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IndetermSoft Set for Digital Marketing Effectiveness Evaluation Driven by Big Data Based on Consumer Behavior

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Abstract: This study proposes the multi-criteria decision-making (MCDM) methodology for Digital Marketing Effectiveness Evaluation Driven by Big Data Based on Consumer Behavior. This study uses two MCDM methods such as the Entropy method to compute the criteria weights and the MARCOS method to rank the alternatives. We used the IndetermSoft set to deal with indeterminacy with different values in the criteria. IndetermSoft is integrated with the MCDM approach. Three experts evaluated the criteria and alternatives. We use seven criteria and ten alternatives. We conducted a comparative analysis to show the effectiveness of the proposed approach. The results show the proposed approach is effective compared to other MCDM methods.

Keywords: IndetermSoft Set; Digital Marketing; Big Data; Consumer Behavior; MCDM Methodology.

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1. Introduction

In the digital era, businesses leverage big data-driven digital marketing strategies to maximize consumer engagement, improve conversion rates, and enhance return on investment (ROI). The effectiveness of digital marketing is no longer solely dependent on traditional advertising but is now heavily influenced by consumer behavior insights derived from vast datasets. Companies collect and analyze real-time data on user interactions, purchasing patterns, and online preferences to personalize marketing strategies[1], [2]. This shift has made it essential to establish a comprehensive evaluation framework that assesses digital marketing effectiveness based on key performance indicators (KPIs) linked to consumer behavior, such as engagement levels, conversion rates, and personalization effectiveness. The evaluation of digital marketing effectiveness requires a multi-criteria decision-making (MCDM) approach that integrates big data analytics with consumer behavior metrics. Various marketing channels, including social media advertising, search engine optimization (SEO), content marketing, and AI-powered personalization, yield different levels of engagement and profitability[2], [3]. By analyzing structured and unstructured data, companies can measure the impact of their marketing campaigns in real time. This data-driven approach not only enhances marketing efficiency but also optimizes resource allocation, allowing businesses to invest in strategies that yield the highest ROI. Moreover, advanced analytics techniques, such as predictive modeling and machine learning, enable organizations to anticipate consumer needs and improve marketing precision.

However, despite its advantages, evaluating digital marketing effectiveness presents challenges. The sheer volume of consumer data, data privacy concerns, and the dynamic nature of consumer behavior make it difficult to establish a one-size-fits-all evaluation model. Additionally, the rapid evolution of digital platforms requires continuous adaptation to new trends, algorithms, and consumer expectations[4], [5]. Businesses must ensure that their evaluation frameworks are scalable, adaptable, and capable of handling uncertainty, MCDM methods essential for balancing multiple factors such as cost-effectiveness, engagement, and brand influence. By employing big data-driven evaluation frameworks, companies can develop more targeted, efficient, and responsive marketing strategies. A well-structured evaluation approach enables businesses to identify weaknesses in their marketing efforts, optimize campaign performance, and build stronger relationships with consumers. The integration of big data and consumer behavior analytics into digital marketing effectiveness evaluation is not just a competitive advantage—it is a necessity in the modern digital landscape[6], [7]. As businesses continue to refine their approaches, the ability to accurately measure and adapt to changing consumer behaviors will determine long-term success in the highly competitive digital marketplace.

1.1 IndetermSoft

IndetermSoft is an advanced extension of soft set theory designed to handle indeterminate and uncertain information in decision-making problems. Traditional soft sets provide a mathematical framework for dealing with uncertainty, but they assume that the membership values of elements in the set are well-defined. However, in real-world scenarios, information can often be incomplete, inconsistent, or indeterminate, making it difficult to reach precise conclusions. IndetermSoft addresses this limitation by introducing indeterminate elements, allowing for a more flexible and realistic approach to uncertain data processing[8], [9]. In IndetermSoft theory, elements in a soft set can belong to a parameter partially, fully, or indeterminately. This means that instead of simply having a clear membership value, an element's association with a given attribute can be ambiguous or undefined due to missing data, conflicting information, or lack of certainty.[10], [11] This characteristic makes IndetermSoft particularly useful in medical diagnosis, environmental assessments, risk management, and artificial intelligence, where uncertain or conflicting data is common.

Example of IndetermSoft

Consider a medical diagnosis problem where a doctor needs to assess whether a patient has a disease based on symptoms. Traditional soft set theory assumes that a symptom is either present or absent, but in many cases, the presence of a symptom may be uncertain or indeterminate due to ambiguous test results or incomplete patient history.

The rest of this study is organized as follows: Section 2 shows the methods of this study to compute the criteria weights and rank the alternatives. Section 3 shows the results of the proposed approach. Section 4 shows the analysis of this study. Section 5 shows the conclusions of this study.

2. Methods

This section shows the steps of two MCDM methods to compute the criteria weights and rank the alternatives. These methods are used with IndetermSoft to deal with indeterminacy in the criteria and alternatives evaluation.

Entropy Approach

This method is used to compute the criteria weights.

Build the decision matrix.

Experts and decision-makers use a scale between 0.1 and 0.9 to evaluate the criteria and alternatives. Then we combined these values by the average method.

Normalize the decision matrix.

