CASE STUDY TO CONTRAST TOPSIS AND MODIFIED TOPSIS WITH EQUI-CREDITED AND NONEQUI-CREDITED CRITERIA

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ABSTRACT

In the automotive industry, supplier selection is a critical process, fundamental to the efficient functioning of businesses within this sector. This research paper addresses the imperative need for an effective supplier selection methodology amidst the myriad of options available in the market. It introduces a novel approach designed to identify the most suitable products in the market. The proposed method leverages various adaptations of the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) technique to tackle Multiple Attribute Decision Making (MADM) problems, with the primary objective of assessing decision-making efficiency.

The study embarks on a comprehensive comparative analysis of various TOPSIS variants, aiming to discern the most effective method through a correlation-based ranking approach. This rigorous examination extends to encompass both equal and unequal credit criteria, elucidating the nuances and distinctions between these two widely used approaches. By shedding light on the strengths and limitations of these methodologies, the research seeks to offer clarity to decision-makers facing a diverse array of decision-making challenges.

In addition to its immediate implications for the automotive industry, this research contributes to the broader field of decision science. It provides a robust framework for addressing complex MADM problems and lays the groundwork for enhanced decision-making across various domains. Future research endeavours may explore broader subjects, building upon the foundational insights presented in this paper and extending its application to diverse areas of study.

Keywords: Multiple Attribute Decision Making (MADM); TOPSIS; Modified TOPSIS; Equi-credited Criteria; Comparative Analysis

1. INTRODUCTION

In the domain of Multiple Attribute Decision Making (MADM), choosing the right decision-making approach is a pivotal and essential stage. that significantly influences the quality of decision outcomes. Among the various methodologies available, the Technique for Order Preference by Similarity to Ideal

Solution (TOPSIS) has gained widespread recognition for its simplicity and effectiveness in helping decision-makers identify the most suitable alternative from a set of options. However, as decision-making scenarios become increasingly complex, the need for more robust and adaptable approaches becomes evident.

This paper aims to explore and compare two such approaches within the MADM context: the traditional TOPSIS methodology and its innovative counterpart, "modified TOPSIS." While both methodologies share a common goal of aiding in multi-criteria decision-making, they exhibit distinct characteristics and address specific challenges differently.

In the following sections, we will delve into the principles and applications of TOPSIS and modified TOPSIS, highlighting their respective strengths and weaknesses. By contrasting these two methodologies, we aim to provide decision-makers with valuable insights into when and how to choose between them, depending on the nature of the decision problem at hand. This comparative analysis will shed light on the unique contributions of modified TOPSIS, particularly its incorporation of an entropy-based objective credit allocation process and a novel approach to attribute credit distribution, which set it apart from the traditional TOPSIS method.

The extensive utility of the Method for Ranking by Similarity to the Ideal Solution (TOPSIS) is well-documented, as it has been widely used in addressing real-world challenges in Multiple Attribute Decision Making (MADM) [4]. Beyond its fundamental application, TOPSIS has served as the basis for various derivative strategies and has been a cornerstone in the MADM domain [5]. TOPSIS helps organizations choose the right outsourcing providers by considering factors like cost, quality, and expertise. In manufacturing, TOPSIS assists in selecting processes and equipment based on cost, efficiency, and environmental impact. Investors and analysts use this method to evaluate and rank companies based on financial metrics, aiding investment decisions. Service providers employ it to assess and improve service quality by considering criteria like response time and customer satisfaction . TOPSIS aids students and parents in selecting schools or universities by evaluating factors such as academic reputation and location. Engineers and designers use it to make informed choices about technologies and materials for projects. Many companies apply this method for product procurement decisions, comparing features, cost, and quality. Organizations prioritize strategic options using TOPSIS, factoring in market potential, risk, and resource requirements. This method also heps in defence and security, for example in mission planning by considering mission success probability and resource availability etc.

On the other hand, the modified TOPSIS variant has found relevance in various practical scenarios. It is employed to estimate attribute weights in comparative studies, a crucial step in multi-criteria decision-making [6]. Additionally, It is used to create objective composite indices, aiding decision-makers in fields like economics and performance evaluation[7]. Beyond these applications, modified TOPSIS has been implemented in resource management, aiding in efficient resource allocation and utilization [8]. It has also been employed to select suitable software solutions, to compare alternatives in various contexts, to help in decision-making, to assess sustainability in projects, products, or processes, considering environmental, social, and economic aspects, to select material, machine, technology, etc. and even the development of novel decision-making methodologies [9-19]. These practical applications underscore the adaptability and usefulness of both TOPSIS and modified TOPSIS in addressing a wide range of decision-making challenges across various industries and domains.

