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Interpreting the Determinants of Sensitivity in MCDM Methods with a New Perspective: An Application on E-Scooter Selection with the PROBID Method

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ABSTRACT

It is not a desirable situation when input parameters excessively affect the results of a system as well as imply unwarranted drift and inefficiency. This situation, which expresses dependence or sensitivity to inputs, is also considered a problem in the multi-criteria decision-making (MCDM) methodology family, which has more than 200 members. A newly produced MCDM method is first subjected to sensitivity tests. MCDM methods are generally evaluated for their sensitivity to weighting methods. Sensitivity is affected by many different parameters such as data, normalization, fundamental equation, and distance type. The common methodical approach for sensitivity analysis is to check whether the best alternative changes with the alteration of weight coefficients. It is problematic to identify sensitivity only in the situation where the ranking position of the best alternative changes. In this study, the sensitivity of the entire ranking is based on a holistic view. Moreover, in the classical method, there is no reference point for sensitivity. Each different MCDM result is compared to each other and it is claimed that the method that produces rankings that are significantly different from the others is poor. We reinterpret sensitivity using the relationship between dynamic MCDM-based performance and static price towards the selection of an environmentally friendly, traffic-saving performance electric scooter. Two PROBID variants as well as the CODAS method are used in this study to deepen the accuracy in the comparison. Additionally, how four types of weighting methods and six types of normalization types affected MCDM sensitivity is measured with a different statistical framework. The finding from a total of 72 different MCDM rankings is striking: If the sensitivity of an MCDM method is generally high, the correlation between that MCDM method and the external anchor (price) is low. Conversely, if sentiment is low, a high correlation with price results. These matching patterns are a unique discovery of this work.

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1. Introduction

According to the Brundtland report published by the United Nations World Commission on Environment and Development, sustainability is more than environmental sustainability in the established sense [1]. In other words, what is meant by sustainability is that while ensuring human development, plant and animal species should not be harmed, otherwise the opportunities of future generations may be significantly limited. Thus, the concept of sustainability refers to the preservation and preservation of natural systems that provide life to maintain the ecological structure of the world and to meet the needs of future generations. This also forms the basis of sustainable development for countries [2]. According to Qureshi & Lu [3], sustainable transportation has distinguished itself as sustainable development and transportation systems have an optimal use purpose by considering future generations. Contrary to a sustainable transportation system, situations such as unbearable traffic congestion, accidents, air pollution, and depletion of fuel resources are experienced in many megacities today [4]. Technology development regarding carbon emissions in the transportation sector mostly occurs in the form of improving fuel efficiency. The impact of technological developments in the transportation sector consists of the development of alternative fuels such as electric vehicles and increasing the efficiency of the fuels of today's vehicles [5]. Many countries in the world, especially developed countries, are considering regulatory measures for the use of electric vehicles, which is one of the solution suggestions to reduce carbon emissions and sustainability of transportation. Motor vehicles mostly fulfill the need to transport cargo and passengers, which is important for the country's economy. Approximately one-quarter of the greenhouse gas emissions released into the world's atmosphere come from oil-powered motor vehicles [6]. For sustainable transportation, sustainable development of electric vehicle design is required so that economic efficiency can be achieved. It may be possible to decarbonize the transportation sector to a large extent in the future, and electric vehicles will be useful in this regard. In particular, electric vehicles can be expected to contribute to a high reduction in greenhouse gas emissions. The spread of micromobility as an ecological and non-motorized transportation option for short-distance transportation will undoubtedly contribute to this. There is a consensus that the transition from classical vehicles to alternative electric vehicles, especially e-bikes and e-scooters, will lead to an overall reduction in greenhouse gas emissions. The use of e-scooters and e-bikes is especially important for projects to implement green settlements. There are many advantages and practicalities of using an e-bike or e-scooter; i.e. it is environmentally friendly, does not waste time in traffic, is less troublesome and comfortable for the vehicle user compared to traditional vehicles (e.g. bicycles and scooters), covers more distance with less power, does not cause parking problems compared to cars, and can accustom individuals to an exercise and sporty life, It supports smartphone applications (e.g. payment and navigation, etc.), is fast and cheap, requires less costly transportation infrastructure, has accessible vehicle charging sharing stations, etc. [7].

As an alternative means of transportation to public transportation or automobiles, e-scooters ease travel in congested and crowded areas. For example, it can be said that it is a less costly vehicle compared to classical motor vehicles to reach the distance between public transportation stops and the final transportation point [8]. E-scooters are one of the new players in alternative electric transportation. Many e-scooters are available on the market for different needs. Nowadays, an easy choice is not possible as many important performance and quality characteristics of any product are defined. Although some criteria are more prominent, ultimately there may be many performance criteria that determine the price of a commercial product. How important which criterion is for a preference is another important assignment problem. Moreover, which alternative is the best can only be solved with a multi-criteria decision-making (MCDM) evaluation methodology in the space of multiple criteria and alternatives [9, 10]. Addressing complex decision problems with a single selection criterion is quite risky.

In the current literature, there are a limited number of studies based on MCDM methodology regarding the selection of the best "e-scooter", which is an example of micro-mobility. For example, Ziemba & Gago [7] used MCDM consensus in selecting e-scooters for a car-sharing system in Poland. The authors in this study aim to choose the best vehicles through the car-sharing system. In this study, where PROMETHEE, an "outranking" method, was used with a group decision support system, the most suitable e-scooter alternative was proposed. In addition, sensitivity, compensability, or stability analyses were also conducted, claiming to provide robustness and confirmability in the study. In his study focused on methodology development, Ayyildiz [8] proposed a new Pythagorean fuzzy MCDM methodology based on the experience and knowledge of experts for e-scooter charging station location selection. SWARA method was used to assign weight coefficients and the CODAS method was used to rank the alternatives (and determine the best one) with a fuzzy-oriented design. Chawla et al. [11] in their study for e-scooter selection, applied fuzzy AHP in weight calculation and preferred the TOPSIS method to find the ranking of alternatives. An analysis of the sensitivity to the weight coefficient was also performed to check the robustness and stability of the model. Altay et al. [12] used the integrated spaced type-2 fuzzy BWM-MARCOS model for the location selection of e-scooter sharing stations on a university campus example. Sensitivity analysis of the results was also performed. By highlighting the weight of the major criterion and keeping the other minor criteria at the same weight, it was observed how much the results were affected by the major criterion. Thus, it was seen that the changing weight coefficient importance value affected the selection of the best alternative scooter-sharing location. In fact, in our opinion, when you increase the weight coefficient of a criterion excessively, it should be quite natural for different alternatives to come to the fore. Some alternatives may have different advantages for different criteria. In their study, Patil & Majumdar [13] applied MCDM methods (VIKOR, RIM, TOPSIS, MOORA, and WASPAS) through a case study of India to prioritize the basic criteria affecting the use of electric two-wheelers. The results obtained from the analysis revealed that purchasing cost and operating costs were perceived as basic features. Among vehicle-related features, range, and maximum speed are the main impressive features. As a result, a series of strategies are proposed in this study to develop basic strategies to make the electric two-wheeler more attractive. In their study, Kizielewicz & Dobryakova [14] used the MCDM method, COMET, to determine the electric scooter evaluation model for the sustainable development of cities. Deveci et al. [15] aimed to propose a decision-making model based on q-step fuzzy sets to prioritize the safe e-scooter alternative in the study. In other words, the study aimed to produce a decision-making model for e-scooter safety against accidents and injuries with the help of alternative prioritization. The authors stated that a detailed stability analysis was carried out to determine the degree to which the proposed model is affected by changes in parameter values. The concept of “stability” was used in this study instead of “sensitivity”. In this research, stability analysis findings on how and to what extent the criterion weight coefficients affect the final results were shared.