The decision matrix is normalized between the criteria and alternatives such as:

$$q_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (1)$$

Where x_{ij} refers to the value in the decision matrix, $i = 1, \dots, m; j = 1, \dots, n$

Compute the entropy

$$p_j = -h \sum_{i=1}^{m} q_{ij} \ln q_{ij} \quad (2)$$

$$h = \frac{1}{\ln m} \quad (3)$$

Compute the criteria weights

$$w_j = \frac{1-p_j}{\sum_{j=1}^{n} 1-p_j} \quad (4)$$

MARCOS Approach

This method is used to rank the alternatives.

We start with the decision matrix to compute the ideal and anti-ideal solution.

$$AAI = \min_i x_{ij} \ positive \ and \ \max_i x_{ij} \ negative \tag{5}$$

$$AI = \max_i x_{ij} \ positive \ and \ \min_i x_{ij} \ negative \tag{6}$$

Normalize the decision matrix

$$s_{ij} = \frac{x_{ij}}{x_{ai}} \ positive \tag{7}$$

$$s_{ij} = \frac{x_{ai}}{x_{ij}} \ negative \tag{8}$$

Compute the weighted matrix

$$y_{ij} = w_j s_{ij} \tag{9}$$

Compute the utility degree of alternatives

$$D_i^- = \frac{k_i}{k_{aai}} \tag{10}$$

$$D_i^+ = \frac{k_i}{k_{ai}} \tag{11}$$

$$k_i = \sum_{i=}^{n} y_{ij} \tag{12}$$

Compute the utility function of alternatives

$$f(D) = \frac{D_i^- + D_i^+}{1 + \frac{1 - f(D_i^-)}{f(D_i^-)} + \frac{1 - f(D_i^+)}{f(D_i^+)}} \tag{13}$$

$$f(D_i^-) = \frac{D_i^+}{D_i^- + D_i^+} \tag{14}$$

$$f(D_i^+) = \frac{D_i^-}{D_i^- + D_i^+} \tag{15}$$

Rank the alternatives.

IndetermSoft Set

Smarandache presented it in 2022[12], [13], [14]. Let H be a non-empty subset of U, P(H) be the powerset of H, and U be a universe of discourse. Assume that a is an attribute and that A is a collection of its values.

Then $F: A \to P(H)$ is referred to as an IndetermSoft Set if: i) there is some indeterminacy in the set A; ii) or the set P(H) has some indeterminacy; iii) there exists at least one attribute-value $v \in A$ such that $F(v)$ = indeterminate (unclear, incomplete, conflicting, or not unique); iv) or any two or all three of the aforementioned circumstances

The IndetermSoft Set is a specific instance of the NeutroFunction, which was defined in 2014–2015 and is a function that is only partially well-defined (inner-defined), partially indeterminate, and partially outer-defined due to its degree of indeterminacy. A completely well-defined extension of the classical function is the NeutroFunction.

Since certain sources are unable to give precise or comprehensive information on the sets A, H, or P(H), as well as on the function F, IndetermSoft Set, an extension of the classical (determinate) Soft Set, deals with indeterminate data. We discovered indeterminacy in the real world; we did not introduce any.

Since many sources provide knowledge that is not accurate like in the Soft Set but rather approximate, ambiguous, partial, and contradictory, we still must cope with these kinds of circumstances.

Example:

Let a set of attributes select the best location with a set of attributes. We have attributes of area and price, these attributes have values such as area = (large, small), price=(low, high). These values have indeterminacy.

We can select a location based on these values.

We select location 1 or location 2 if the area is large and the price is low.

We select location 3 or location 4 if the area is large and the price is high.

3. Results and Discussion

This section shows the results of the two MCDM methods through a case study to show the validation of the methods. Three experts have a scale between 0.1 to 0.9 to evaluate the criteria and alternatives. Seven criteria and ten alternatives are used in this study. The criteria of this study are: Customer Retention, Conversion Rate, Data-Driven Decision-Making, Customer Engagement, Return on Investment, Personalization Effectiveness, and Social Media Influence. Ten alternatives of this study such as Influencer Marketing, Social Media Advertising, Video Marketing, Search Engine Optimization, AI-powered chatbots and Personalization, Pay-Per-Click Advertising, Content Marketing, Email Marketing, Affiliate Marketing, and Mobile Marketing.

Entropy Approach Results

We build the decision matrix. Experts and decision-makers use a scale between 0.1 and 0.9 to evaluate the criteria and alternatives. Then we combined these values by the average method.

We normalize the decision matrix using Eq. (1) as shown in Fig 1.

We compute the entropy using Eq. (2) as shown in Fig 2.

We compute the criteria weights using Eq. (4) as shown in Fig 3.

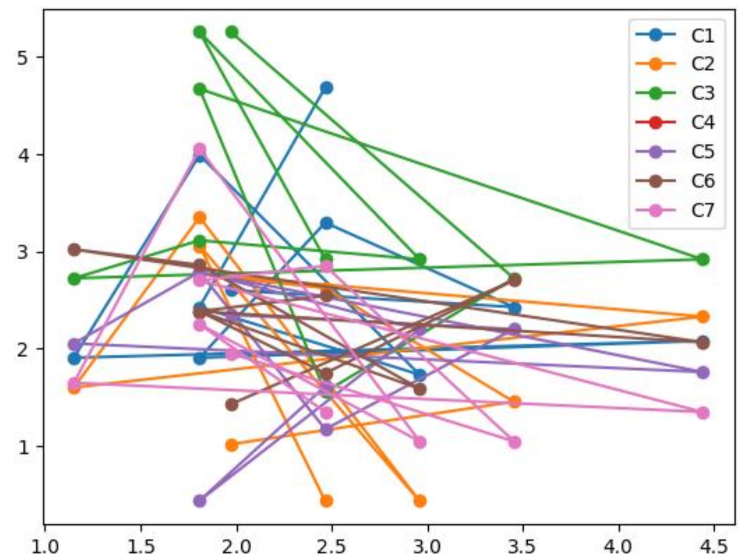

Fig 1. The normalization values by Entropy methods.