TOPSIS stands as a foundational method within the domain of Multicriteria Decision-Making (MADM), enjoying widespread popularity across various applications and serving as a basis for the development of numerous related methodologies. The modified TOPSIS, an extension of the original TOPSIS framework, has gained prominence due to its innovative approach to objective weight determination, rooted in the entropy theory of Shannon [20]. Both the standard TOPSIS method and its modified versions, necessitate the establishment of discrete attribute credit values as a prerequisite for their calculations. In TOPSIS, these attribute weights signify The decision maker's subjective preferences in relation to the criteria. On the contrary, in the modified TOPSIS approach, attribute weights are established by assessing their importance through entropy-based analysis. Although these methods exhibit mathematical similarities, utilizing the same Euclidean distance measure, they significantly differ in how they handle and apply attribute credits.

The decision-making landscape often presents a challenge for stakeholders when it comes to choosing between these two closely related methods. Their mathematical resemblance and applicability to similar MADM problems, such as water resource management [21], airline assessment [22,23], and supplier selection [24], complicate the decision-making process. As a result, there is a compelling requirement for a comprehensive assessment and comparison of these methodologies to clarify their appropriateness and define their specific areas of application.

Our exploration commences with a thorough introduction to the TOPSIS, modified TOPSIS, equal credit-based TOPSIS, and unequal credit-based TOPSIS algorithms, followed by an exhaustive presentation of case study comparisons and a rigorous mathematical analysis. This endeavor aims to provide decision-makers and researchers with valuable insights into the intricacies of these methodologies, facilitating informed choices in selecting the most suitable approach for their specific decision-making scenarios.

2. FRAMEWORK FOR PROBLEM

Before delving into the application of various TOPSIS approaches to address a specific Multiple Attribute Decision Making (MADM) problem, it is imperative to establish a comprehensive understanding of the general MADM problem framework that underpins all the proposed methodologies.

2.1 Problem Definition

The overarching objective of the Generic Multiple Attribute Decision Making (MADM) problem is to assess and prioritize alternatives labelled as P_m (where m = 1, 2,… , M) based on a collection of attributes denoted by n (where n = 1, 2, …, N). The alternatives, represented by the set A_m, encompass the available options for the decision-maker to rank. On the other hand, the attributes represented by Q_n signify the factors that influence the decision maker's ranking of the alternatives P_m. Attribute Credits, denoted as C_n (where n = 1, 2, …, N), express the relative significance of these attributes Q_n. Attribute credits can be depicted as

$$C = C_n \tag{1}$$

The decision maker's inclinations for each alternative P_m concerning each attribute Q_n are recorded in a performance rating matrix A, defined as

C = Cn (Equation 1)

$$A = [a_{mn}], (\mathrm{m} = 1,2, \dots, \mathrm{M}; n = 1,2, \dots, \mathrm{N}). \tag{2}$$

Using the decision matrix A and the credit vector C as defined in Equations (1) and (2), the MADM problem R is expressed in Equation (3) [25]

$$R = \{A, C\} \tag{3}$$

To solve the given MADM problem R, various MADM methods can be applied. These methods typically involve: (a) Normalization procedure: This procedure transforms the performance ratings $[a_{mn}]$, into a consistent measurement unit. (b) Score Aggregation: An overall credited score $S_m(m = 1,2, \dots, M)$ for each alternative is calculated by merging the attribute credits and performance ratings. . The ultimate ranking of the alternatives is established based on these overall scores.

2.2 Methodology Overview

The methodologies discussed in this paper, including TOPSIS, modified TOPSIS, and equal credit-based TOPSIS, are designed to address this general MADM problem framework. Each methodology offers a unique approach to leveraging attribute credits, performance ratings, and other relevant factors to rank the alternatives effectively.

In the subsequent sections, we delve into the specific characteristics and application of these methodologies, highlighting their individual strengths and approaches to solving MADM problems. By establishing this foundational understanding, we pave the way for a comprehensive exploration of their practical implications and comparative analysis when applied to a real-world MADM scenario.