In MCDM methodology, sensitivity analysis is a matter of the degree of impact of a certain input or parameter change on the final results [16, 17]. Frequently, attempts have been made to measure the effect of changing the weight coefficients of the criteria on the sensitivity of the ranking. But instead of the entire ranking, it is generally checked whether the order of the best alternatives in the literature has changed [18]. Although sensitivity to weight coefficients is mentioned in the literature, sensitivity analysis can cover all MCDM components. These are data, criterion, alternative, weight coefficient, normalization type, etc. It may be related to the change of components such as Moreover, even the variation of the MCDM-based algorithm can be a measure of sensitivity. On the other hand, the common opinion among MCDM authors is that for a good MCDM method, sensitivity to input parameters must be weak. In other words, it is recommended and emphasized that the best alternative should not change easily despite parameter changes. Thus, MCDM methods with high stability are the most preferable methods. However, it is doubtful that we have any solid, convincing, and sufficient evidence as to how and to what extent poor sensitivity, insensitivity, or hypersensitivity weakens or perfects an MCDM method.

In this study, it is investigated and questioned whether low sensitivity, insensitivity, or stability makes an MCDM method perfect. A few important deficiencies in the literature stand out to us. The first is that the direction of sensitivity (positive, neutral, or negative) is not clear. Although sensitivity can be determined, the base reference point for this sensitivity is not clear, especially when comparing different sequences. Comparison only makes sense if it is made in the light of a criterion. Secondly, the determination that all types of sensitivity are negative is actually generalist and in this respect resembles a problematic prejudice. For example, if we consider the sensors in automobiles or radar devices, their sensitivity is quite high and it is also positive because they serve the purpose. Of course, we cannot claim that MCDM works with the same logic as sensors for now. But this example shows the fallacy of the claim that all types of sensitivity are negative. Third, the literature somehow defines sensitivity not by the final MCDM ranking but by the best alternative in the ranking. However, the degree to which the entire ranking is affected is more important than the impact of a single alternative. This approach is also more convincing in terms of the abundance of evidence and generalizability. In this study, we question the classical sensitivity analysis through the electric scooter selection case and compare it with the alternative model we propose. Our suggestion consists of making the comparison of MCDM final results fair and reasonable by comparing them with another related ranking. Of course, it may not be easy to find or produce a reference ranking associated with MCDM final results. It is possible to find or produce this for many problems. For example, in choosing a commercial product, there will likely be a relationship between a performance-oriented MCDM ranking and a "price" ranking. Companies selling the product are generally very adept at determining the price of this product. They know that performance and product quality move linearly with price. As a result of competition, there is generally a relationship between product performance quality and price. Here, the sensitivity analysis of MCDM's final results can be easily observed with the price constant. We can see this approach with a similar logic in the studies of Elma et al. [19] and Baydaş et al. [20]. In these studies, financial performance was calculated with MCDM, the direction of the share price and parameter change were determined, and the most appropriate MCDM method was determined and recommended. Unlike these studies, we focused on the aspect of sensitivity rather than the MCDM method recommendation. More clearly, it will be investigated whether sensitivity has positive or negative aspects. We also sought to discover whether there were matching patterns in the data, which was each author's aim.

The remainder of the article is structured as follows. The second part overviews used methods and materials. The third part provides the analysis of the study. The fourth part shows the findings. The last section shows evaluations of the results.

2. Method and Material

In this study, we methodologically investigate whether the choice of the best e-scooter alternative, one of the environmentally friendly micromobile vehicles, is a reasonable choice from the perspective of sensitivity analysis. As it is known, there are more than 200 MCDM methods, and although there is no solid consensus on which one to choose, there is an effort to provide some kind of robustness, stability, and verification by performing a sensitivity analysis of the selected MCDM methods. In this study, we focused on questioning and objectively criticizing classical verification analysis. Moreover, we tried to develop and deepen an alternative sensitivity analysis. Below is information about the methodology we use for e-scooter selection.

Table 1
Normalization methods, MCDM methods, performance criteria, and weighting techniques used in this study

Normalization Method	Weighting Method	MCDM Methods	Performance Criteria
Sum, Vector, Min-Max, Max, Rank Based, and Z-Score Normalization	ENTROPY, Equal (mean), CRITIC, SD	PROBID, S-PROBID and CODAS	Engine Power, Range, Speed, Charging Time and Battery Voltage

The diagram showing the methodology applied in this study is shown in Figure 1.

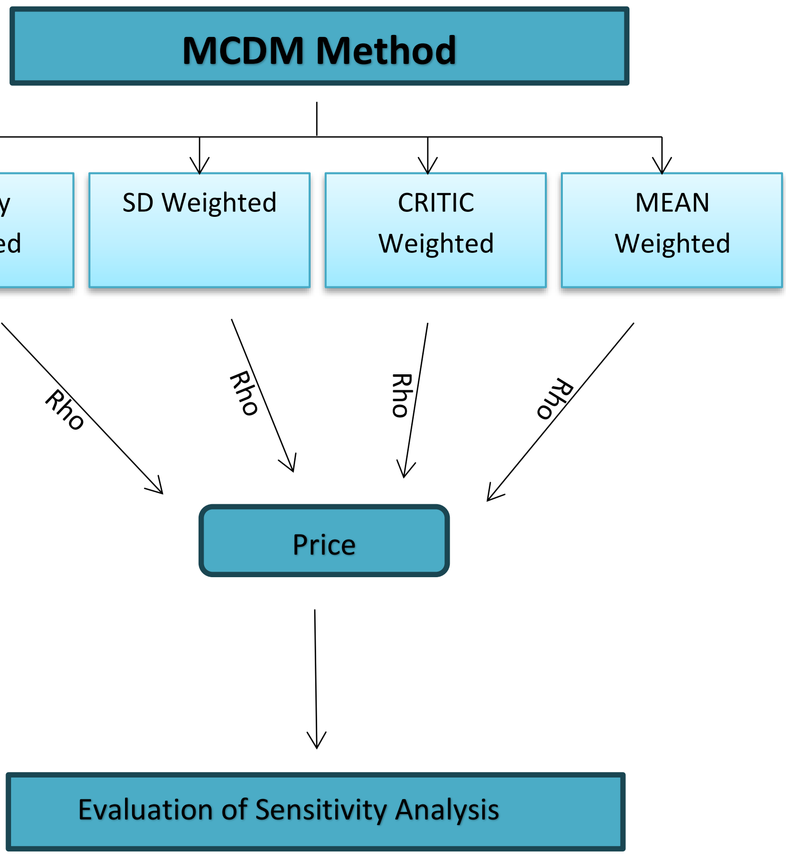

Fig. 1 The flow chart of the methodology used in this research

2.1 Performance Criteria

Descriptive descriptions of the e-scooter performance criteria used in this study are provided below.