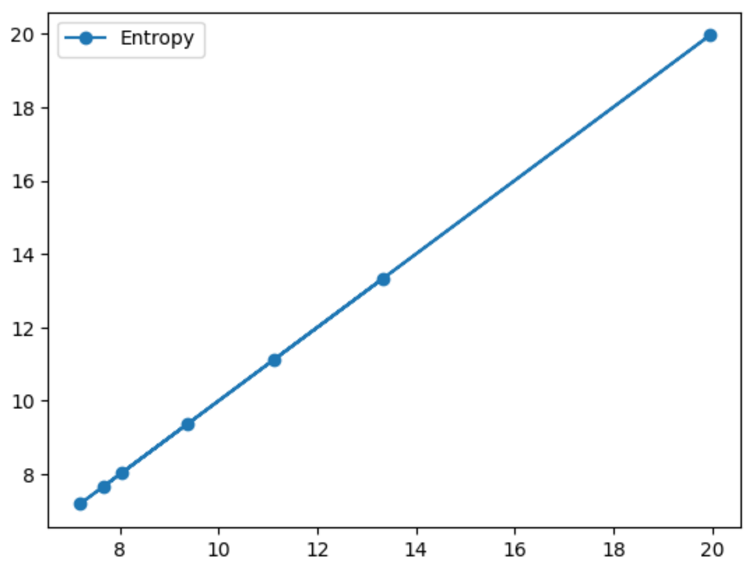

Fig 2. Entropy values.

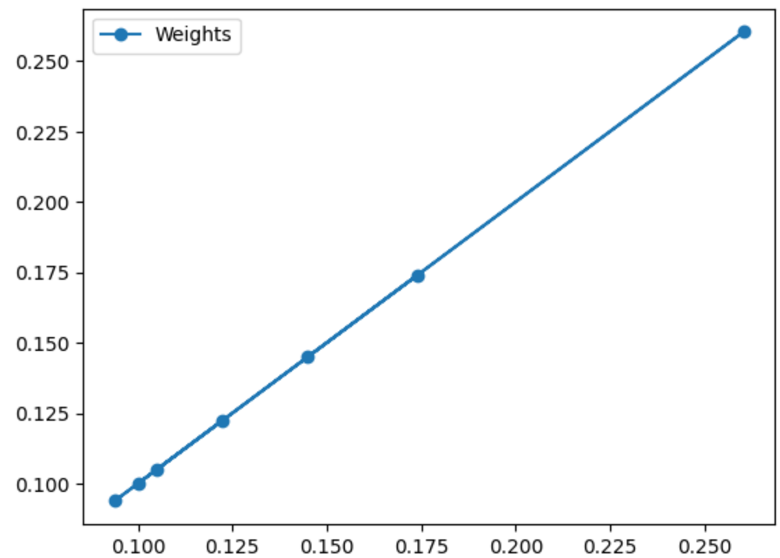

Fig 3. The criteria weights.

MARCOS Approach Results

We applied the IndetermSoft set to deal with indeterminacy in the criteria values. We have indeterminacy in the first criterion and its values are Strong, Moderate, and Weak. So, we ranked the alternatives based on these values. In the first, we let use the Strong value and then apply the MARCOS methods. The suggestions for using the values are:

$$\left\{\begin{array}{c} \text{Strong,} \\ \text{Moderate,} \\ \text{Weak,} \\ \text{Strong, Moderate} \\ \text{Strong, Weak} \\ \text{Moderate, Weak} \\ \text{Strong, Moderate, Weak} \end{array}\right\}$$

And other criteria have values of {High, Moderate, Medium, High, High, Strong}.

In the Strong value:

We normalize the decision matrix using Eq. (7) as shown in Fig 4.

We compute the weighted matrix using Eq. (9) as shown in Fig 5

Then we compute the utility degree of alternatives using Eqs. (10-12).

Then we compute the utility function of alternatives using Eq. (13).

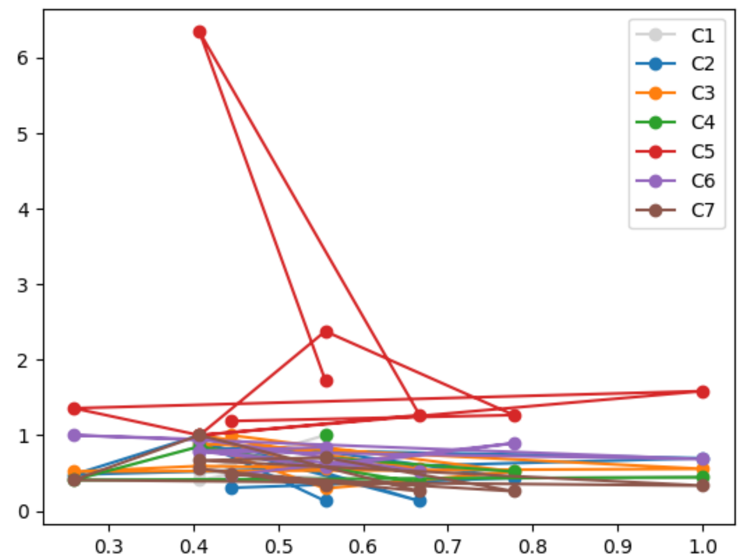

Fig 4. The normalization matrix.

