Journal of Intelligent Management Decision
https://www.acadlore.com/journals/JIMD

Does the Performance of MCDM Rankings Increase as Sensitivity Decreases? Graphics Card Selection and Pattern Discovery Using the PROBID Method

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Received: 02-01-2024 **Revised:** 03-10-2024 **Accepted:** 03-25-2024

Citation: M. Baydaş, M. Kavacık, and Z. Y. Wang, "Does the performance of MCDM rankings ıncrease as sensitivity decreases? Graphics card selection and pattern discovery using the PROBID method," *J. Intell Manag. Decis.*, vol. 3, no. 2, pp. 91–103, 2024. https://doi.org/10.56578/jimd030203.

Abstract: In general, a stable and strong system shouldn't have an overly sensitive/dependent response to inputs (unless consciously and planned desired), as this would reduce efficiency. As in other techniques, approaches, and methodologies, if the results are excessively affected when the input parameters change in MCDM methods, this situation is identified with sensitivity analyses. Oversensitivity is generally accepted as a problem in the MCDM (Multi-Criteria Decision Making) methodology family, which has more than 200 members according to the current literature. The MCDM family is not just a weight coefficient-sensitive methodology. MCDM types can also be sensitive to many different calculation parameters such as data type, normalization, fundamental equation, threshold value, preference function, etc. Many studies to understand the degree of sensitivity simply monitor whether the ranking position of the best alternative changes. However, this is incomplete for understanding the nature of sensitivity, and more evidence is undoubtedly needed to gain insight into this matter. Observing the holistic change of all alternatives compared to a single alternative provides the researcher with more reliable and generalizing evidence, information, or assumptions about the degree of sensitivity of the system. In this study, we assigned a fixed reference point to measure sensitivity with a more robust approach. Thus, we took the distance to the fixed point as a base reference while observing the changeable MCDM results. We calculated sensitivity to normalization, not just sensitivity to weight coefficients. In addition, past MCDM studies accept existing data as the only criterion in sensitivity analysis and make generalizations easily. To show that the model proposed in this study is not a coincidence, in addition to the graphics card selection problem, an exploratory validation was performed for another problem with a different set of data, alternatives, and criteria. We comparatively measured sensitivity using the relationship between MCDM-based performance and the static reference point. We statistically measured the sensitivity with four types of weighting methods and 7 types of normalization techniques with the PROBID method. The striking result, confirmed by 56 different MCDM ranking findings, was this: In general, if the sensitivity of an MCDM method is high, the relationship of that MCDM method to a fixed reference point is low. On the other hand, if the sensitivity is low, a high correlation with the reference point is produced. In short, uncontrolled hypersensitivity disrupts not only the ranking but also external relations, as expected.

Keywords: Multi-Criteria Decision Making (MCDM); Sensitivity analysis; Graphics card selection

1 Introduction

A graphics card is the computer hardware that transforms the digital data processed on the computer into an image that the user can understand and sends it to the monitor. A monitor is a device for displaying this image. Graphics cards are either fixed to the mainboard (onboard) or external in all computers [1]. A graphics card must be used to do data mining [2]. The processing power of the graphics card determines the quality of the resolution [3]. Located between the processor and the monitor, the graphics card is one of the main parts of the computer. The video card, with its software and hardware features, enables the creation and projection of high-resolution images onto the monitör. It allows graphics, pictures, movies and videos to be created and transferred to the screen. The display of more brilliant and clear colors in games is directly related to the graphics card. For this reason, good image quality depends on the graphics card [4]. Fast processing of data is also important. A video card with this capacity will take the graphics load from the computer, ensuring no performance loss and providing high-resolution graphics [5]. With the latest developments in the information sector, there is almost no field where computers are not used. Böyük et al. [6] used deep learning-based computers equipped with advanced graphics cards to detect the location of vehicles in traffic with unmanned aerial vehicles. Due to the complexity of today's video games and the demand for high screen resolution, video cards are equipped with high-performance GPUs (graphics processing units) [7]. While "graphics card" is often used interchangeably with "graphics processing unit" (GPU), it's important to note that the GPU is merely one element within the broader graphics card assembly [8].

Undoubtedly, dealing with complex decision problems with a single or a few selection criteria creates inefficiency in today's conditions and this is quite harmful. The widely used methodology to choose the best graphics card or the best alternative is MCDM (Multi-Criteria Decision Making) [9–11].