Engine power: Engine power refers to performance and is measured in watts [14]. As with other scooters, engine power is very important for e-scooters, especially for rough roads [21].

Range: It is a measure of how many kilometers an electric vehicle can travel on a full battery [22]. While e-scooters are good for acceleration in city traffic, their range is more limited than motorcycles [21].

Speed: Particularly, the maximum speed criterion is taken into account. It refers to the kilometers traveled by the e-scooter per hour [14]. Some countries have limited the speed of e-scooters. This limitation is thought to increase the safety of the e-scooter [15].

Charging time: It is among the most important features of a battery charger [23]. In daily use, especially e-scooters' fast charging is among the preferred factors [24].

Battery voltage: The high battery voltage ensures that the e-scooter charges quickly [14]. On the other hand, it is stated that as the slope, wheel radius, and weight of the driver increases, the battery voltage declines [25].

2.2. Normalization, Weighting, and Statistical Methods used in This Study:

The normalization/transformation, weighting, and statistical methods used in this study are shown below.

Table 2
Demonstration of different normalization, weighting and statistical methods and equations

Transformation/Normalization method	***Equation***
Sum	$F_{ij} = \frac{f_{ij}}{\sum_{k=1}^{m} f_{kj}} \quad i \in \{1,2,\ldots,m\};\ j \in \{1,2,\ldots,n\}$
Vector	$F_{ij} = \frac{f_{ij}}{\sqrt{\sum_{k=1}^{m} {f_{kj}}^2}} \quad i \in \{1,2,\ldots,m\};\ j \in \{1,2,\ldots,n\}$
Minimum-maximum	$F_{ij} = \frac{f_{ij} - min_{i\in m} f_{ij}}{max_{i\in m} f_{ij} - min_{i\in m} f_{ij}} \quad i \in \{1,2,\ldots,m\};\ j \in \{1,2,\ldots,n\}\ for\ benefit\ objectives$ $F_{ij} = \frac{max_{i\in m} f_{ij} - f_{ij}}{max_{i\in m} f_{ij} - min_{i\in m} f_{ij}} \quad i \in \{1,2,\ldots,m\};\ j \in \{1,2,\ldots,n\}\ for\ cost\ objectives$
Maximum	$F_{ij} = \frac{f_{ij}}{max_{i\in m} f_{ij}} \quad i \in \{1,2,\ldots,m\};\ j \in \{1,2,\ldots,n\}\ for\ benefit\ objectives$ $F_{ij} = \frac{min_{i\in m} f_{ij}}{f_{ij}} \quad i \in \{1,2,\ldots,m\};\ j \in \{1,2,\ldots,n\}\ for\ cost\ objectives$
Ranking based	**For each criterion, the best value is assigned first rank, while the worst value is ranked n. rank is assigned. Thus, the weighted preference function for the unit cell in each criterion column is calculated as follows:** $F_{ij} = r_{ij} \times w_j$ **where r_{ij} is the rank of solution i for criteria j.** **Note: This transformator or data converter method is recommended as an alternative to the normalization method. This method is used instead of normalization techniques in the FUCA method.**
Z-Score	$n_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} = \frac{x_{ij} - \frac{\sum_{i=1}^{m} x_{ij}}{m}}{\sqrt{\frac{\sum_{i=1}^{m}(x_{ij} - \mu_j)^2}{m}}} \quad n_{ij} = -\frac{x_{ij} - \mu_j}{\sigma_j}$
Weighted methods	
Entropy	**Normalize the first decision matrix:** $F_{ij} = \frac{f_{ij}}{\sum_{k=1}^{m} f_{kj}} \quad i \in \{1,2,\ldots,m\};\ j \in \{1,2,\ldots,n\}$

	Calculate the Entropy of values of each criteria: $$E_j = -\frac{1}{\ln(m)}\sum_{i=1}^{m}(F_{ij}\ln F_{ij}) \quad j \in \{1,2,\dots,n\}$$ **Determine the weight for each criteria:** $$w_j = \frac{1-E_j}{\sum_{j=1}^{n}(1-E_j)} \quad j \in \{1,2,\dots,n\}$$
SD (Standard Deviation)	$for\ benefit\ and\ cost\ criteria$ $F_{ij} = \frac{f_{ij}-min_{i\in m}f_{ij}}{max_{i\in m}f_{ij}-min_{i\in m}f_{ij}}$ $$F_{ij} = \frac{max_{i\in m}f_{ij}-f_{ij}}{max_{i\in m}f_{ij}-min_{i\in m}f_{ij}}$$ **Calculate the standard deviation of values of each criteria:** $$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}(F_{ij}-\overline{F_j})^2}{m}}$$ $j \in \{1,2,\dots,n\}$
CRITIC weighted method (criteria importance through intercriteria correlation)	**Phases 1: "m" is the number of rows and "n" is the number of columns;** $F_{ij} = \frac{f_{ij}-min_{i\in m}f_{ij}}{max_{i\in m}f_{ij}-min_{i\in m}f_{ij}} \quad i \in \{1,2,\dots,m\};\ j \in \{1,2,\dots,n\}\ If\ it\ is\ beneficial$ $F_{ij} = \frac{max_{i\in m}f_{ij}-f_{ij}}{max_{i\in m}f_{ij}-min_{i\in m}f_{ij}} \quad i \in \{1,2,\dots,m\};\ j \in \{1,2,\dots,n\}\ If\ it\ is\ cost-oriented$ **Phases 2: A binary correlation matrix is created to measure the dependency/correlation between two criteria.** $\rho_{jk} = \frac{\sum_{i=1}^{m}(F_{ij}-\overline{F_j})(F_{ik}-\overline{F_k})}{\sqrt{\sum_{i=1}^{m}(F_{ij}-\overline{F_j})^2}\sqrt{\sum_{i=1}^{m}(F_{ik}-\overline{F_k})^2}} \quad j,k \in \{1,2,\dots,n\}$ **Phases 3: The standard deviation of the criteria is calculated.** $\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}(F_{ij}-\overline{F_j})^2}{m}} \quad j \in \{1,2,\dots,n\}$ **Here,** $\overline{F_j} = \frac{1}{m}\sum_{i=1}^{m}F_{ij}$. **It is the arithmetic mean of the jth normalized objective values. Finally, the weight coefficients for each criterion are determined as follows.** $c_j = \sigma_j\sum_{k=1}^{n}(1-\rho_{jk}) \quad j \in \{1,2,\dots,n\} \quad w_j = \frac{c_j}{\sum_{k=1}^{n}c_k} \quad j \in \{1,2,\dots,n\}$
Equal	**Mean/equal weighting method: The equal weighting method is the simplest way to create weights for each criterion. It is based on the assumption that all n criteria are of equal importance. It is based on the assumption that all n criteria are of equal importance and therefore equal weight coefficients are assigned to each: wj= 1/n j = ∈{ 1, 2, ...n}**
Statistical Method Used	
The Spearman **rank correlation, coefficient measures the statistical dependence between two ranking-based variables:** $r_s = 1 - \frac{6\sum di^2}{n\,(n^2-1)}$ **Here** r_s **is the symbol for Spearman's Rho coefficient.** di **is the symbol for the difference between pairwise rankings. And** n **represents the number of alternatives in the formula.**	

Source: [26], [27], [28] and [32]

2.3 MCDM Method: Preference Ranking On the Basis of Ideal-average Distance (PROBID) Method

In this study, two MCDM methods were used: PROBID and sPROBID. In 2021, Wang et al. [29] developed the PROBID method followed a similar methodology to the distance-based TOPSIS and

VIKOR methods. sPROBID can be considered a simple variation of PROBID. However, the calculation steps and the order they produce may differ.