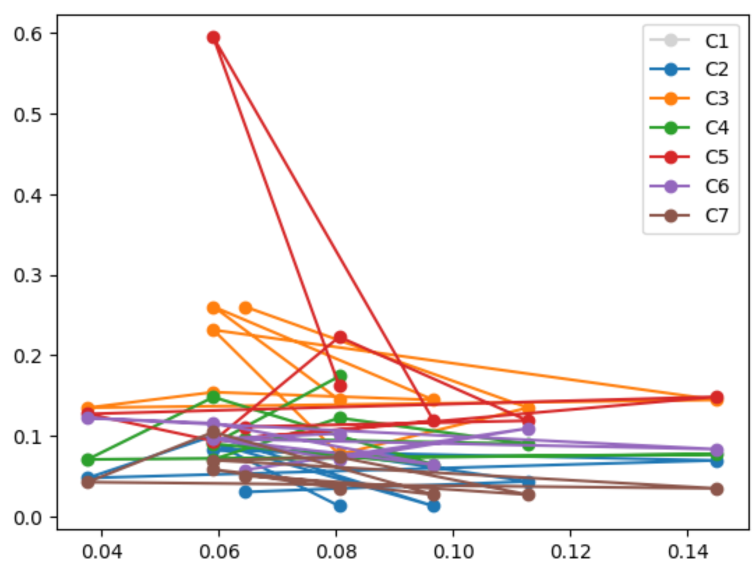

Fig 5. The weighted matrix.

In the Moderate value:

We normalize the decision matrix using Eq. (7) as shown in Fig 6.

We compute the weighted matrix using Eq. (9) as shown in Fig 7

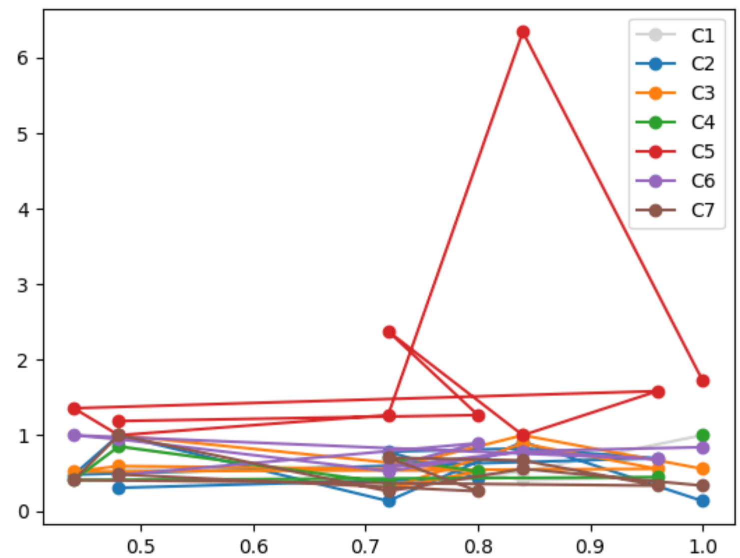

Fig 6. The normalization matrix.

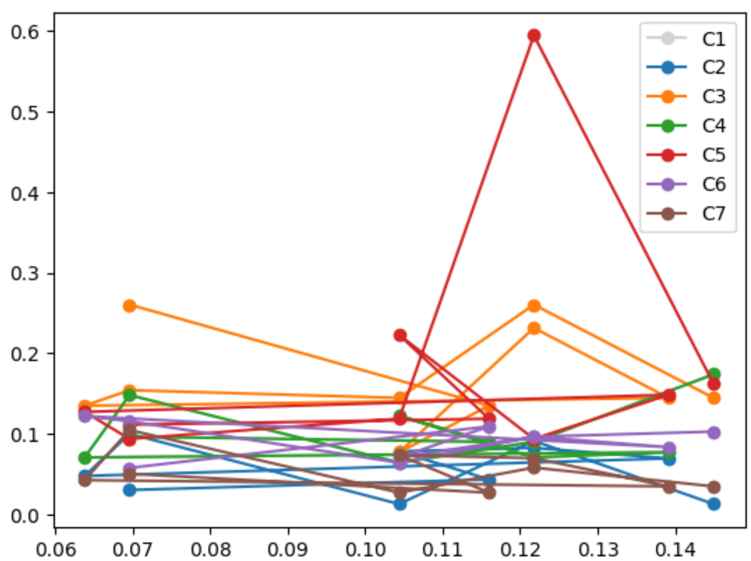

Fig 7. The weighted matrix.

In the Weak value:

We normalize the decision matrix using Eq. (7) as shown in Fig 8.

We compute the weighted matrix using Eq. (9) as shown in Fig 9.