3. HISTORICAL OVERVIEW OF VARIOUS METHODS USED

3.1 The TOPSIS method

TOPSIS operates on the foundational principle that the optimal solution is characterized by its proximity to the positive-ideal solution while maintaining a substantial distance from the negative-ideal solution. The ranking of alternatives is determined by computing an overall index based on the distances from these ideal solutions. [26].

The TOPSIS method can be elucidated as a series of steps outlined below:

Step 1: Compute the normalized performance ratings.

Vector normalization is utilized to derive normalized performance ratings from Equation (2). In this process, each performance rating a_{mn} in matrix A is divided by its norm. The normalized ratings, denoted as b_{mn}(where $\mathrm{m} = 1,2, \dots, \mathrm{M}; \mathrm{n} = 1,2, \dots, \mathrm{N}$) can be calculated using Equation (4).

$$b_{mn} = \frac{a_{mn}}{\sqrt{\sum_{\mathrm{m}=1}^{M} a_{mn}^2}} \tag{4}$$

This type of conversion process simplifies attribute comparisons by using units that have no dimensions. Nevertheless, it encounters difficulties in facilitating direct comparisons due to variations in scale lengths [27]. The normalized performance ratings, denoted as b_{mn}, can be organized into a matrix B, as demonstrated in Equation (5).

$$\mathrm{B} = [b_{mn}] \tag{5}$$

Step 2: Incorporate credits with ratings.

The credited and normalized performance ratings, denoted as s_{mn} (where m = 1, 2, …, M; n = 1, 2, …, N), are computed using Equations (1) and (5), as illustrated in Equation (6). These credited ratings are then aggregated to create the credited-normalized decision matrix, denoted as S in Equation (7).

$$s_{mn} = C_n * b_{mn}; (\mathrm{m} = 1,2, \dots, \mathrm{M}; \mathrm{n} = 1,2, \dots, \mathrm{N}) \tag{6}$$

$$S = [s_{mn}] \tag{7}$$

Step 3: Find positive and negative ideal solutions.

$P^+ \ and \ P^-$ are used to signify the sets representing the positive and negative ideal solutions, respectively, and these sets can be identified through the utilization of Equation (7).

$$P^+ = [s_1^+, s_2^+, \dots, s_N^+] \tag{8}$$

$$P^- = [s_1^-, s_2^-, \dots, s_N^-] \tag{9}$$

Where,

$$s_n^+ = \begin{cases} \max s_{mn}, \text{ if n is a benefit attribute} \\ \min s_{mm}, \text{ if n is a cost attribute} \end{cases}$$

$$s_n^- = \begin{cases} \min \ s_{mn}, \text{ if n is a benefit attribute} \\ \max \ s_{mn}, \text{ if n is a cost attribute} \end{cases}$$

Step 4: Determine the divergence values.

The divergence measurement assesses how far each alternative rating is from both the positive and negative ideal solutions, and this is accomplished using the Euclidean distance principle. Equations (10) and (11) outline the process for computing positive and negative divergence, respectively.

$$T_m^+ = \sqrt{\sum_{n=1}^{N}(s_{mn} - s_n^+)^2} \tag{10}$$

$$T_m^- = \sqrt{\sum_{n=1}^{N}(s_{mn} - s_n^-)^2} \tag{11}$$

Step 5: Compute the comprehensive preference score.

The comprehensive preference score S_m for each alternative P_m is determined as indicated in Equation (12).

$$S_m = \frac{T_m^-}{T_m^- + T_m^+} \tag{12}$$

Alternatives are ranked based on higher S_m values.

3.2 The Modified TOPSIS method

Modified TOPSIS integrates attribute credits with performance ratings in a distinct manner when compared to the TOPSIS method. Like the TOPSIS approach, it derives the overall performance score based on the distance from positive and negative solutions, where the distance is influenced by the alternative credits. In the modified TOPSIS, alternative credits are incorporated into the calculation of Euclidean distances. This modification aims to retain all the advantageous features of TOPSIS while addressing the issue of using non-credited Euclidean distances in the original TOPSIS method.The modified TOPSIS method is explained through the following stages.

Step 1: Normalization of the initial decision matrix.

The process of normalizing the decision matrix follows a similar approach to that of TOPSIS and results in a matrix representation as shown in Equation (5).

Step 2: Determination of the ideal solutions.

