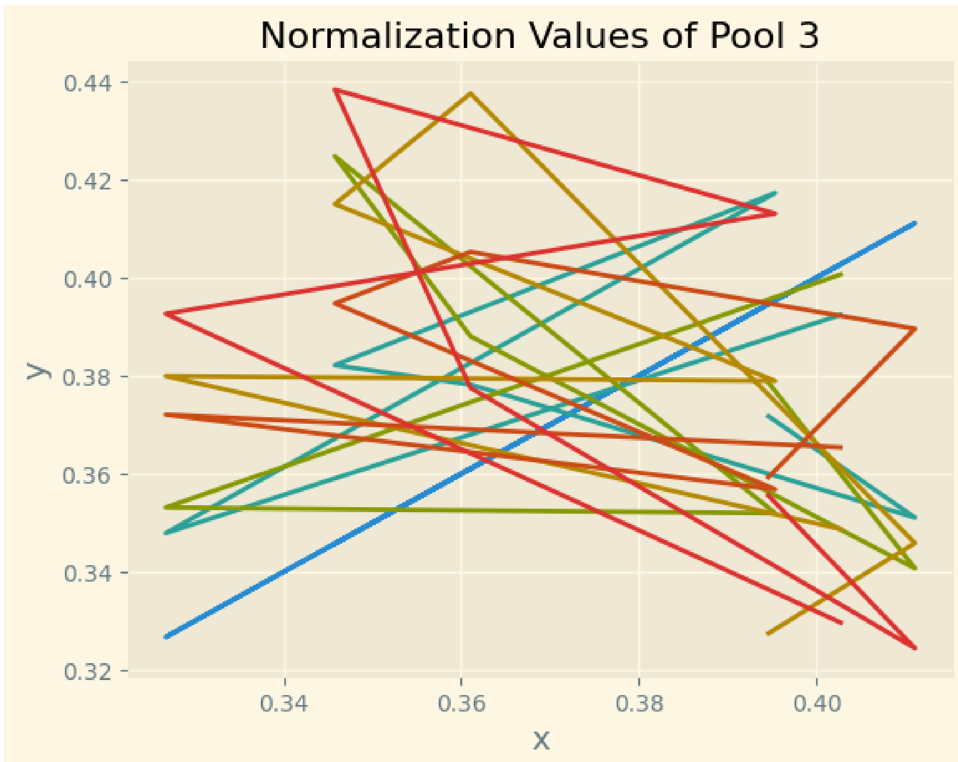

Fig 6. The normalization values.

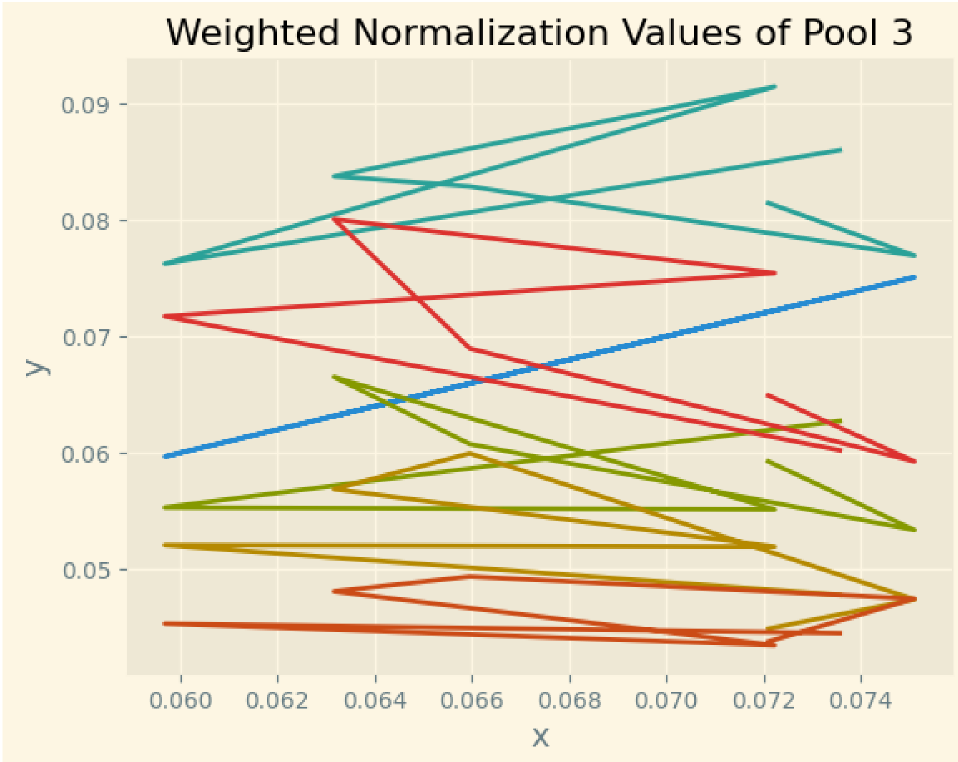

Fig 7. The weighted normalized decision matrix.