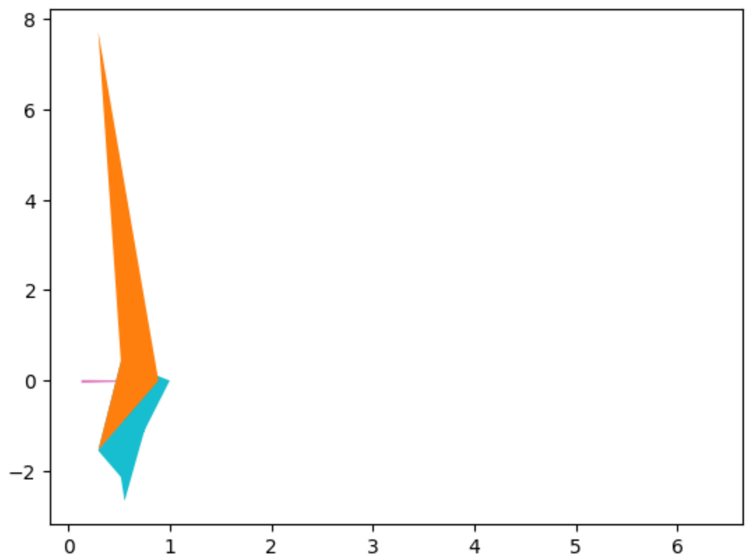

Fig 8. The normalization matrix.

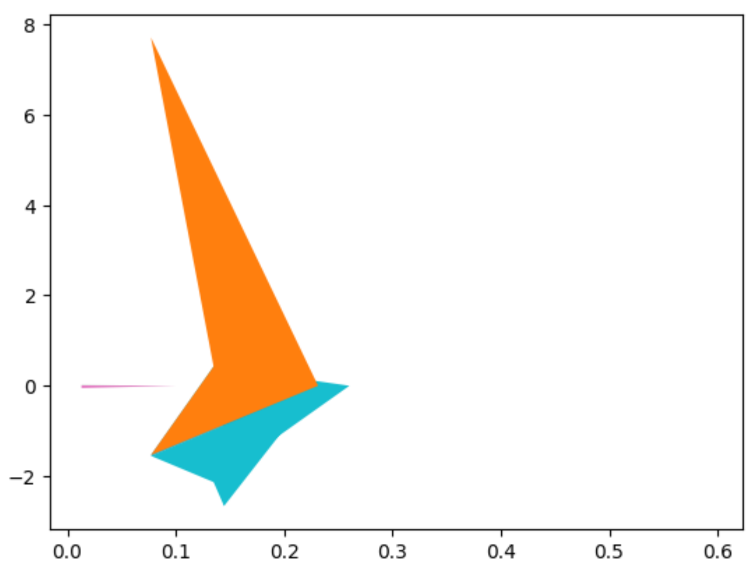

Fig 9. The weighted matrix.

In the Strong and Moderate value:

We normalize the decision matrix using Eq. (7) as shown in Fig 10.

We compute the weighted matrix using Eq. (9) as shown in Fig 11.

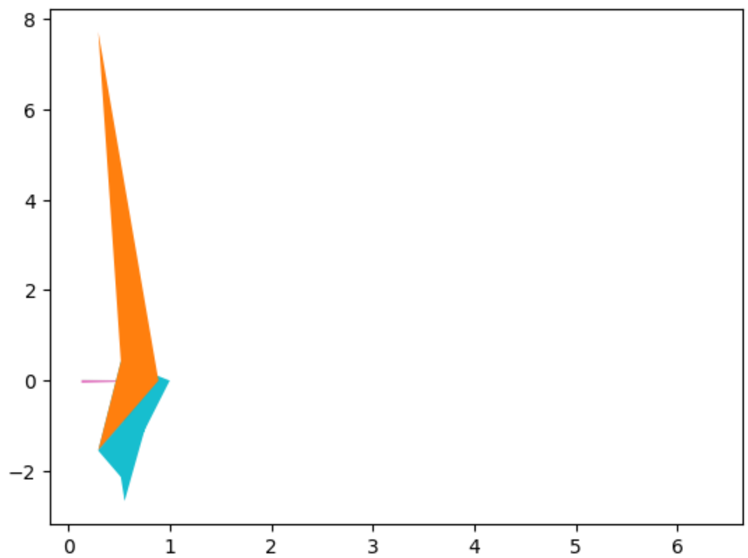

Fig 10. The normalization matrix.

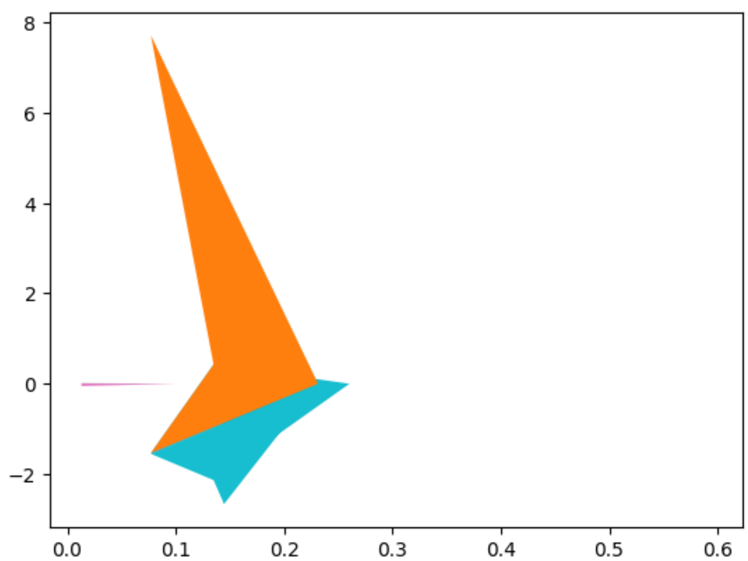

Fig 11. The weighted matrix.