The positive and negative ideal solutions are defined by U^+ and U^- respectively. These solutions can be derived based on the normalized performance ratings as described in Equation (5)

$$U^+ = [b_1^+, b_2^+, \ldots, b_N^+] \tag{13}$$

$$U^- = [b_1^-, b_2^-, \ldots, b_N^-] \tag{14}$$

Where,

$$b_n^+ = \begin{cases} \max\ b_{mn};\ \text{for benefit attribute} \\ \min b_{mn};\ \text{for cost attribute} \end{cases}$$

$$b_n^- = \begin{cases} \min b_{mn};\ \text{for benefit attribute} \\ \max\ b_{mn};\ \text{for cost attribute} \end{cases}$$

Step 3: Calculation of credited Euclidean distance

The Euclidean distances, taking attribute credits into account, are computed for each alternative P_m in relation to the positive and negative ideal solutions using Equations (1), (5), (13), and (14) as

$$V_m^+ = \sqrt{\sum_{n=1}^{N} C_n (b_{mn} - b_n^+)^2} \tag{15}$$

$$V_m^- = \sqrt{\sum_{n=1}^{N} C_n (b_{mn} - b_n^-)^2} \tag{16}$$

Where, $C_n(\mathrm{n} = 1,2, \ldots, \mathrm{N})$ are credits for attributes $C_n(\mathrm{n} = 1,2, \ldots, N)$.

Step 4. Calculation of the comprehensive performance score.

The comprehensive score for each alternative P_m is determined using Equation (17) as

$$S_m = \frac{V_m^-}{V_m^- + V_m^+} \tag{17}$$

Performance score S_m is utilised to rank the competing alternatives. A higher score value indicates a better alternative performance.

The Performance score, denoted as S_m serves as the basis for ranking the competing alternatives, with a higher score signifying superior performance among the alternatives.

3.3 Rank Correlation

Rank correlation is a statistical measure that measures the extent of similarity amongst two ranking sets. It helps to assess how well the rankings of the same items or alternatives align across different methods or criteria. Several rank correlation coefficients are commonly utilized, among them Spearman's rank correlation coefficient and Kendall's rank correlation coefficient are most popular. In this case, we will compute Spearman's Rank Correlation Coefficient. Spearman's Rank Correlation Coefficient (ρ) assesses the monotonic relationship between two sets of rankings. It takes into account the relative order of items in both rankings, regardless of the actual values of the ranks.

Spearman's ρ has a potential range of -1 to 1:

- A value approaching 1 signifies a robust positive correlation, implying that both rankings move in the same direction.
- A value approaching -1 implies a substantial negative correlation, indicating that the rankings move in opposite directions.
- A value approaching 0 suggests a weak or negligible correlation between the rankings.

4. COMPARING TOPSIS, MODIFIED TOPSIS UNDER EQUI-CREDITED AND NONEQUI-CREDITED CRITERA

The comparison between the TOPSIS and modified TOPSIS methods encompasses two distinct credit scenarios:

(a) Unequal Credits: In this scenario, each attribute is assigned a unique credit weight.

(b) Equal Credits: Here, all attributes are assigned equal credit weights.

To conduct this comparative analysis, data were gathered for 12 car alternatives falling within a specific price range of 13 to 18 lakhs. The data encompassed vehicles with similar attributes, sourced from online platforms such as CarWale, CarDekho, and others. Subsequently, an average matrix was constructed, where each row corresponds to a car alternative, and each column represents the key attributes considered during the car selection process. Numerical values were assigned to these attributes across various car models based on the data collected, as presented in Table 1.

Table 1 : Performance Matrix

Performance Matrix	DESIGN AND DIMENSIONS	INTERIOR LOOK AND QUALITY	SPACE AND COMFORT	BOOT SPACE AND PRACTICALITY	FEATURES AND SAFETY EQUIPMENT	ENGINE CAPACITY	RIDE, HANDLING & BRAKING	MILEAGE	PRICE	FUEL TANK CAPACITY	FUEL RANGE	REVIEW RATING
Maruti Suzuki Ertiga	90	90	100	36	60	75	90	100	70	75	100	90
Mahindra XUV 700	92	86	75	41	98	100	86	82	60	100	100	92
Hyundai Creta	86	86	75	74	60	80	92	76	72	84	100	96
Kia Seltos	84	90	75	74	60	75	83	83	65	84	100	90
MG Astor	80	75	75	84	98	75	70	74	65	80	85	99
Maruti Suzuki Vitara breeza	90	86	75	56	80	80	86	86	80	80	85	88
Maruti Suzuki Grand Vitara	82	92	75	64	80	75	84	93	85	75	100	99
Honda new City	86	88	75	86	98	75	80	91	85	67	100	82
Hyundai Venue	88	88	75	60	80	80	88	89	90	75	100	88
Tata Nexon	88	88	75	60	98	50	90	81	92	74	100	88
Toyota Urban Cruiser	82	82	75	56	80	65	76	93	95	80	85	74
MG Hector	86	86	100	100	98	75	84	61	96	100	100	86