Pool 4

We normalize the decision matrix as shown in Fig 8.

Then we obtain the weighted normalized decision matrix as shown in Fig 9.

Then we compute the value of y_i and then we rank the alternatives.

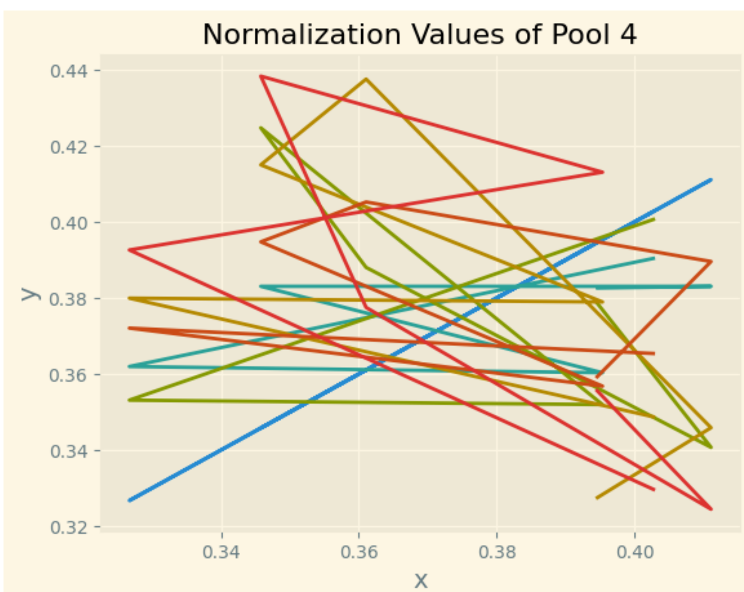

Fig 8. The normalization values.

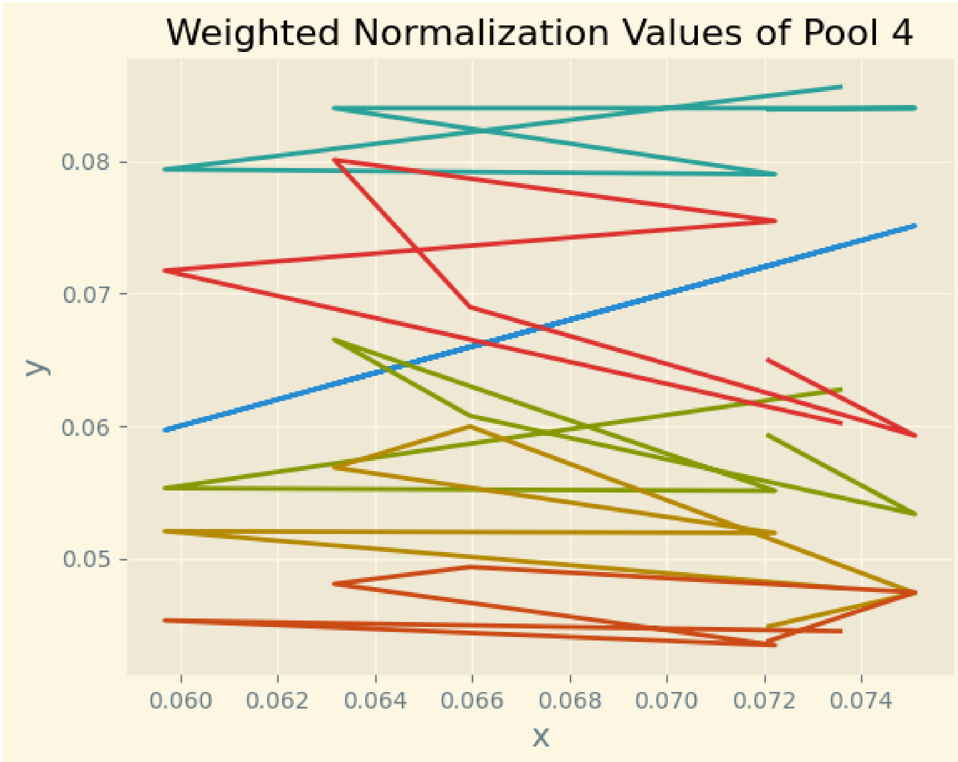

Fig 9. The weighted normalized decision matrix.