In the Strong and Weak value:

We normalize the decision matrix using Eq. (7) as shown in Fig 12.

We compute the weighted matrix using Eq. (9) as shown in Fig 13.

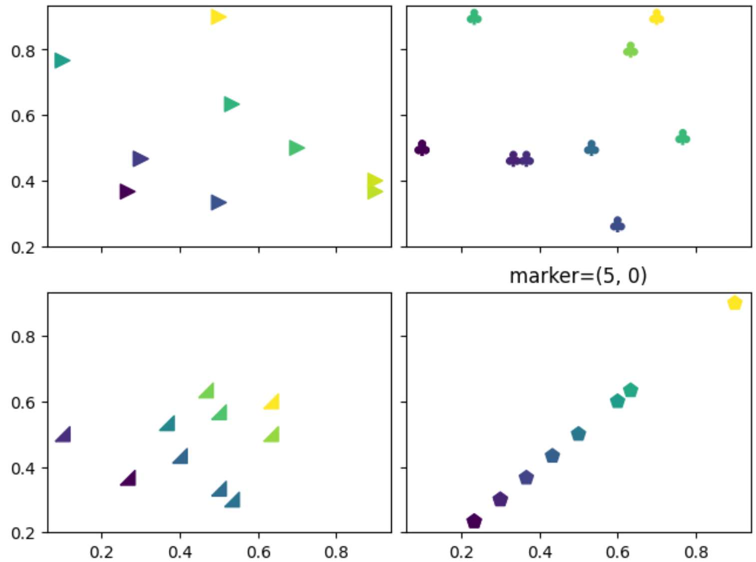

Fig 12. The normalization matrix.

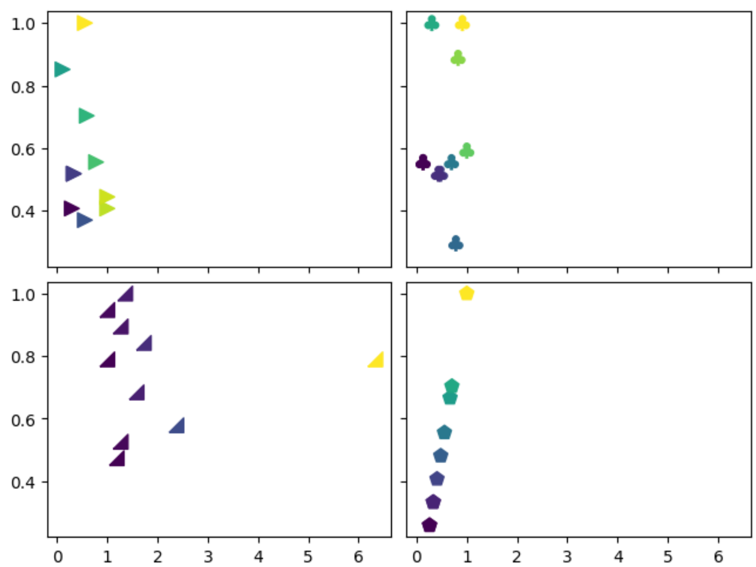

Fig 13. The weighted matrix.

In the Moderate and Weak value:

We normalize the decision matrix using Eq. (7) as shown in Fig 14.

We compute the weighted matrix using Eq. (9) as shown in Fig 15.

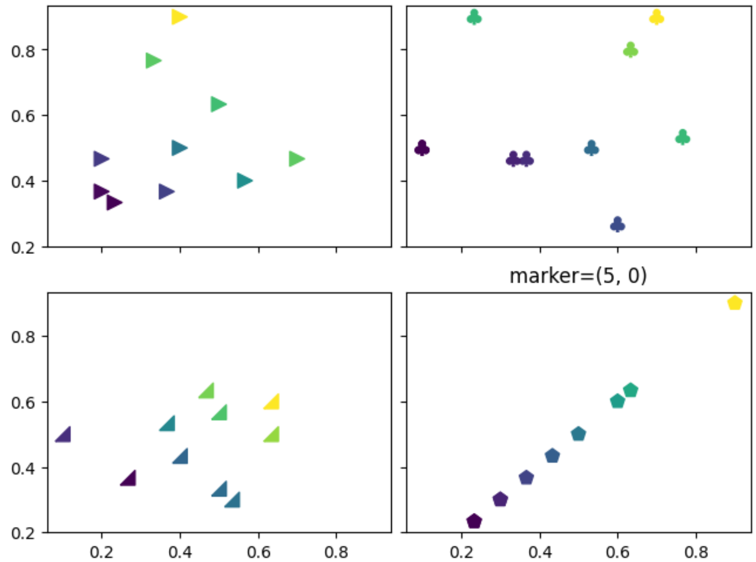

Fig 14. The normalization matrix.

