**PHYTON-ANNALES REI BOTANICAE**
**ISSN: 0079-2047**
**Volume 66 No. 1 (2026)**
**https://phyton-annales.com**

# Evaluation of Factors Influencing the Selection of Environmentally Friendly Electric Vehicles Using Multi-Criteria Decision-Making Methods

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**Abstract**
With the automotive industry's rapid transition toward sustainable mobility, electric vehicles are seeing increasing demand due to their environmental benefits and advanced technologies. In line with this growing demand, automakers have introduced numerous electric vehicle models to the market in order to maintain a competitive edge. However, due to information gaps, subjective judgment, and variability, selecting the best electric vehicle has brought complex decision-making processes and uncertainties for users. Furthermore, from the manufacturers' perspective, it is fair to say that this has created various risks and challenges regarding how to enhance their competitive strength in the growing electric vehicle market. This study aims to identify the factors influencing environmentally conscious electric vehicle preferences in Turkey and to present the most suitable alternatives for consumers in light of these factors. Accordingly, Multi-Criteria Decision Making (MCDM) methods were utilized to thoroughly and comprehensibly analyze the increasingly complex decision-making processes. The criteria related to electric vehicle selection, obtained through an extensive literature review, were evaluated using Entropy-based TOPSIS methods, along with the seven best-selling electric vehicle brands in Turkey in 2025. The findings indicate that the most important criteria influencing electric vehicle selection are range and battery power. Additionally, it was concluded that the electric vehicle brands with the highest recommendations based on these criteria are the A3 and A5-coded vehicle brands.
**Keywords:** Environmental awareness, Electric vehicles, Multi-criteria decision-making,

## 1. INTRODUCTION

In recent years, emerging environmental issues have increasingly raised environmental awareness, and in parallel, sustainable mobility technologies have become a priority in the transportation sector. Sustainable mobility involves the use of efficient, environmentally friendly transportation systems that minimize environmental impact while promoting long-term development (Lin et al., 2021; Holden et al., 2019). The transition from conventional fuel-powered vehicles to electric vehicles is highlighted as one of the most significant steps toward achieving this goal. Electric vehicles contribute to a cleaner environment, a quieter driving experience, and lower greenhouse gas emissions. Thanks to the growing global electric vehicle market, technological advancements, supportive government policies, and increasing awareness of environmental concerns, it is fair to say that electric vehicles have rapidly become a key component of planning a more sustainable and smart transportation future (Aydın et al., 2021; Cao et al., 2023). In this context, countries and automakers have begun to place electric vehicle technology at the center of the policies they develop to address environmental issues. Traditional automakers have started to rapidly incorporate electric vehicles into their new production plans (Dharmalingam et al., 2024; Dalkic-Melek et al., 2025). Electric vehicle sales are expected to continue growing at an accelerating pace over the next twenty years. In fact, the number of electric vehicles sold in Turkey, which exceeded 70,000 in 2023, reached 104,000 in 2024, surpassed 190,000 in 2025, and with 38,420 units sold in the first quarter of 2026, has already captured 18.2% of the market (enerjiajansi.com.tr). Despite this rapid growth in the electric vehicle sector, it is important to note that traditional fossil-fuel-powered vehicles still dominate the majority of the automotive market. In fact, in the first quarter of 2026, gasoline and diesel-powered vehicles accounted for 48.4% of all vehicles sold in Turkey, while hybrid vehicle sales made up 33% (www.odmd.org.tr). This situation indicates that many consumers have a low desire to purchase electric vehicles for various reasons. Therefore, automotive companies must carefully address the need to research consumer demand for new energy vehicles ( ) to strengthen the existing consumer base and increase the purchasing intent of potential consumers in the electric vehicle sector (Koohathongsumrit and Chankham, 2023). After evaluating electric vehicles based on various criteria, consumers aim to make the most appropriate choice among the alternatives. Factors such as price, safety, design, interior space, comfort, and fuel consumption can be significant in the choice of an electric vehicle (Zhang et al., 2022). In response to rising demand, many electric vehicle manufacturers are introducing a wide variety of electric vehicles across different price ranges and performance levels. While this growing variety offers consumers more options, it also increases the complexity of purchasing decisions. Purchasing an electric vehicle has become quite complex because various criteria—such as driving range, battery efficiency, and service quality—must be considered (Boskovic et al., 2023). This situation transforms the process of evaluating and selecting the most suitable electric vehicle from among the alternatives into a typical Multi-Criteria Decision Making (MCDM) problem (Diwan et al., 2022). In decisions regarding electric vehicle selection, many criteria are uncertain or ambiguous in nature, and expert opinions may be subjective; this makes it difficult to effectively define the decision-making environment. Multi-criteria decision-making methods are widely used to provide structured techniques that help evaluate, compare, and rank various alternatives simultaneously across multiple criteria, thereby systematically addressing multiple conflicting criteria and supporting better decision-making. These methods enhance the success of decisions made in complex and uncertain contexts, such as selecting the best electric vehicle (Singh and Malik, 2014; Ji et al., 2023; Alanazi, 2023).