The mathematical equations of the PROBID method can be seen below. The basic concept of the PROBID method is that it covers ideal solutions from the most positive ideal solution (PIS) to the most negative ideal solution (NIS). PROBID has six stages in total [29]:

Phase 1. By applying Vector transformation, an initial decision matrix containing m rows and n columns is obtained.

$$\boldsymbol{F_{ij}} = \frac{\boldsymbol{f_{ij}}}{\sqrt{\sum_{k=1}^{m} \boldsymbol{f_{kj}}^2}} \quad \boldsymbol{i} \in \{\boldsymbol{1}, \boldsymbol{2}, \dots, \boldsymbol{m}\};\ \boldsymbol{j} \in \{\boldsymbol{1}, \boldsymbol{2}, \dots, \boldsymbol{n}\} \tag{1}$$

Phase 2. A weighted decision matrix is obtained by multiplying each column by a determined weight coefficient:

$$\boldsymbol{v_{ij}} = \boldsymbol{F_{ij}} \times \boldsymbol{w_j} \quad \boldsymbol{i} \in \{\boldsymbol{1}, \boldsymbol{2}, \dots, \boldsymbol{m}\};\ \boldsymbol{j} \in \{\boldsymbol{1}, \boldsymbol{2}, \dots, \boldsymbol{n}\} \tag{2}$$

Phase 3. The highest value of PIS is determined as ($A_{(1)}$), 2nd PIS ($A_{(2)}$), 3rd PIS ($A_{(3)}$), …, and *m*th PIS ($A_{(m)}$) (i.e. the most NIS).

$$\boldsymbol{A_{(k)}} = \{ (\boldsymbol{Large}(\boldsymbol{v_j}, \boldsymbol{k}) | \boldsymbol{j} \in \boldsymbol{J}), \quad (\boldsymbol{Small}(\boldsymbol{v_j}, \boldsymbol{k}) | \boldsymbol{j} \in \boldsymbol{J'}) \} = \{\boldsymbol{v_{(k)1}}, \boldsymbol{v_{(k)2}}, \boldsymbol{v_{(k)3}}, \dots, \boldsymbol{v_{(k)j}}, \dots, \boldsymbol{v_{(k)n}}\} \tag{3}$$

where $k \in \{1,2,\dots,m\}$, J = set of benefit objectives from {1, 2, 3, 4, …, n}, J' = set of cost objectives from {1, 2, 3, 4, …, *n*}, $Large(v_j, k)$ means the *k*th largest value in the *j*th weighted normalized objective column (i.e. v_j) and $Small(v_j, k)$ means the *k*th smallest value in the *j*th weighted normalized objective column (i.e. v_j). Then, find the average value of each objective column.

$$\overline{\boldsymbol{v}}_{\boldsymbol{j}} = \frac{\sum_{k=1}^{m} \boldsymbol{v_{(k)j}}}{\boldsymbol{m}} \quad \textbf{for } \boldsymbol{j} \in \{\boldsymbol{1}, \boldsymbol{2}, \dots, \boldsymbol{n}\} \tag{4}$$

The average solution is then:

$$\overline{\boldsymbol{A}} = \{\overline{\boldsymbol{v}}_{\boldsymbol{1}}, \overline{\boldsymbol{v}}_{\boldsymbol{2}}, \overline{\boldsymbol{v}}_{\boldsymbol{3}}, \dots, \overline{\boldsymbol{v}}_{\boldsymbol{j}}, \dots, \overline{\boldsymbol{v}}_{\boldsymbol{n}}\} \tag{5}$$

Phase 4. Calculate the Euclidean distance of each solution to each of the *m* ideal solutions as well as to the average solution:

$$\boldsymbol{S_{i(k)}} = \sqrt{\sum_{j=1}^{n} (\boldsymbol{v_{ij}} - \boldsymbol{v_{(k)j}})^2} \quad \boldsymbol{i} \in \{\boldsymbol{1}, \boldsymbol{2}, \dots, \boldsymbol{m}\};\ \boldsymbol{k} \in \{\boldsymbol{1}, \boldsymbol{2}, \dots, \boldsymbol{m}\} \tag{6}$$

Then, the distance to an average solution is found as:

$$\boldsymbol{S_{i(avg)}} = \sqrt{\sum_{j=1}^{n} (\boldsymbol{v_{ij}} - \overline{\boldsymbol{v}}_{\boldsymbol{j}})^2}\ \boldsymbol{i} \in \{\boldsymbol{1}, \boldsymbol{2}, \dots, \boldsymbol{m}\} \tag{7}$$

Phase 5. At this stage, the overall positive-ideal distance, which is the weighted total distance of a solution to the first half of the ideal solutions, is determined:

$$S_{i(PIS)} = \begin{cases} \sum_{k=1}^{\frac{m+1}{2}} \frac{1}{k} S_{i(k)} \; i \in \{1,2,\dots,m\} \; when\; m\; is\; an\; odd\; number \\ \sum_{k=1}^{\frac{m}{2}} \frac{1}{k} S_{i(k)} \; i \in \{1,2,\dots,m\} \; when\; m\; is\; an\; even\; number \end{cases} \tag{8}$$

And, determine the overall negative-ideal distance, which is essentially the weighted sum distance of one solution to the second half of ideal solutions.

$$S_{i(NIS)} = \begin{cases} \sum_{k=\frac{m+1}{2}}^{m} \frac{1}{m-k+1} S_{i(k)} \; i \in \{1,2,\dots,m\} \; when\; m\; is\; an\; odd\; number \\ \sum_{k=\frac{m}{2}+1}^{m} \frac{1}{m-k+1} S_{i(k)} \; i \in \{1,2,\dots,m\} \; when\; m\; is\; an\; even\; number \end{cases} \tag{9}$$

Here, weight is increasing with the ideal solution number (i.e. k increasing to m). Overall positive-ideal and negative-ideal distances of each solution (i = 1, 2, ..., m) are thus calculated by equations 8 and 9 respectively.