Table 2 illustrates Normalization matrix [b_{mn}] using the formula $b_{mn} = \frac{a_{mn}}{\sqrt{\sum_{m=1}^{M} a_{mn}^2}}$

Table 2. Normalized Matrix

Normalized Matrix	Maruti Suzuki Ertiga	Mahindra XUV 700	Hyundai Creta	Kia Seltos	MG Astor	Maruti Suzuki Vitara breeza	Maruti Suzuki Grand Vitara	Honda new City	Hyundai Venue	Tata Nexon	Toyota Urban Cruiser	MG Hector
DESIGN AND DIMENSIONS	0.31156	0.30846	0.30108	0.29954	0.28652	0.31896	0.28078	0.29239	0.30247	0.30515	0.29866	0.27555
INTERIOR LOOK AND QUALITY	0.31156	0.28835	0.30108	0.32094	0.26861	0.30478	0.31502	0.29919	0.30247	0.30515	0.29866	0.27555
SPACE AND COMFORT	0.34618	0.25147	0.26257	0.26745	0.26861	0.2658	0.25681	0.25499	0.25778	0.26008	0.27316	0.3204
BOOT SPACE AND PRACTICALITY	0.12462	0.13747	0.25907	0.26388	0.30084	0.19846	0.21914	0.29239	0.20623	0.20806	0.20396	0.3204
FEATURES AND SAFETY EQUIPMENT	0.20771	0.32858	0.21006	0.21396	0.35098	0.28352	0.27393	0.33319	0.27497	0.33983	0.29137	0.314
ENGINE CAPACITY	0.25963	0.33529	0.28007	0.26745	0.26861	0.28352	0.25681	0.25499	0.27497	0.17338	0.23674	0.2403
RIDE, HANDLING & BRAKING	0.31156	0.28835	0.32209	0.29597	0.2507	0.30478	0.28763	0.27199	0.30247	0.31209	0.2768	0.26914
MILEAGE	0.34618	0.27494	0.26607	0.29597	0.26503	0.30478	0.31844	0.30939	0.3059	0.28088	0.33872	0.19545
PRICE	0.24232	0.20117	0.25207	0.23179	0.23279	0.28352	0.29105	0.28899	0.30934	0.31903	0.346	0.30759
FUEL TANK CAPACITY	0.25963	0.33529	0.29408	0.29954	0.28652	0.28352	0.25681	0.22779	0.25778	0.25661	0.29137	0.3204
FUEL RANGE	0.34618	0.33529	0.35009	0.3566	0.30442	0.30124	0.34241	0.33999	0.34371	0.34677	0.30958	0.3204
REVIEW RATING	0.31156	0.30846	0.33609	0.32094	0.35456	0.31187	0.33899	0.27879	0.30247	0.30515	0.26952	0.27555

Table (3, 4) determine the credited normalized decision matrix: Assign credits to each factor to reflect their relative importance. The credits should be determined based on the significance of each factor in the overall evaluation. Multiply each column of the normalized decision matrix by its corresponding credit. Consider two cases for comparative study

Case 1: The 12 attributes are given unequal credits as per customer's perspectives.

Case 2: The 12 attributes are given equal credits.

Table 3. Unequal Credit Matrix as per Market Survey

DESIGN AND DIMENSIONS	INTERIOR LOOK AND QUALITY	SPACE AND COMFORT	BOOT SPACE AND PRACTICALITY	FEATURES AND SAFETY EQUIPMENT	ENGINE CAPACITY	RIDE, HANDLING & BRAKING	MILEAGE	PRICE	FUEL TANK CAPACITY	FUEL RANGE	REVIEW RATING
0.5	0.5	0.75	0.75	1	1.25	1	0.75	1.25	1.5	0.25	0.5

Table 4. Equal Credit matrix

DESIGN AND DIMENSIONS	INTERIOR LOOK AND QUALITY	SPACE AND COMFORT	BOOT SPACE AND PRACTICALITY	FEATURES AND SAFETY EQUIPMENT	ENGINE CAPACITY	RIDE, HANDLING & BRAKING	MILEAGE	PRICE	FUEL TANK CAPACITY	FUEL RANGE	REVIEW RATING
0.8333	0.8333	0.8333	0.8333	0.8333	0.8333	0.8333	0.8333	0.8333	0.8333	0.8333	0.8333

Table 5 include an "Overall Score" and a corresponding "Rank" for each car for TOPSIS method in case of unequal credits.