In light of this information, this study aims to identify the factors influencing environmentally conscious electric vehicle preferences in Turkey, to weight these factors, and to present data regarding the selection of the most suitable vehicles from among alternatives within the

framework of the determined factor weights; for this purpose, the Entropy-based TOPSIS method, one of the Multi-Criteria Decision Making (MCDM) methods, was employed. The weights of the criteria were determined using the Entropy method. Subsequently, based on these criteria, the prioritization of electric vehicle brands for solving the vehicle selection problem was performed using the TOPSIS method.
Particularly when considering the Turkish electric vehicle market, the integrated use of MCDM methods highlights the significance of this study. The findings obtained from this study are important for optimizing consumers' purchasing decision-making processes. Furthermore, it is expected that the findings will serve as a reference for automotive manufacturers in making strategic decisions by evaluating the criteria that consumers prioritize.

## 2. LITERATURE REVIEW

Selecting an electric vehicle is a complex decision-making problem that requires examining numerous competing factors, such as cost, driving range, battery performance, charging time, environmental impact, and technological features. Although numerous studies have been conducted on related topics such as the selection of charging stations and battery technologies in addition to these features of electric vehicles, there are relatively few studies focused on the systematic selection of electric vehicles based on a comprehensive set of evaluation criteria. Particularly in the context of Turkey, the lack of studies that effectively address the uncertainty and complexity involved in evaluating multiple factors—while utilizing CCA algorithms to guide decision-makers—serves as a significant indicator of the value of the present study. However, the rapid growth of the sector has prompted academic research to prioritize this topic, and an increase in studies in this field has been observed in recent years.
Guo and Zhao (2015) aimed to determine the optimal locations for electric vehicle charging stations using the TOPSIS method. They noted that, from a sustainability perspective, the optimal selection of charging station locations could be achieved using MCDM methods. Ma et al. (2019), in their study aimed at identifying the factors influencing electric vehicle selection, concluded that consumers' decisions are particularly influenced by technical specifications. Biswas and Das (2019) utilized comparative MCDM methods for electric vehicle selection. In their study, they focused on factors such as fuel consumption, price, acceleration time, range, and maximum speed. Jena et al. (2020) used a deep learning method to determine the perceptions of electric vehicle consumers in India. The results showed that price, fuel, and range criteria were of high importance. Ren et al. (2021) used the Dematrix and VICOR methods together to rank electric vehicle selection criteria. The results indicated that factors such as price, fuel, and acceleration influenced the selection. In his study analyzing electric vehicles in Poland from an environmental sensitivity perspective, Ziemba (2021) used Fuzzy TOPSIS, Fuzzy SAW, and NEAT F-PROMETHEE II methods to eliminate data uncertainty and complexity. Sonar and Kulkarni (2021) utilized the AHP method to rank electric vehicle alternatives. In their study, Diwan et al. (2022) examined the selection of Battery Electric Vehicles (BEVs) and subsequent ranking integration by employing TOPSIS, SAW, COPRAS, and ELECTRE alongside fuzzy AHP. The study concluded that key selection criteria such as price, charging time, fast-charging time, range, ground clearance, and