To better visualize the calculations of ideal and non-ideal distances, a small dataset with 4 Pareto-optimal solutions (S_1, S_2, S_3, S_4) and 2 objectives (F1 and F2) is plotted in Figure 2. As shown, the green (continuous) arrowed line $S_{4(3)}$, for example, represents the Euclidean distance between optimal solution S_4 to the 3rd PIS ($A_{(3)}$). Following equations (8) and (9), $S_{4(pos\text{-}ideal)} = S_{4(1)} + (\frac{1}{2})\, S_{4(2)}$ and $S_{4(neg\text{-}ideal)} = (\frac{1}{2})\, S_{4(3)} + S_{4(4)}$.

Phase 6. Calculate the *PIS/NIS* ratio (R_i) and then the performance score (P_i) of each solution as follows:

$$R_i = \frac{S_{i(pos-ideal)}}{S_{i(neg-ideal)}} \quad i \in \{1,2,\dots,m\} \tag{10}$$

$$P_i = \frac{1}{1+R_i^2} + S_{i(avg)} \quad i \in \{1,2,\dots,m\} \tag{11}$$

On the other hand, the MCDM method called sPROBID is a simple variation of PROBID. The first 4 steps of sPROBID are the same as those of PROBID. In stage five, instead of using the first half of ideal solutions to find $S_{i(PIS)}$ and the second half of ideal solutions to find $S_{i(NIS)}$, sPROBID considers only the top and bottom quarters of ideal solutions for finding $S_{i(PIS)}$ and $S_{i(NIS)}$, respectively.

$$S_{i(pos-ideal)} = \begin{cases} \sum_{k=1}^{m\backslash 4} \frac{1}{k} S_{i(k)} \; i \in \{1,2,\dots,m\} \; when\; m \geq 4 \\ S_{i(1)} \; i \in \{1,2,\dots,m\} \quad when\; 0 < m < 4 \end{cases} \tag{12}$$

Here, $m\backslash 4$ is the integer quotient of m divided by 4, which discards the remainder and retains only the integer portion. In case the number of Pareto-optimal solutions is smaller than 4, only the Euclidean distance between optimal solution S_i and the most PIS is taken.

$$\boldsymbol{S_{i(neg-ideal)}} = \begin{cases} \sum_{k=m+1-(m\backslash 4)}^{m} \frac{1}{m-k+1} S_{i(k)} \; i \in \{1,2,\dots,m\} \;\; when\, m \geq 4 \\ S_{i(m)} \; i \in \{1,2,\dots,m\} \qquad\qquad when\, 0 < m < 4 \end{cases} \tag{13}$$

where $m + 1 - (m\backslash 4)$ gives the starting position of calculating negative-ideal distance. If fewer than 4 non-dominated solutions exist, only the Euclidean distance between optimal solution S_i and the mth PIS (i.e., most NIS) is taken.

In step six of sPROBID, the final score is simplified to the ratio of negative-ideal distance over positive-ideal distance.

$$\boldsymbol{P_i} = \frac{S_{i(NIS)}}{S_{i(PIS)}} \quad i \in \{1,2,\dots,m\} \tag{14}$$

The farther a solution is from NIS and the closer it is from PIS, the higher the performance score P_i. The solution with the highest P_i is recommended to the decision maker.

2.4 Combinative Distance-based Assessment (CODAS)

In the CODAS method, which has become popular in the last five years, the ranking performance of an alternative is measured by its distance from the negative ideal point [30]. Each pair of alternatives is compared according to their distance from this ideal value. Here, the superiority of the alternatives over each other can be determined by two criteria. The priority criterion is the Euclidean distance of the considered alternatives to the negative ideal (in cases where the Euclidean distance cannot be used, taxi distance is preferred as an alternative). This distance-based method, somewhat similar to TOPSIS, is preferred in cases where the best alternative has the farthest distance from the negative ideal.

3. Application

This study aims to make the selection of the candidate with the best performance among environmentally and traffic-friendly electric scooter alternatives more efficient, fair, and accurate. In this direction, we focused on questioning and developing "sensitivity analysis", which is a frequently used method in the evaluation of MCDM methods. As is known, classical sensitivity analyses generally only deal analytically with whether the ranking position of the "best" alternative has changed. However, in this study, we suggest that it is more convincing to deal with the sensitivity of all ranking alternatives from a “holistic perspective”. For this purpose, we chose a problem with as many alternatives as possible.

As a matter of fact, in this study, we focused on the selection of an e-scooter consisting of 50 alternatives and five criteria. We used the methods whose descriptive explanations are given in detail in the methodology and materials section above in this study. Accordingly, two MCDM methods, four weighting, and six normalization/data converter techniques were used in the study. We objectively determined how and to what extent the ranking was affected when we changed the weight coefficient assignment techniques or normalization type, not only by observing but also by using the Spearman rank correlation, a statistical method. We acted with the assumption that there is an order correlation or relationship between the performance of the e-scooter alternatives we calculated with MCDM and the "price" rankings of these alternative vehicles. We have objectively observed in all trial tests that this assumption is correct and meaningful. We tested sensitivity not only through the classical form of weight coefficient assignment techniques but also through normalization types. We obtained data about e-scooters from "https://www.epey.com" [31], an open-access commercial website.

In this study, classical and the innovative sensitivity analyses we propose are frequently compared methodically within the analysis. As it is known, in classical sensitivity analysis, the weight coefficient, which is one of the input parameters in MCDM methods, is changed and how the ranking results are affected is observed through comparisons. As a common practice, it is generally considered sufficient to simply check whether the best alternative has moved. However, this approach is simple and may contain exceptional findings that prevent generalization. In our opinion, statistically seeing how much the overall final ranking can change with the change of an input parameter is more solid evidence for sensitivity determination. In this study, we will perform a sensitivity analysis of the entire ranking. Comparing the different MCDM rankings obtained with each other is the most important aspect of classical sensitivity analysis. MCDM final rankings can be considered in terms of their degree of similarity/correlation with each other (classical method) or with an external factor (innovative method). Here, we are comparing the innovative sensitivity model and MCDM methods, not with each other, but with a fixed "price" ranking. Thus, we identified a reference point (price) to understand both sentiment and the direction of sentiment.

In this study, where we measured the performance of electric scooters with the MCDM methods CODAS, PROBID, and sPROBID, we first changed only the weight coefficients for the sensitivity analysis kept the other components constant, and obtained the results with statistical correlation.

In this study, first, the effect of weight coefficients on the sensitivity of the MCDM method was analyzed. Moreover, the effect of normalization techniques on the sensitivity of the MCDM method was also analyzed. The price factor was kept constant.

In Table 3 below, the effect (in other words, from an innovative perspective) or sensitivity of both weighting and normalization methods on the PROBID method can be seen collectively. Here you can see the Spearman correlation results between PROBID, an MCDM method, and the price of e-scooter alternatives. While reading the table, please note that we keep the weighting in the columns or the normalization in the rows constant. This way we can better understand the impact of other factors. The numerical values in the table are Spearman rank correlation values. The first of the two rows and columns written in bold is the standard deviation of the values and measures the sensitivity, which was proposed for the first time in this study. The second is the average of the values. While the first criterion measures sensitivity (very sensitive, moderate, or less sensitive), the second criterion provides information about the level of relationship between performance-based MCDM and price (positive, neutral, or negative). After this explanatory information, you can see our findings and analysis in the table below.