Table 5. Result of TOPSIS Method (Unequal Credits)

Result of TOPSIS method	Maruti Suzuki Ertiga	Mahindra XUV 700	Hyundai Creta	Kia Seltos	MG Astor	Maruti Suzuki Vitara breeza	Maruti Suzuki Grand Vitara	Honda new City	Hyundai Venue	Tata Nexon	Toyota Urban Cruiser	MG Hector
Over all Score	0.4105	0.5429	0.49853	0.4769	0.5458	0.5598	0.5002	0.5234	0.5371	0.4661	0.5786	0.5955
Rank	12	5	9	10	4	3	8	7	6	11	2	1

Table 6 represent an "Overall Score" and a corresponding "Rank" for each car for Modified TOPSIS method in case of unequal credits.

Table 6. Result of Modified TOPSIS Method (Unequal Credits)

Result of Modified TOPSIS method	Maruti Suzuki Ertiga	Mahindra XUV 700	Hyundai Creta	Kia Seltos	MG Astor	Maruti Suzuki Vitara breeza	Maruti Suzuki Grand Vitara	Honda new City	Hyundai Venue	Tata Nexon	Toyota Urban Cruiser	MG Hector
Over all Score	0.4247	0.5136	0.4989	0.4876	0.5603	0.5468	0.5132	0.5516	0.5333	0.4783	0.5643	0.5789
Rank	12	7	9	10	3	5	8	4	6	11	2	1

Table 7 include an "Overall Score" and a corresponding "Rank" for each car for TOPSIS method in case of equal credits.

Table 7. Result of TOPSIS Method (Equal Credits)

Result of TOPSIS method - equal credit	Maruti Suzuki Ertiga	Mahindra XUV 700	Hyundai Creta	Kia Seltos	MG Astor	Maruti Suzuki Vitara breeza	Maruti Suzuki Grand Vitara	Honda new City	Hyundai Venue	Tata Nexon	Toyota Urban Cruiser	MG Hector
Over all Score	0.4425	0.4829	0.5081	0.5093	0.5698	0.5288	0.5282	0.5720	0.5276	0.4897	0.5426	0.5584
Rank	1	2	3	4	5	6	7	8	9	10	11	12

Table 8 include an "Overall Score" and a corresponding "Rank" for each car for modified TOPSIS method in case of equal credits.

Table 8. Result of Modified TOPSIS Method (Equal Credits)

Result of Modified TOPSIS method -equal credit	Maruti Suzuki Ertiga	Mahindra XUV 700	Hyundai Creta	Kia Seltos	MG Astor	Maruti Suzuki Vitara breeza	Maruti Suzuki Grand Vitara	Honda new City	Hyundai Venue	Tata Nexon	Toyota Urban Cruiser	MG Hector
Over all Score	0.5584	0.5282	0.5276	0.4897	0.5081	0.5698	0.5720	0.5093	0.5288	0.5426	0.4829	0.4425
Rank	3	6	7	10	9	2	1	8	5	4	11	12

Table (6-8) represent calculation of the proximity to the ideal solution for each alternative in various methods and assigned ranks. These rankings are based on the overall scores calculated using the TOPSIS method and modified method in case of equal and unequal credits. The alternative with the highest score is considered the most favourable according to the criteria used in the analysis. It's worth emphasizing that the rankings are specific to the criteria and credits used in the analysis, and different criteria or credits could lead to different rankings. Additionally, the interpretation of these results should consider the specific context of the process of decision making and the criteria used to evaluate the alternatives. Table 9 represent the ranks obtained in various methods (standard TOPSIS or modified TOPSIS) and the credit scheme (unequal credits or equal credits) assigned to the criteria.