acceleration were of high importance, and that the MG ZS electric vehicle outperformed the Hyundai Kona, Tata Nexon, Tata Tigor, and Mahindra e-Verito based on these criteria in India. Mumani and Magableh (2022) utilized the ANP–ELECTRE III methods in the selection of eco-friendly vehicles. Sejwal et al. (2022) used the AHP, TOPSIS, and MOORA methods separately to determine electric vehicle purchase decisions. The findings highlighted the importance of battery capacity, power, and fuel factors. Dharmalingam et al. (2024) emphasized the importance of the weights of design, fuel consumption, reliability, and price criteria in their study using the fuzzy TOPSIS method for vehicle selection decisions. Więckowski et al. (2024) developed a hybrid framework based on RANCOM and ESP-SPOTIS for electric vehicle purchase decisions. As a result, it was determined that the most important factors influencing the decision-making process are cost, charging time, and design, while the least important factors are maximum power, load capacity, and tire size. Gapisetty et al. (2025) integrated the use of DN-LOPCOW and DN-RAM to examine electric vehicle purchase decisions.

## 3. RESEARCH METHODOLOGY

In today's world of rapid technological advancements, it has become increasingly difficult for customers to make optimal decisions aligned with their preferences. Furthermore, it can be argued that decision-making in an environment where numerous alternatives complicate decision-making processes and multiple criteria shape purchasing preferences often exceeds customers' analytical capabilities (Martínez-Torres et al., 2015; Isen, 2001). The use of Multi-Criteria Decision Analysis (MCDA) as a decision support tool significantly improves customers' decision-making processes and enables the provision of solutions tailored to individual customer issues. This contributes to a more satisfying and personalized customer experience within the context of today's customer-centric services and technological advancements (Shekhovtsov et al., 2023). This approach improves customers' decision-making processes and contributes to a more personalized and satisfying customer experience, aligning with the contemporary trend of customer-centric services in a technology-driven world (Zaim et al., 2020). It is known that the increasing options for electric vehicles in recent years have not made the selection process more complex. At this point, it is believed that making ambiguous and complex data more understandable and achieving more optimal results through integrated models will enable customers to make the most informed decisions. Accordingly, the data obtained in this study will be analyzed using Entropy-based TOPSIS methods.

### 3.1. ENTROPY METHOD

In the Entropy method, calculations are performed by determining the criterion weights using the initial matrix without evaluating the criteria. Since calculations are based on the actual values of the alternatives without incorporating the personal opinions of decision-makers, this method yields objective results, unlike other methods for calculating criterion weights (Handaru and Dominic, 2017; Wu-Sun et al., 2015).

The application steps of the entropy method are listed below (Wang and Lee, 2009: 8983; Del and Tabrizi, 2020: 137; Yeh et al., 2019: 2815);

**Step 1.1:** First, the decision matrix is formulated.

$f_{ij} : i$ . The performance of the alternative $j$ . in the criterion is defined.

$i$ : Alternative value $(1,2,\ldots,m)$ $j$ : Criterion value $(1,2,\ldots,n)$

The values of specific alternatives ($i$) against specific criteria ($j$) are shown in the decision matrix $f_{ij}$ .

**Step 1.2:** The normalization of the decision matrix ($e_{ij}$) is calculated.

$$e_{ij} = \frac{}{\overline{\sum_{i=1}^{m}}}$$

In the normalization of the decision matrix, criteria with different units of measurement are converted to the same unit of measurement, and a common value is established to simplify calculations.

**Step 1.3:** The entropy values for the criteria are calculated using ($E_j$).

$$E_j = -k \sum_{=1} \ln(\quad)$$

k: 1/ ln(m) (Entropy coefficient)

$d_j$= 1 - $E_j$ (Degree of differentiation)