Table 3
Effect of weighting and normalization methods on the PROBID method

	ENTROPY	**Equal**	**SD**	**CRITIC**	**StDv**	**Mean**
Sum	**0.521**	**0.421**	**0.518**	**0.269**	***0.102478***	***0.43225***
Vector	**0.503**	**0.409**	**0.53**	**0.204**	***0.127942***	***0.4115***
Min-Max	**0.584**	**0.768**	**0.757**	***0.786***	***0.081346***	***0.72375***
Max	**0.654**	**0.727**	**0.752**	**0.7**	***0.036321***	***0.70825***
RB	**0.415**	**0.527**	**0.588**	**0.453**	***0.066773***	***0.49575***
Z-Score	**0.281**	**0.317**	**0.454**	**0.26**	***0.075548***	***0.328***
StDv	***0.119801***	***0.166999***	***0.116072***	***0.225334***		
Mean	***0.493***	***0.528167***	***0.599833***	***0.445333***		

For example, in the table above, the meaning of the top row is as follows: SUM normalization was preferred for PROBID and kept constant, to which Entropy, Equal, CRITIC, and SD weighting methods were applied separately. Of course, when these methods are applied, we obtain different rankings. These rankings are compared with each other in the classical method and the sensitivity is tried to be understood. However, according to the principles of comparison in logic, this situation can be more understood through a reference order. According to our preference in this study, the best possible reference ranking is based on the "price" criterion, which is precisely determined and calibrated by the companies, taking into account all the criteria.

We can look at the relationship between price and MCDM-based performance from two perspectives. Firstly, it can be said that the alignment of the order that ensures a potential relationship at the best level and preserves the existing relationship is the best. Secondly, this also means “sensitivity” (the degree of relationship between the price constant and MCDM-based performance). For example, if the relationship between two factors (even though the price is kept constant) increases abnormally due to the numerical change of the input parameter and decreases in the next trial, we can easily talk about hypersensitivity here.

According to Table 3 (and as can be seen better from subsequent analyses), there is a situation similar to data analytics-based pattern matching in our findings. We see this better when we carefully examine the relationship between the final results of the PROBID method and the price. For example, when we look at the correlations between the price and the MCDM results obtained by keeping the SUM method constant and changing the weights, we obtain four different correlation results. We can reinterpret sensitivity by measuring the variability of the correlation results we obtain with standard deviation. Moreover, the average of four different correlation results on the top line will also give an idea. On the other hand, if we look at the top left column in Table 3 with the same approach, we can see the effects of normalization on the MCDM method. By keeping the entropy weighting method constant, it can be understood to what extent other types of normalization affect the relationship with price. Thus, this evaluation can be performed for all rows and columns with two different approaches.

According to Table 3, it is noticeable that the most efficient rankings are produced in positions where sensitivity is low and correlation with price is high. For example, the efficient result in which the second highest correlation (70%) in the matrix is obtained belongs to the Max/CRITIC-PROBID compatible combination (There is a similar pattern in the case where the highest correlation is achieved). On the other hand, it is noteworthy that although the sensitivity of Vector normalization is high, its relationship with price is weak. Again, according to Table 3, the CRITIC method, which has the highest sensitivity, produced the lowest correlation on the general average. On the other hand, while the SD method produced the highest relationship on average, it was the method with the lowest sensitivity. In summary, according to Table 3, it can be said that in cases where sensitivity is low, productive situations arise where the correlation with the third party increases (for both normalization and weighting methods).

The same applies to the sPROBID method below. When we look down the column, we can see the effect of normalization, and when we move down the row to the right, we can see how the weight coefficients affect the relationship with the price. When we look at standard deviation values as a measure of sensitivity, the method with the most fluctuating relationship with price among the weight coefficients is CRITIC while Entropy is more stable. Among normalization techniques, the technique that has the most fluctuating relationship with price is Vector normalization, while the methods that produce a stable relationship are Min-Max and Max methods. On the other hand, while the Vector technique produced the lowest correlation on average as a penalty for sensitivity, Min-Max and Max produced the highest correlations (73% and 71%) as a reward for stability. A similar situation applies to weights. While CRITIC, which is more sensitive, produced a low relationship with price, Entropy and SD methods, which are least sensitive on average, produced higher relationships.

Table 4
Effect of weighting and normalization methods on sPROBID method

	ENTROPY	Equal	CRITIC	SD	StDv	Mean
Sum	0.54	0.419	0.245	0.51	*0.114932*	*0.4285*
Vector	0.531	0.406	0.176	0.515	*0.141776*	*0.407*
Min Max	0.655	0.745	0.774	0.741	*0.044443*	*0.72875*
Max	0.657	0.725	0.705	0.757	*0.036277*	*0.711*
RB	0.634	0.7	0.756	0.747	*0.04837*	*0.70925*
Z-Score	0.472	0.489	0.248	0.604	*0.128921*	*0.45325*
StDv	*0.070854*	*0.145559*	*0.262871*	*0.107213*		
Mean	*0.5815*	*0.580667*	*0.484*	*0.645667*		

Table 4 data show that sPROBID, like PROBID, is consistent with the low sensitivity/high correlation and high sensitivity/low correlation model. Of course, the following question can be expected to come to mind here: The first four calculation steps are common between PROBID and Sprobid. The difference applies to several steps. Therefore, it may seem natural for similar patterns to match in analyses. Here we can continue the analysis for a third method to further clarify the issue.

In Table 5, we chose CODAS, perhaps one of the most interesting methods of the last five years, for analysis. Because the sensitivity of this method is greatly affected by the selected normalization. While CODAS sometimes has high sensitivity, on the contrary, it can sometimes have low sensitivity with a good normalization selection. This shows that low or high sensitivity may not be valid for an MCDM in all conditions. Some sensitivity determinants, such as normalization, are important factors. Max normalization, which is commonly used for CODAS, may not give good results sometimes. CODAS-Max incompatibility can be an inefficiency problem, especially for financial data [32, 19].

Table 5
Effect of the weighting and normalization methods on the CODAS method

	ENTROPY	Equal	CRITIC	SD	StDv	Mean
Sum	0.633	0.692	0.739	0.715	*0.039334*	*0.69475*
Vector	0.643	0.698	0.723	0.716	*0.031377*	*0.695*
Min Max	0.477	0.535	0.338	0.619	*0.10237*	*0.49225*
Max	0.437	0.211	0.063	0.431	*0.157463*	*0.2855*
RB	0.599	0.518	0.36	0.603	*0.098405*	*0.52*
Z-Score	0.679	0.74	0.76	0.762	*0.033596*	*0.73525*
StDv	*0.089418*	*0.179288*	*0.261793*	*0.109369*		
Mean	*0.578*	*0.565667*	*0.497167*	*0.641*		

If Table 5 is examined carefully, it will be seen that the low sensitivity/high correlation and high sensitivity/low correlation patterns in PROBID and sPROBID are also present to a certain extent in CODAS for both weighting and normalization techniques. While entropy and SD stand out as weighting methods that provide low sensitivity, Equal, and CRITIC provide high sensitivity. Remember that these results are also valid for previous methods.