Table 9. Rank assigned by various methods

	Rank by TOPSIS Method - Unequal Credits	Rank by modified TOPSIS Method - Unequal Credits	Rank by TOPSIS Method - Equal Credits	Rank by modified TOPSIS Method - Equal Credits
	R1	R2	R3	R4
MG Hector	1	1	12	12
Toyota Urban Cruiser	2	2	11	11
Maruti Suzuki Vitara breeza	3	5	6	2
MG Astor	4	3	5	9
Mahindra XUV 700	5	7	2	6
Hyundai Venue	6	6	9	5
Honda new City	7	4	8	8
Maruti Suzuki Grand Vitara	8	8	7	1
Hyundai Creta	9	9	3	7
Kia Seltos	10	10	4	10
Tata Nexon	11	11	10	4
Maruti Suzuki Ertiga	12	12	1	3

Here, at a time we have considered two sets of rankings from Table 9 and calculate the correlation between them (e.g., Rank by TOPSIS Method - Unequal Credits vs. Rank by Modified TOPSIS Method - Unequal Credits etc.), using Spearman's rank correlation coefficient to determine the degree of agreement between the rankings obtained from the two methods. The calculated correlation coefficient will help us to understand how closely the rankings from the two methods align.

Table 10. Rank Correlation between various methods

Rank Correlation	R1	R2	R3	R4
R1	1.0000			
R2	0.9371	1.0000		
R3	-0.4895	-0.5804	1.0000	
R4	-0.4476	-0.5664	0.3287	1.0000

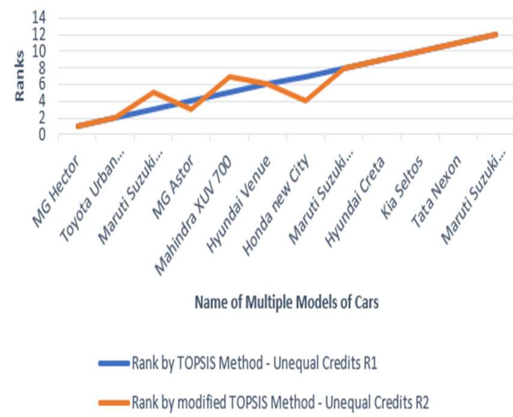

Fig1. TOPSIS & Modified TOPSIS (Nonequi-credits)

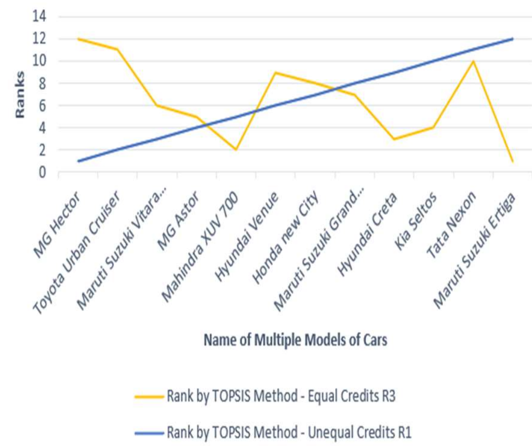

Fig 2. TOPSIS (equi-credits and nonequi- credits)

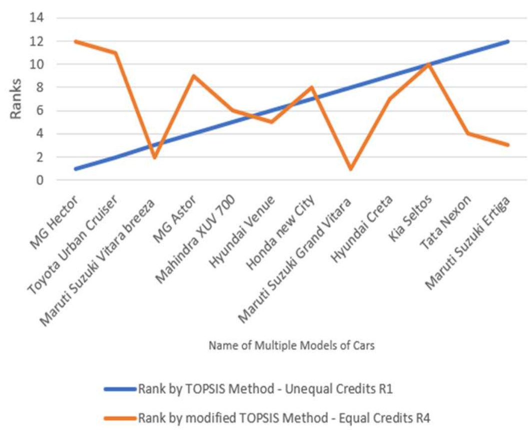

Fig3.TOPSIS (Nonequicredits) & Modified TOPSIS(equicredits)

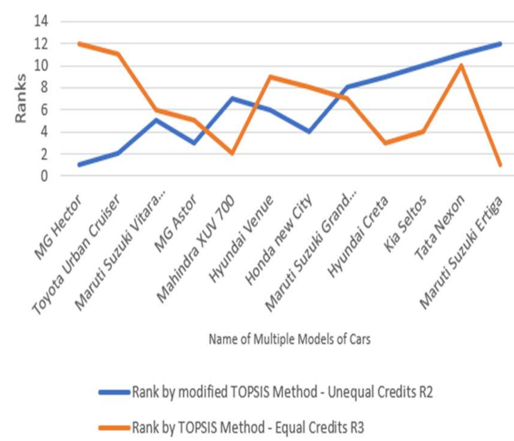

Fig4.Modified TOPSIS (Noneqi) & TOPSIS (equicredits)