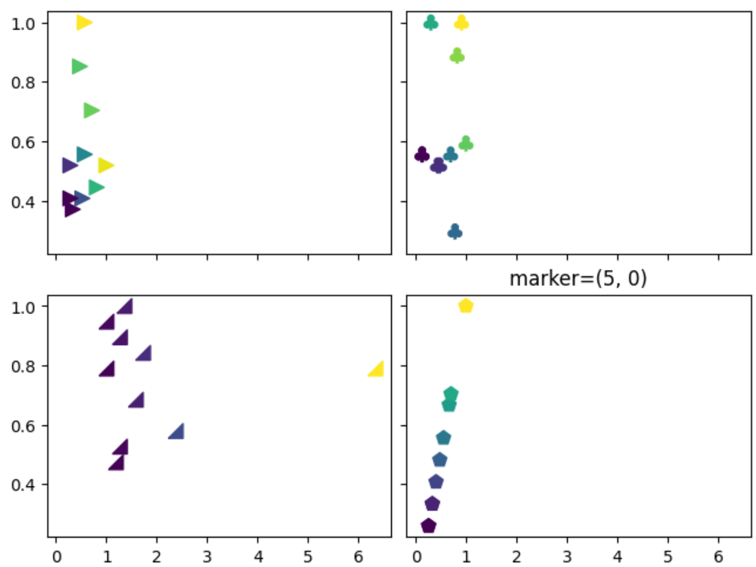

Fig 15. The weighted matrix.

In the Strong, Moderate, and Weak value:

We normalize the decision matrix using Eq. (7) as shown in Fig 16.

We compute the weighted matrix using Eq. (9) as shown in Fig 17.

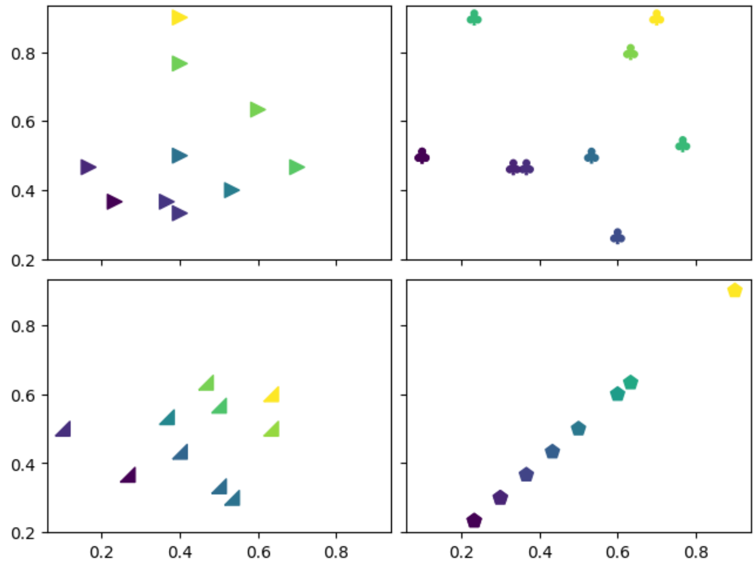

Fig 16. The normalization matrix.

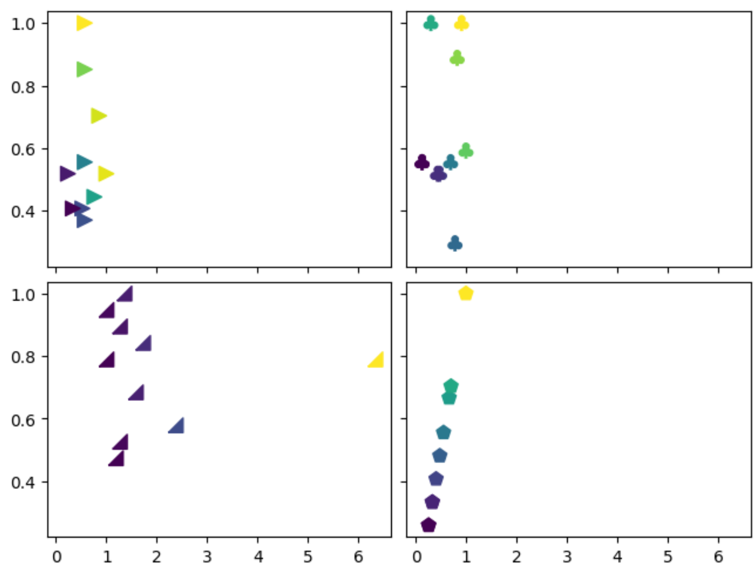

Fig 17. The weighted matrix.

Then we finally ranked the alternatives as shown in Fig 18.