On the other hand, we also focus on how normalization affects sensitivity. Sum, Vector, and Z-score, which are low-sensitivity normalization methods, also produced the highest correlations with price. While Z-score produced a relatively low level of sensitivity and relationship in previous MCDM methods, it achieved a very good fit with CODAS and produced the highest relationship with price. In contrast to this situation, it is significant that the Max normalization commonly used for CODAS produces high sensitivity and low correlation with price. So, while Max normalization is a good partner for PROBID variants, the same cannot be said for CODAS. When we put together all the alternative combinations of the three methods (combination of the three tables), the partners that produce the most sensitive/lowest relationship (StDv:0.157/rho:0.285) are the CODAS-Max combination on average. With these results, it can be said that the unverifiable trend in the literature that low sensitivity is positive is highly confirmed (with the solid findings of this study). It seems that the pattern-matching findings suggest that the low sensitivity of the MCDM rankings may indeed mean that they will generally produce a high correlation with price. And this can also be interpreted as a positive meaning. However, we recommend that the approach here be deepened further, without haste and with patience, and this is necessary. This will be possible by testing as many data type/MCDM basic equation/normalization type/weighting technique combinations as possible in this model.

4. Discussion

The application of our study differs from classical sensitivity approaches measuring the stability of MCDM methods (CODAS and PROBID derivatives) in several points:

• First of all, the direction of sensitivity is tried to be determined in terms of standard deviation and its relationship with an external factor. For this, our base reference point for sensitivity is the price of electric scooters. In classical sensitivity analysis, a reference point is not selected for MCDM results.

• On the other hand, we question the claim that all types of sensitivity are negative.

• Another issue is that the degree to which the entire ranking is affected is more important than the impact of a single alternative. And this statistical approach is evidentially more convincing. However, classical sensitivity analysis generally observes the local movements of the best alternative in this ranking rather than the MCDM rankings.

• Moreover, the basic idea of this study is to evaluate sensitivity holistically, not only through weight coefficients but also through all MCDM components. For example, normalization type is also an input parameter, and its effects on sensitivity were investigated in this study.

• It seems that the MCDM methods that produce the best rankings are those with low sensitivity (as highlighted in the literature). But at the same time, these are methods that produce an interestingly stable and good correlation with an external order. Indeed, MCDM methods with low sensitivity produced a good relationship with price on average. The opposite is also true (high sensitivity/low relationship production).

• Finally, in this study, the method to be followed in determining the best alternative was investigated. Pattern matching results showed that generally low sensitivity and high correlations were achieved simultaneously for all methods. We can say that these two matches make general sense, but exceptions and some nuances are also vital. So, what results should we base on when determining the best alternative? Pattern matching from data analytics implies that, for now, combinations that produce low sensitivity and high correlation with price produce more quality rankings. But as we said, this is a general evaluation and there may always be exceptions. For example, for PROBID derivatives, the Min-Max/CRITIC partnership produced the best possible relationship. On the other hand, for CODAS, the Z-Score/SD and Z-Score-CRITIC partnership produced the best result available. This result we obtained for the Best alternative does not conflict much with our generally matching pattern model. However, although CRITIC normally raises sensitivity in weighting, Min-Max sensitivity in normalization lowers it. Ultimately, Min-Max/CRITIC partners produced the most positive results for both PROBID and sPROBID. Thus we come to this conclusion. We can choose the best alternative from the order that best produces the relationship with price. However, on average, this does not conflict much with the low sensitivity/high possible relationship

Spectrum of Engineering and Management Sciences
Volume 2, Issue 1 (2024) 17-35

or high sensitivity/low possible relationship model (matching patterns). In other words, the best alternative is expected to be located within or close to the matching patterns. This shows that there may be minor contradictions between holistic and generalizing judgments and real local results.

Each of the graphs below clearly shows the impact of the weighting methods on the MCDM final results for each method, or the innovative sensitivity of the MCDM methods, according to the correlations they produce. If we pay attention to the images, the CRITIC method, while having high sensitivity, produced a low correlation with price. While SD and Entropy Methods had low sensitivity, they produced a high correlation with price.

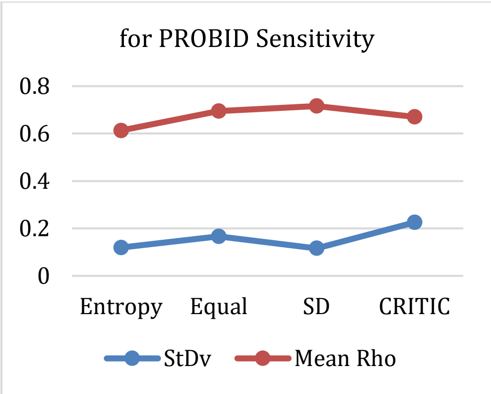

Fig. 2 Sensitivity results for the PROBID method

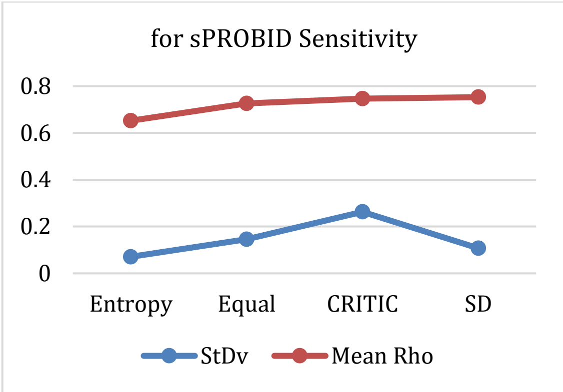

Fig. 3 Sensitivity results for the sPROBID method

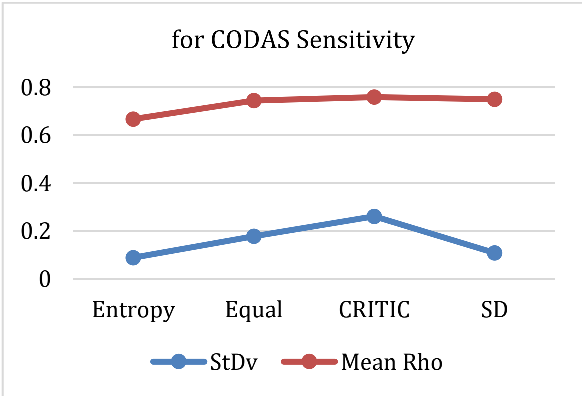

Fig. 4 Sensitivity results for the CODAS method

Each of the graphs below shows the impact of normalization methods on MCDM final results or the innovative sensitivity of MCDM methods for each method. If we pay attention to the images, the Vector method, while having high sensitivity, produced a low correlation with price. While Max and Min-Max normalization methods had low sensitivity, they produced a high correlation with price.