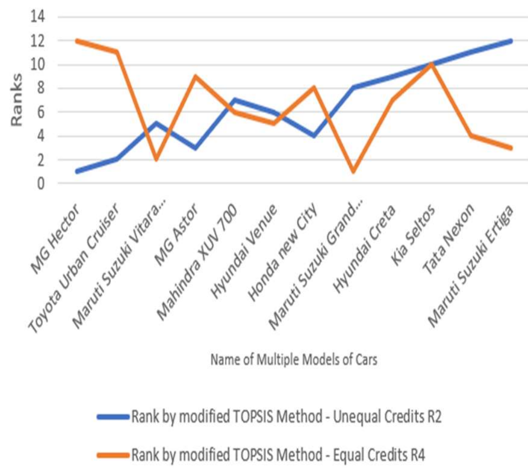

Fig 5. Modified TOPSIS (equi and nonequi-credits)

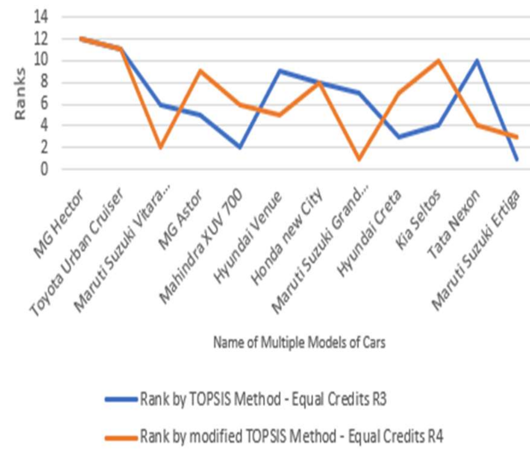

Fig 6. TOPSIS and Modified TOPSIS (equi & non-equi credits)

Fig 1,2,3,4,5,6 represent the comparison of ranks obtained in various methods under different credit criteria as well as two methods of multi-criteria decision making.

4. CONCLUSION

In this comprehensive analysis, we evaluated 12 different car brands using four distinct methods: TOPSIS with unequal credits, Modified TOPSIS with unequal credits, TOPSIS with equal credits, and Modified TOPSIS with equal unequal credits. The aim was to gauge the consistency and divergence among the rankings derived from these methods and subsequently assess their applicability in decision-making scenarios. Our investigation led to insightful findings that shed light on the strengths and limitations of each method.

Firstly, the rank correlation matrix provided valuable insight into the relationships between the methods. The diagonal values, representing the self-correlations, were consistently high, indicating that each method's ranking of its own set of car brands was relatively stable across the methodologies. This internal consistency suggests that each method consistently identifies certain car brands as more preferable or less preferable.

Furthermore, the negative correlations, such as those observed between R1 and R2, R1 and R3, and R3 and R4, signal cases where the methods' rankings diverged significantly. These discrepancies could arise from inherent differences in the algorithms and criteria used by the methods. For instance, a negative correlation might suggest that a brand highly ranked by one method is comparatively lower ranked by another, highlighting the importance of considering multiple methods to capture a holistic view.

The positive correlations between certain methods, such as the strong positive correlation between R1 and R2, and R2 and R3, indicate instances where the methods exhibited similar ranking trends. This alignment could stem from similarities in the underlying decision-making principles or the treatment of credits and preferences.

In summary, the findings emphasize the nuanced interplay between the methods' rankings. TOPSIS and Modified TOPSIS, both with unequal credits, demonstrated a noticeable level of agreement, while TOPSIS and Modified TOPSIS with equal unequal credits exhibited a more mixed pattern. This suggests that the choice of credit distribution significantly influences the congruence between these methods. Therefore, decision-makers should carefully consider the method selection and credit assignment based on the context and goals of the decision problem.

It's important to note that each method has its own set of assumptions and strengths, which may render them more suitable for specific decision scenarios. By comparing these methods and assessing their rank correlations, we've contributed to a deeper understanding of their performance characteristics. This study lays the foundation for more informed decision-making processes by providing insights into how these methods can be employed effectively across different contexts.

However, as with any analytical study, our work has limitations. Here, we are not claiming that any of the car brands are better as compared to others, as factors such as data quality, method assumptions, and the specific criteria used can impact the results. Future research can delve further into exploring the reasons behind the observed correlations and examine the methodologies in various real-world decision scenarios.

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