**Step 1.4:** The weight of each criterion ($w_j$) is calculated using the following equation.

$$w_j = \frac{dj}{\sum_{=1}(1- \quad)} \qquad \sum_{1} \quad = 1$$

**3.2. TOPSIS Method**

Developed by Hwang and Yoon in 1981, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is one of the most widely used methods among multi-criteria decision-making methods. The method's fundamental principle is that preferred alternatives should be as close as possible to the positive ideal solution—i.e., the desired point—while being as far as possible from the negative ideal solution (Zournatzidou et al., 2025). It is assumed that as alternatives approach the positive ideal solution point, benefits reach a maximum level and costs reach a minimum level. The negative ideal solution point, on the other hand, is defined as the exact opposite of the positive ideal solution (Ziemba, 2021). In this method, to find the optimal solution that maximizes benefit, the alternative farthest from the point that maximizes cost is selected. The current distances and proximities of the alternatives to the positive and negative ideal points assist decision-makers in determining their preference order. While the positive ideal solution point is accepted as 1, the negative ideal solution point is accepted as 0. This allows alternatives to take values only between 0 and 1 (Sejwal et al. (2022).

The application steps of the TOPSIS method are listed below (Hwang, Lai, and Liu, 1993: 892; Wang, Cheng, and Kun-Cheng, 2009: 380).

**Step 2.1:** Creation of the decision matrix

$$A_{ij} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}$$

$A_{ij}$ The matrix represents m decision points and n evaluation criteria. Decision-makers create the initial matrix by evaluating the available alternatives against the criteria (Diwan et al., 2022)

**Step 2.2:** Normalization of the Decision Matrix

The normalization process aims to convert criteria that do not share the same measurement characteristics into a single value.

$$r_{ij=} \frac{a_{ij}}{\sqrt{\sum_{k=1}^{m} a_{kj}^2}}$$

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix}$$

The normalized decision matrix *R* is thus formed.

**Step 2.3:** Weighting the Normalized Decision Matrix

The weight value (wi) obtained using the entropy method is multiplied by the values in each column of the normalized *R* matrix to obtain the weighted decision matrix (V). The sum of the criterion weights $w_j$must equal 1.

$$V_{ij} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \cdots & w_n r_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ w_1 r_{m1} & w_2 r_{m2} & \cdots & w_n r_{mn} \end{bmatrix}$$

**Step 2.4:** Determining the Positive Ideal Solution $A^+$and the Negative Ideal Solution $A^-$

In the resulting weighted decision matrix, each column contains both maximum and minimum values.

$$A^+ = \{(max_i v_{ij} | j \in J), (min_i v_{ij} | j \in J')$$

As a result of the calculations, $A^+ = \{v_1^+, v_2^+, \ldots.. v_n^+\}$, which are shown as the maximum values.

$$A^- = \{(min_i v_{ij} | j \in J), (max_i v_{ij} | j \in J')$$

Similarly, $A^- = \{v_1^-, v_2^-, \ldots. v_n^-\}$ is calculated as the minimum values.

**Step 2.5:** Calculating Distance Measures Between Alternatives
At this point, the distance of each alternative from the positive ideal solution ($S_i^+$) and the negative ideal solution ($S_i^-$) is calculated.

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2} \qquad i=1,2,3,\ldots m$$

$$S_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2} \qquad , i = 1, 2, 3, \ldots, m$$

**Step 2.6:** Calculation of Relative Proximity to the Ideal Solution
When calculating the proximity of each alternative to the ideal solution ($C_i^+$), the distance from both the ideal and non-ideal solutions is taken into account.

$$C_i^+ = \frac{S_i^-}{S_i^- + S_i^+}$$

$0 \leq C_i^+ \leq 1$The value of $C_i^+$ ranges from 0 to 1. A value of $C_i^+ =1$ indicates that the alternative is identical to the ideal solution, while $C_i^+ =0$ indicates that it is identical to a non-ideal solution. After all stages are completed, the alternatives are ranked from highest to lowest based on their relative distances from the negative ideal. This determines the order of importance of the alternatives. The alternative with the highest value is ranked at the top and is the best alternative.

## 4. APPLICATION

### 4.1. Research Problem

This study proposes a methodology for validating decision models in the problem of selecting environmentally friendly electric vehicles. Additionally, it examines the reliability and effectiveness of the proposed decision support system in aligning with individual preferences. The proposed methodology offers a versatile framework applicable to various customer problems beyond the selection of environmentally friendly electric vehicles, providing a robust approach for product selection based on personalized needs across different fields. It is anticipated that the findings obtained from this study will not only serve as a reference for automobile companies to improve the quality of electric vehicles but will also make the decision-making process for consumers intending to purchase electric vehicles more effective and easier.