Then we rank the alternatives in each pool as shown in Fig 10. Then we show alternative 4 is the best and alternative 6 is the worst.

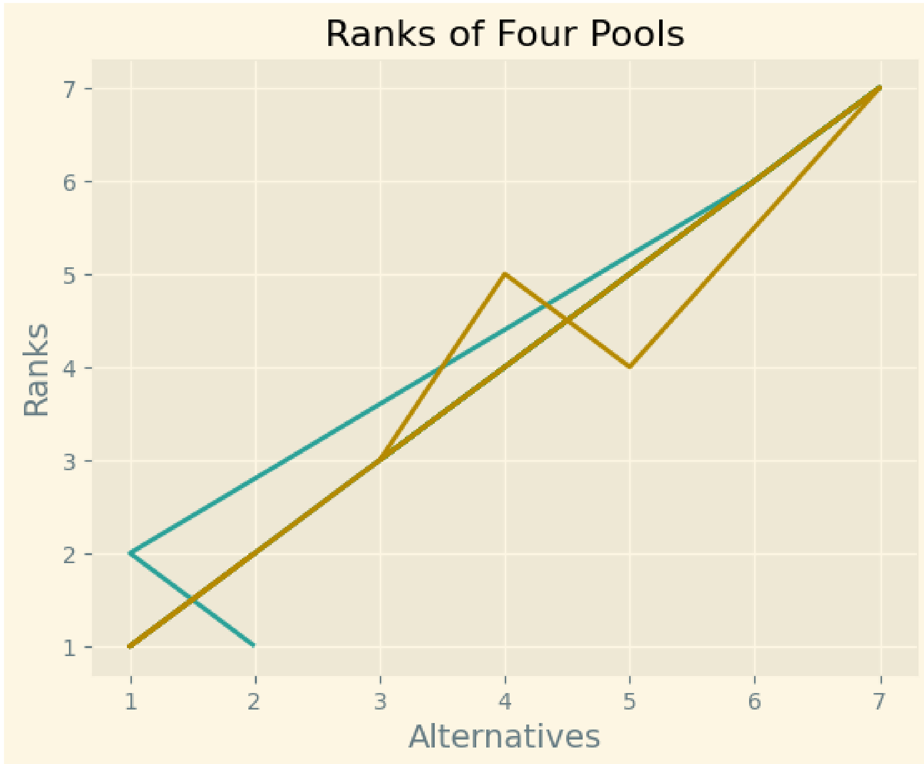

Fig 10. Different ranks of 4 pools.

4. Conclusions and Implications

This study used two MCDM methods to compute the criteria weights by the LBWA and MOORA method to rank the alternatives. We used the SuperHyperSoft set to deal with criteria and sub criteria. Six criteria and seven alternatives are used in this study. We proposed four pools as four HyperSoft sets to show the different sub criteria values. The results show alternative 4 is the best and alternative 6 is the worst.

The assessment of teaching effectiveness in educational technology within vocational colleges highlights the significant impact of digital learning tools on student engagement, skill acquisition, and instructional quality. However, effectiveness varies based on instructor competency, student adaptability, and technological infrastructure. Institutions that provide adequate teacher training, robust digital support, and industry-aligned curriculum designs tend to achieve better learning outcomes.

A key insight from this research is that merely integrating technology into vocational education does not guarantee improved teaching effectiveness. The quality of implementation, accessibility of resources, and engagement strategies play a crucial role in determining whether educational technology leads to better learning experiences. The findings suggest that blended learning models, real-time assessment tools, and AI-driven personalized learning significantly contribute to student success when properly managed.

Moreover, the connection between digital learning tools and industry needs must be continually evaluated. As vocational education directly prepares students for real-world job markets, institutions must ensure that technological advancements in education align with evolving industry requirements. The study suggests that stronger collaborations between vocational colleges and industry stakeholders can enhance curriculum relevance and ensure that students gain practical, in-demand skills.

While educational technology presents significant opportunities for enhancing vocational education, a structured evaluation process is essential to measure its effectiveness. By adopting a multi-criteria approach, vocational institutions can optimize teaching strategies, refine technology integration, and ultimately improve student learning outcomes. Future research should explore longitudinal assessments of digital learning tools to ensure their sustained effectiveness in vocational education.

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