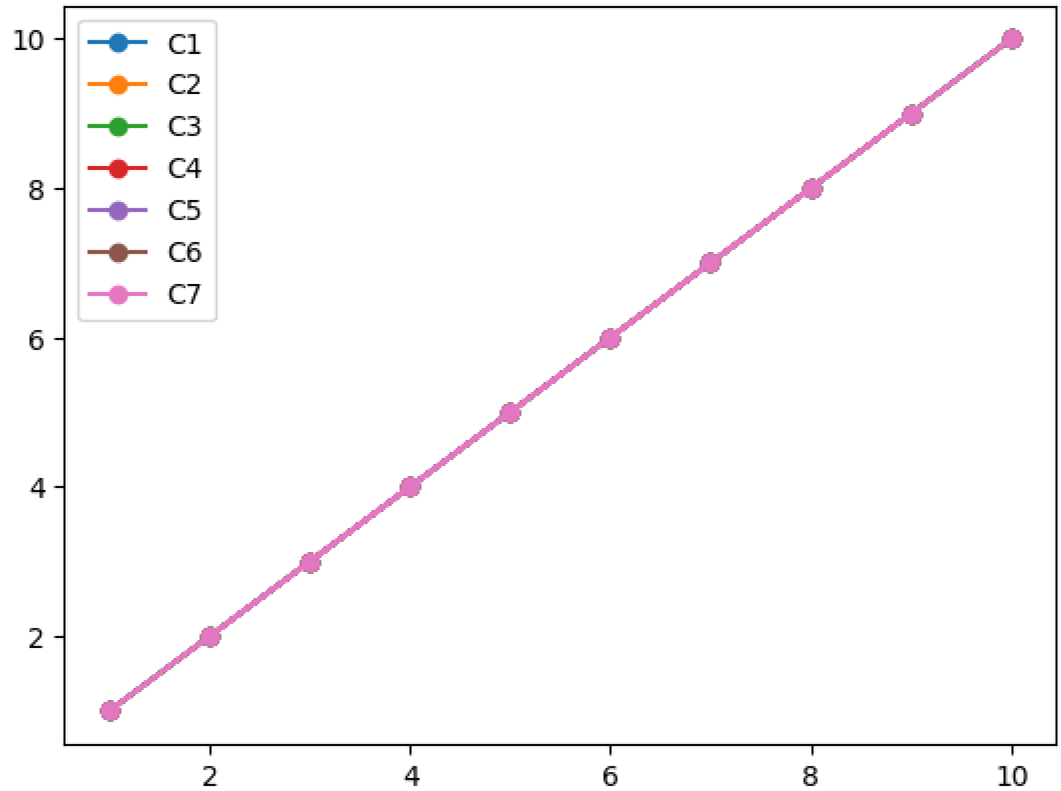

Fig 18. The final ranks.

4. Analysis

This section shows the comparative analysis between the proposed approach and other MCDM methods to show the effectiveness of the proposed approach. We compared our model with four MCDM methods as shown in Fig 19. The results showed that all models show alternative 2 is the best and alternative 3 is the worst. So, the results showed that our model is effective compared to other MCDM methods.

MARCOS method is effective compared to other MCDM methods because it deals with positive and negative criteria by computing the ideal and anti-ideal solution for negative and positive criteria. It has the utility degrees and utility functions of all alternatives. The utility function is used to rank the alternatives.

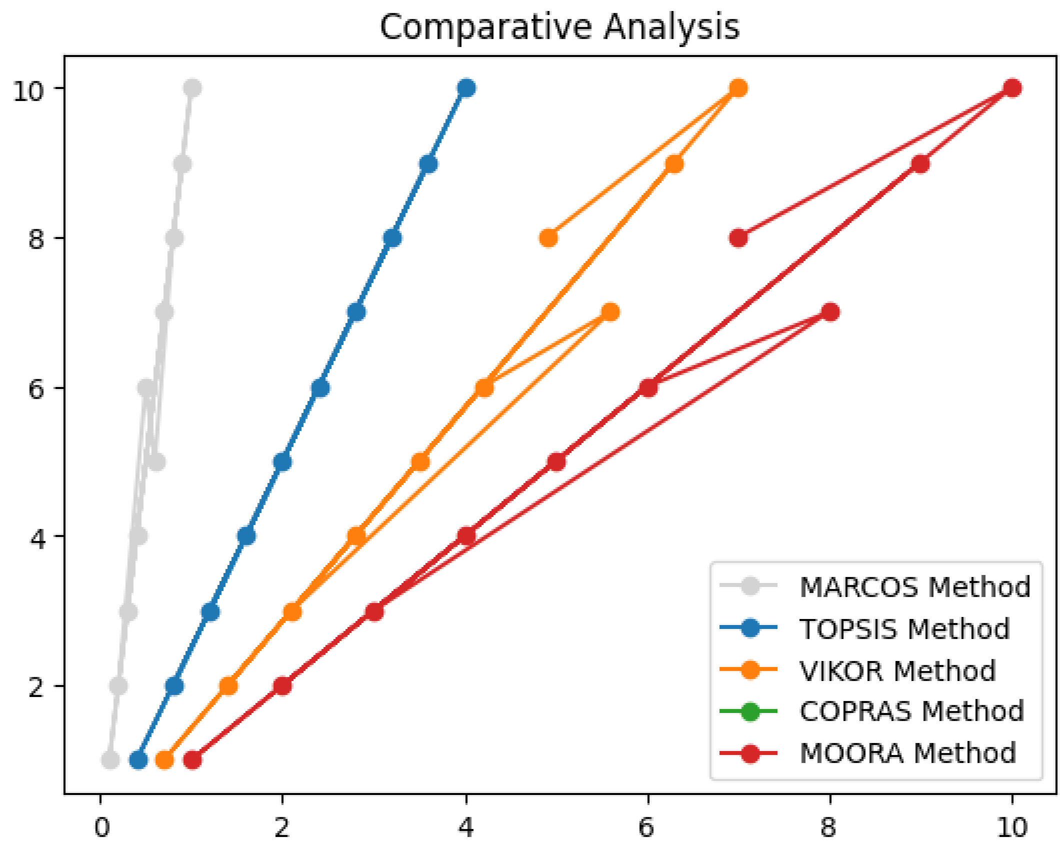

Fig 19. Comparative results

5. Conclusions

The IndetermSoft set is used in this study to treat the indeterminacy in the values of the criteria. IndetermSoft set is combined with two MCDM methods such as the Entropy method to compute the criteria weights and the MARCOS method to rank the alternatives. In this study, we have indeterminacy in the first criterion with three values such as strong, moderate, and weak. We change these values by seven cases. Then we ranked the alternatives under these cases. The results show alternative 2 is the best and alternative 3 is the worst. We compared the proposed approach with the different MCDM methods. The results show the proposed approach is effective compared to other MCDM methods.

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