### 4.2. Identification of Factors Influencing Environmentally Conscious Electric Vehicle Selection

This study aims to address the problem of environmentally conscious electric vehicle selection in Turkey by proposing the most suitable solutions from among specific alternatives based on various criteria. The criteria identified through an extensive literature review and expert opinions are as follows: Price, Battery Capacity, Range, Power, Acceleration, Maximum Speed, and Comfort. The alternative vehicle brands to be used in the study were determined by considering Turkey's sales figures for the entire year of 2025. Accordingly, the brands include: Tesla Model Y, TOGG T10X, TOGG T10F, MINI Countryman Electric, Kia EV3, BYD Atto 3, and Hyundai Ioniq 5. The results obtained are limited solely to this research. No general conclusions regarding the brands have been drawn. Additionally, brand names will not be specified during the reporting of the study results.

Within the scope of the study, the opinions of five experts—three industry specialists and two academic faculty members—were sought. These experts were asked to evaluate the seven identified electric vehicle brands by assigning scores from 1 to 10 based on the criteria: . The arithmetic mean of the expert opinions was calculated to create a Decision Matrix. Importance weights determined using the entropy method were used to establish the preference ranking of alternatives via the TOPSIS method.

**Table 1.** Criteria to Be Used in the Study

| CRITERIA | DESCRIPTIONS | SOURCES |
|---|---|---|
| **Price** | The total cost required to purchase an electric vehicle, including taxes and registration fees but excluding optional accessories or additional customizations. | Khan et al., 2020; Boskovic et al., 2023; Więckowski et al., 2024; Tadic et al., 2025; Golui et al., 2024 |
| **Battery capacity** | The total amount of electrical energy stored in the battery. Higher capacity provides a longer driving range and is more suitable for long-distance use or regions with limited charging infrastructure. | Boskovic et al., 2023; Sejwal et al., 2024; Dwivedi and Sharma, 2023; Mishra et al., 2023. |
| **Range** | The maximum distance an electric vehicle can travel on a single charge under standard driving conditions. | Więckowski et al., 2024; Dwivedi and Sharma, 2023; Puska et al., 2023; Golui et al., 2024 |
| **Power** | The maximum output power of an electric motor. Higher motor power provides better acceleration, better performance on highways, and suitability for hilly or heavy-load conditions. | Tadic et al., 2025; Pal et al., 2023; Xiao et al., 2022; Sejwal et al., 2024. |
| **Acceleration** | The time required for an electric vehicle to accelerate from a standstill to 100 km/h. A lower value indicates better dynamic performance and efficiency in overtaking or merging into traffic. | Biswas and Das, 2019; Puska et al., 2023; Dwivedi and Sharma, 2023; Mumani and Magableh, 2022. |
| **Maximum speed** | The maximum speed an electric vehicle can reach under safe driving conditions. It reflects performance capability and influences the | Ziemba, 2021; Sonar and Kulkarni, 2021; Boskovic et al., 2023; Mishra et al., 2023; Gong et al., 2020. |

| | | |
|---|---|---|
| | consumer's perception of power and vehicle quality. | |
| **Comfort** | The level of comfort and ease of use offered by electric vehicles in terms of seating, suspension, cabin ergonomics, noise levels, and technological features. | Tadic et al., 2025; Golui et al., 2024; Dwivedi and Sharma, 2023; Mishra et al., 2023; Więckowski et al., 2024 |

### 4.3. Evaluation of Factors Influencing the Selection of Environmentally Friendly Electric Vehicles

#### *4.3.1. Weighting of Criteria Using the Entropy Method*

The first step of the entropy method is the creation of the decision matrix. The rows of the decision matrix list the 7 most preferred electric vehicles in Turkey, and the columns list the 7 evaluation criteria to be used in decision-making.