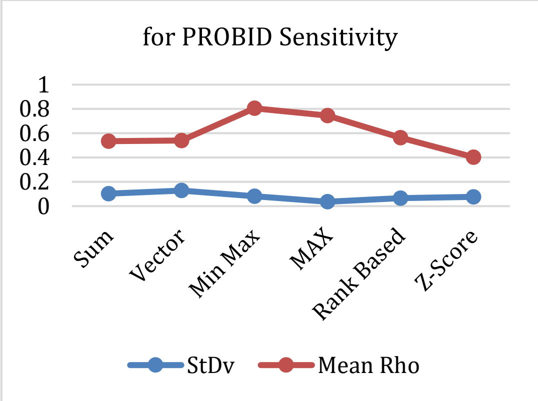

Fig. 5 Sensitivity results for the PROBID method

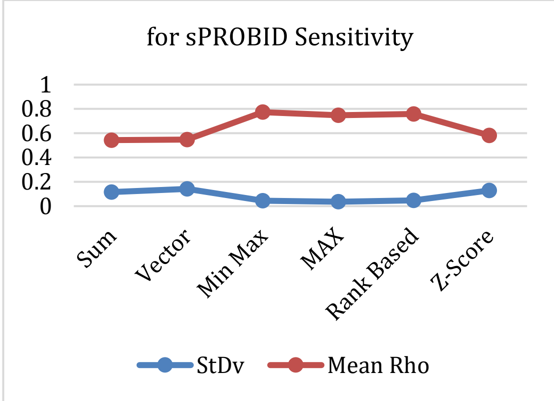

Fig. 6 Sensitivity results for the sPROBID method

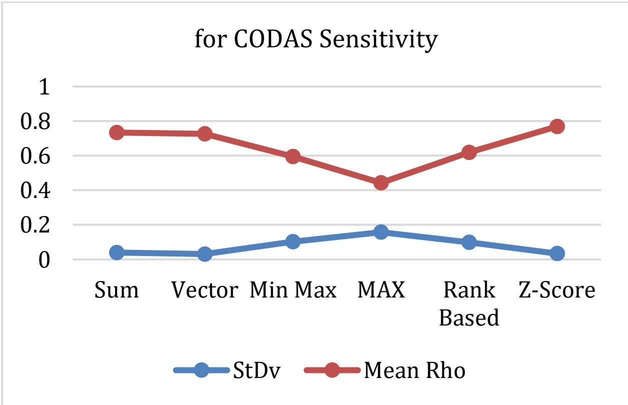

Fig. 7 Sensitivity results for the CODAS method

On the other hand, while Z-Score could not produce good results for PROBID, it produced the best results for CODAS. This behavior of Z-Score implies that it is a compatible pair with CODAS. We can also say that the sensitivity of each method is not always the same in absolute terms. In other words, input parameters also change the sensitivity of the methods. For example, when CRITIC increases the sensitivity of all methods, while Entropy and SD decrease it, it may be thought that this is an expected development. On the other hand, Z-Score does not show the same behavior in all methods. While Z-Score normalization reduces the sensitivity of CODAS, on the contrary, it increases the sensitivity of the PROBID method.

Finally, the combination that produces the highest correlation among all alternative combinations is 78.6% for PROBID (with Min-Max/CRITIC), 77.4% for sPROBID (with Min-Max/CRITIC combination), and 76.2% for CODAS (with SD/Z-Score combination). While PROBID derivatives are often used by their authors with Vector normalization, CODAS uses Max normalization. However, the consistent results we obtained for these data sets indicate that this may be a wrong choice because the findings indicate that this choice should be Min-Max for PROBID derivatives and Z-Score for CODAS. Finally, authors should always consider whether weightings and normalization types are heavily influenced by the data type.

5. Conclusion

In recent years, sensitivity analyses have been identified with the concepts of robustness, reliability, stability, or verification in the comparison, selection, or objective evaluation of MCDM methods and are still widely used by authors as a serious criterion. As it is known, when you change any input parameter in the MCDM method calculation, this can greatly affect the final results of MCDM and change the results. However, since there is no reference point for sensitivity, there is confusion about which MCDM method is better, more robust, or more reliable. This situation is undesirable according to classical comparison principles and poses some problems. In this context, in this study focusing on the selection of electric scooters, the final results of MCDM were evaluated with the "price" rankings of the same products, which are a fixed external reference, with a different approach. Thus, the story of change in MCDM rankings can be better understood while keeping a ranking sequence constant. In the study, we wanted to observe different input parameters for sensitivity. To keep the scope wide, four different weighting methods and six data conversion/normalization methods were determined as input parameters, and their impact on the rankings was evaluated based on price. The MCDM-based e-scooter performance results of this study produced 72 different rankings. The procedure operated in two directions. On the one hand, the effect of the weightings was observed with Spearman correlation by keeping the normalization constant, and then, on the other hand, the effect of the normalization was observed statistically by keeping the weighting constant. All obtained MCDM rankings were examined collectively by combining the fixed price ranking and Spearman correlation. Overall, there were high and significant correlations between MCDM rankings and price, which was what we expected.

According to the findings obtained from this study, it can be said that two important patterns are constantly matched. We measured sentiment by standard deviation and external correlations by Spearman correlation. MCDM rankings, which had consistently low sensitivity in the data, produced high correlations with price. Or the high-sensitivity MCDM rankings produced consistently low correlations with price. MCDM rankings, which have a mediocre sensitivity, generally produced a mediocre relationship with price as a group. These general findings seem to confirm the approach in classical sensitivity analysis, which cannot be verified in the first place. In other words, as is widely known, it is recommended that the sensitivity level for an MCDM be stable or low, which is what robustness and reliability require.

However, although classical sensitivity analysis gives an idea about which method may be best, which is the best alternative, or where to look for it, it does not provide sufficient insight. At this point, our innovative sentiment analysis gives us more solid insights. Although it may initially be logical to look for the best alternative in the MCDM rankings, which have low sensitivity and high correlation with price, the best alternative may not be in the efficient location we are looking for. For example, the best alternative may sometimes not be included in good efficient MCDM combinations, as in the case of bad students in good schools and good students in bad schools. If we take the MCDM method, which has the highest correlation with price among the 72 MCDM rankings, as a basis, the situation confirms exactly what we said. Accordingly, the three combinations that produce the highest correlation with price in all alternative combinations are 78.6% for PROBID (with Min-Max/CRITIC), 77.4% for sPROBID (with Min-Max/CRITIC combination) and 76.2% for CODAS (SD/ with the Z-Score composite). In this case, there is an interesting situation if we consider the combination of 78.6% (with Min-Max/CRITIC) for PROBID. Min-max normalization in this fitted combination normally leads MCDM to low sensitivity for this data set. On the other hand, CRITIC wants to lead to high sensitivity.

In short, when we classify the best or worst MCDM rankings as a group, the correlation with high sensitivity/low price, respectively; or there is a match such as low sentiment/correlation with high price. However, if we base on the hypothesis that it is a singular case that produces the best result, that is, if we accept the order that produces the best correlation with the price as the best (for the Min-Max/CRITIC/PROBID combination it was 78.6%). Accordingly, the best alternative in the ranking produced by the Min-Max/CRITIC/PROBID combination is Dualtron Victor. The best alternative for sPROBID is the Dualtron Eagle Pro and for CODAS the Dualtron Victor e-scooter brand.

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