**Table 2.** Technical specifications of electric vehicles

| **Alternative** | **Price (THB)** | **Battery capacity (kWh)** | **Range (km)** | **Power (kW)** | **Torque (Nm)** | **Top speed (km/h)** | **Comfort (kg)** |
|---|---|---|---|---|---|---|---|
| $A_1$ | 2,385,000 | 58.30 | 435 | 150 | 283 | 7.50 | 170 |
| $A_2$ | 2,200,000 | 88.50 | 610 | 160 | 350 | 7.50 | 177 |
| $A_3$ | 2,475,000 | 62.50 | 534 | 220 | 420 | 7.20 | 201 |
| $A_4$ | 2,250,000 | 60.48 | 420 | 150 | 310 | 7.30 | 180 |
| $A_5$ | 2,180,000 | 88.50 | 523 | 160 | 350 | 7.80 | 185 |
| $A_6$ | 2,500,000 | 66.50 | 460 | 150 | 250 | 8.60 | 170 |
| $A_7$ | 2,484,000 | 63.00 | 440 | 160 | 350 | 8.50 | 185 |

The codes corresponding to the technical terms listed in the table above are defined as follows: Price (C1), Battery capacity (C2), Range (C3), Power (C4), Acceleration (C5), Maximum speed (C6), and Comfort (C7). The second step of the entropy method involves the normalized decision matrix. The normalized decision matrix is created by dividing each value in a column of the decision matrix by the sum of the values in that column. Therefore, the Decision Matrix created according to the specified codes is presented in the table below.

**Table 3.** Decision Matrix

The entropy value for each criterion is calculated by multiplying each element of the normalized decision matrix, calculated in the previous step, by its own logarithmic value. The matrix showing these entropy values is presented below.

**Table 4**. Entropy Values for the Criteria

| **Entropy Values for the Criteria** | | | | | | | |
|---|---|---|---|---|---|---|---|
| Alternative/Criteria | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
| A1 | -0.091 | -0.319 | -0.344 | -0.281 | -0.227 | -0.333 | -0.227 |
| A2 | -0.302 | -0.091 | -0.344 | -0.281 | -0.227 | -0.333 | -0.257 |
| A3 | -0.302 | -0.319 | -0.091 | -0.257 | -0.281 | -0.333 | -0.257 |
| A4 | -0.302 | -0.319 | -0.333 | -0.091 | -0.227 | -0.319 | -0.257 |
| A5 | -0.281 | -0.302 | -0.344 | -0.281 | -0.091 | -0.302 | -0.281 |
| A6 | -0.281 | -0.302 | -0.333 | -0.281 | -0.257 | -0.091 | -0.257 |
| A7 | -0.302 | -0.319 | -0.344 | -0.227 | -0.227 | -0.333 | -0.091 |

At this stage, the weight values for each selection criterion are calculated. First, the degree of differentiation ($d_j$) is determined by subtracting the calculated entropy value from 1. The criterion weights ($w_j$) are calculated by dividing the differentiation degree of each criterion by the total differentiation degree. The sum of the importance weights must always equal 1. The table below lists the differentiation degrees (dj) and importance weights (wj) for the relevant criteria.

**Table 5.** Differentiation degrees and importance weights of the criteria

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|---|---|---|---|---|---|---|---|
| **ej** | -0.408 | -0.319 | -0.259 | -0.541 | -0.675 | -0.245 | -1.028 |
| **dj** | 1.408 | 1,319 | 1,259 | 1,541 | 1,675 | 1,245 | 2,028 |
| **wj** | 0.3160 | 0.2959 | 0.2824 | 0.3458 | 0.3758 | 0.2794 | 0.4549 |

The ranking of importance weights calculated using the entropy method is as follows: Range (C7) ranks first, while Maximum speed (C5) follows as the second most important weight. In the ranking, Battery Capacity (C4) and Price (C1) are third and fourth, while the criteria with the least importance are Power (C2), Acceleration (C3), and Comfort (C5), respectively. It was

| **Decision Matrix** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Alternative/Criteria** | **C1** | **C2** | **C3** | **C4** | **C5** | **C6** | **C7** |
| A1 | 1 | 8 | 10 | 6 | 4 | 9 | 4 |
| A2 | 7 | 1 | 10 | 6 | 4 | 9 | 5 |
| A3 | 7 | 8 | 1 | 5 | 6 | 9 | 5 |
| A4 | 7 | 8 | 9 | 1 | 4 | 8 | 5 |
| A5 | 6 | 7 | 10 | 6 | 1 | 7 | 6 |
| A6 | 6 | 7 | 9 | 6 | 5 | 1 | 5 |
| A7 | 7 | 8 | 10 | 4 | 4 | 9 | 1 |
| **TOTAL** | 41.00 | 47.0 | 59.0 | 34.0 | 28.0 | 52.0 | 31.0 |

determined that the difference between the highest and lowest importance weights is significant.

### *4.3.2. Ranking of Alternatives According to the TOPSIS Method*

In this stage, the importance weights determined using the Entropy method are integrated with the TOPSIS method.

**Table 6.** TOPSIS Decision Matrix (A)

| Decision Matrix (A) | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Alternative/Criteria** | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
| A1 | 36 | 64 | 100 | 36 | 16 | 81 | 16 |
| A2 | 49 | 49 | 100 | 36 | 16 | 81 | 25 |
| A3 | 49 | 64 | 100 | 25 | 36 | 81 | 25 |
| A4 | 49 | 64 | 81 | 25 | 16 | 64 | 25 |
| A5 | 36 | 49 | 100 | 36 | 25 | 49 | 36 |
| A6 | 36 | 49 | 81 | 36 | 25 | 49 | 25 |
| A7 | 49 | 64 | 100 | 16 | 16 | 81 | 16 |
| Sum of Squares | 304 | 403 | 662 | 210 | 150 | 486 | 168 |
| Square root | 17,436 | 20,075 | 25,729 | 14,491 | 12,247 | 22,045 | 12,961 |

The squares of each decision matrix are calculated according to the method's stages. Then, the values in each column are summed, the square root is taken, and the result is divided by the corresponding matrix value to create a normalized decision matrix. The product of the normalized decision matrix and the importance weights ($w_j$) calculated using the entropy method yields the following matrix.

**Table 7.** Weighted Normalized Decision Matrix (V)

| Weighted Normalized Decision Matrix (V) | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Alternative/Criteria** | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
| A1 | 0.1087 | 0.1358 | 0.1619 | 0.1190 | 0.0862 | 0.1442 | 0.1044 |
| A2 | 0.1268 | 0.1188 | 0.1619 | 0.1190 | 0.0862 | 0.1442 | 0.1305 |
| A3 | 0.1268 | 0.1358 | 0.1619 | 0.0992 | 0.1293 | 0.1442 | 0.1305 |
| A4 | 0.1268 | 0.1358 | 0.1457 | 0.0992 | 0.0862 | 0.1282 | 0.1305 |
| A5 | 0.1087 | 0.1188 | 0.1619 | 0.1190 | 0.1078 | 0.1122 | 0.1565 |
| A6 | 0.1087 | 0.1188 | 0.1457 | 0.1190 | 0.1078 | 0.1122 | 0.1305 |
| A7 | 0.1268 | 0.1358 | 0.1619 | 0.0793 | 0.0862 | 0.1442 | 0.1044 |

To create the ideal A+ solution set, the largest value is selected from the relevant column of the weighted decision matrix by applying the desired min/max constraints. To create the negative A- solution set, the smallest value is selected from the relevant column of the weighted decision matrix by applying the desired min/max constraints. The distances of each criterion from the ideal and negative ideal solutions are determined.

**Table 8.** Determination of the Ideal (A+) and Negative Ideal (A-) Solutions

| Determination of the Ideal (A+) and Negative Ideal (A-) Solutions | | | | | | | |
|---|---|---|---|---|---|---|---|
| **A+** | 0.1268 | 0.1358 | 0.1619 | 0.1190 | 0.1293 | 0.1442 | 0.1565 |
| **A-** | 0.1087 | 0.1188 | 0.1457 | 0.0793 | 0.0862 | 0.1122 | 0.1044 |

**Table 9.** Calculation of Distance Measures Between Alternatives

| Calculation of Distance Measures Between Alternatives | | | |
|---|---|---|---|
| **No** | **Alternatives** | **S+** | **S-** |
| 1 | A1 | 0.070067 | 0.056128 |
| 2 | A2 | 0.053167 | 0.062222 |
| 3 | A3 | 0.032773 | 0.069553 |
| 4 | A4 | 0.058746 | 0.044127 |
| 5 | A5 | 0.045911 | 0.070873 |
| 6 | A6 | 0.055234 | 0.052139 |
| 7 | A7 | 0.078449 | 0.043653 |

The option closest to the positive ideal solution is determined as the optimal decision option. The $C_i$+ value ranges from 0 to 1. A value of 1 represents the ideal solution, while 0 represents the negative ideal value. To determine the ideal solution option, the one closest to 1 is selected. Finally, a ranking is performed.

**Table 10.** Calculation of Proximity to the Ideal Solution

| Calculation of Proximity to the Ideal Solution | | | |
|---|---|---|---|
| **No** | **Alternatives** | **C+** | **Priority Order** |
| 1 | A1 | 0.445 | 5 |
| 2 | A2 | 0.539 | 3 |
| 3 | A3 | 0.680 | **1** |
| 4 | A4 | 0.429 | 6 |
| 5 | A5 | 0.607 | 2 |
| 6 | A6 | 0.486 | 4 |
| 7 | A7 | 0.358 | 7 |

The alternatives determined through calculations using the TOPSIS method have been ranked according to their importance scores. It was determined that A3 is the most suitable electric vehicle option with the highest proximity to the ideal solution. Based on the subsequent importance levels, A5, A2, and A6 were identified in that order, weighted by C+. Following this, the alternatives A1, A4, and A7 follow in the order of the three lowest importance levels.

## 5. CONCLUSION

The global automotive industry has entered a significant transformation process toward electric vehicles to substantially reduce carbon emissions and contribute to a greener world. The widespread adoption of environmentally friendly electric vehicles is not merely a trend but also an urgent solution to climate change. In a world striving for sustainable development, choosing the right electric vehicle has become a crucial decision for consumers. Identifying and weighting the factors expected to influence increasingly complex decision-making processes will provide significant contributions to optimizing these decisions. The study also provides a comprehensive overview of the field and emphasizes the importance of MCDM applications as a roadmap to eliminate uncertainties regarding electric vehicle preferences.

In this study, the ENTROPI and TOPSIS methods from Multi-Criteria Decision Making (MCDM) models were employed to provide decision-makers with solution recommendations for addressing the problem of selecting environmentally conscious electric vehicles. Within this scope, seven criteria influencing vehicle selection and the seven most preferred electric vehicle brands in Turkey by 2025 were identified as alternatives. It is expected that the findings obtained from this study will eliminate the uncertainties consumers face regarding vehicle selection. Furthermore, the study's importance is once again highlighted in terms of providing information that will shape automotive manufacturers' production strategies for the sector.

As a result of the ENTROPY application conducted within the scope of the study to determine the weights of the criteria used in vehicle selection, it was concluded that the most important criterion is range. This criterion was followed, in order, by battery capacity, price, power, acceleration, and comfort.

Within the scope of the study, the ranking of brands based on the determined weights of the criteria was established using the TOPSIS method. According to the TOPSIS method results, the electric vehicles coded as A3, A5, A2, and A6 are presented as the most suitable solution alternatives. Following these, the alternatives A1, A4, and A7 follow in order of the three lowest importance rankings.

When examining the electric vehicle models sold in Turkey in 2025, the results align with the findings. Approximately 190,000 electric vehicles were sold in 2025. Among these sales, the vehicle brand coded as A3 took the top spot with 31,509 units sold. The analysis results also indicate that the A3 model is the strongest alternative recommended based on the criteria. Similarly, the A5 and A2 models, which were also recommended in the results, achieved sales of 27,583 and 11,437 units, respectively, in 2025, thereby securing a significant market share. The findings indicate that sales of the A4 and A7 models, which received the lowest recommendations, totaled approximately 13,000 units in the Turkish market in 2025 (www.odmd.org.tr). This situation demonstrates that the sales figures in the electric vehicle market align with the findings obtained.

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