It can be said that in the existing literature there are some limited studies based on the MCDM methodology regarding the selection of the best "graphics card" to assist decision makers. For example, Avunduk et al. [12] conducted a study to decide on the most suitable graphics card for cryptocurrency mining using the BWM-Topsis method. According to the model obtained as a result of the applied method, the most suitable graphics card was found to be rx580. Through a case study, Lee et al. [13] analyzed the usage and speed of graphics cards based on Monte Carlo method. For cryptographic processing, the potential of using Graphics Processing Units (GPUs) in symmetric key encryption is being investigated by Cook et al. [14]. Komatitsch et al. [15] transferred the numerical simulation of seismic waves generated by earthquakes around the world to graphics cards using the CUDA method. Tests and measurements have shown that performance accelerates by a quarter in best use.

Sensitivity analysis for MCDM is a concept directly related to the degree of impact of a numerical change of an input parameter on the final results [16]. It can be said that measuring the effect of weight coefficient assignment on the sensitivity of the MCDM ranking is the first application that comes to mind in the literature. However, the common tendency in the literature is that instead of the entire ranking, it is generally checked whether the order of the best alternative in a ranking has changed. However, sensitivity analysis can cover all MCDM input components (such as normalization type, alternative, criterion, data type, threshold value, preference function, basic equation component, etc.). There is already sufficient consensus that sensitivity to input parameters should be poor for an MCDM method. Determination, stability, perseverance, and weak sensitivity are the sought-after and desired characteristics of an MCDM. However, it is not clear whether the determining factor of sensitivity is the weight coefficient of an MCDM method, the MCDM basic equation, or other elements such as data type, normalization, and threshold value. Accepting only the weight coefficient as a sensitivity determinant would be an incomplete approach in this regard. Moreover, in our opinion, all components may share in the determination of sensitivity. However, it cannot be said that this issue has been discussed comprehensively and in depth enough in the literature [17, 18].

In this study, we would like to draw attention to a few important deficiencies mentioned above in the literature. In the literature, sensitivity is often determined by simply looking at whether the best alternative has changed. According to reasonable comparison rules, a sensitivity analysis should be made by looking at the sensitivity of the entire ranking. Additionally, sensitivity is frequently identified with the original fundamental equation of MCDM. However, the type of the normalization component can change, so this is not a static choice. Normalization for each MCDM can also be a decisive measure of sensitivity, like the basic MCDM equation. Thus, it is necessary to remember that the whole we call MCDM is not just the basic equation and has other parts as well. Another point is that sensitivity does not always have to be negative. For example, electronic device sensors are very sensitive, and their benefit lies in their sensitivity. Positive and smart sentiment solutions can also be developed for the MCDM methodology in the future.

The exploratory model in this study, unlike the classical sensitivity analysis, is tested on two different problems rather than a single problem type by expanding the scope. Although we perform the sensitivity analysis on computer graphics card brands, alternatively we also do it based on MCDM calculations based on country economic performance selection. The data range, number of alternatives, number of criteria, and even the weight coefficients of these three problems are completely different from each other. Moreover, we measure sensitivity with a fixed reference order. When we changed the input parameters (weight coefficient, normalization, and data type) of the MCDM methods we determined, that we obtained 56 different MCDM rankings. We suggest that the change or sensitivity in the rankings can only be measured accurately by comparing them with a fixed reference ranking. For example, "price" for a computer graphics card and "GDP per capita" for a country's economic performance can be a fair reference point. This is a reasonable choice because we can predict that as a result of competition, there should be a close relationship between performance and price. In this study, we focused on the discovery of determinants of the degree of sensitivity of MCDM methods through data analytics.

2 Method and Material

In this study, the best computer graphics card selection, which is a selection problem for decision-makers, will be selected with the MCDM method and additionally with an innovative sensitivity analysis model validation. In other words, whether choosing the best alternative is a reasonable choice is discussed within the framework of sensitivity analysis. Which weight coefficient and which normalization method will be chosen will also be revealed with this sensitivity analysis approach. Stability, robustness, and verification degree will be investigated by performing a sensitivity analysis of a selected MCDM. In this study, as an alternative to classical confirmation analysis, we focused on how the correlation between 56 different MCDM rankings changes with a fixed reference point (price). Table 1 below is information about the methodology we use in selecting a computer graphics card.

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

Normalization Method	Weighting Method	MCDM Methods	Performance Criteria
Rank Based, Decimal, Z-Score, Sum, Vector, Min-Max and Max Normalization	CRITIC, SD, ENTROPY, Mean	PROBID	Memory size, Memory speed (MHz), GPU cores, Memory interface width (bits), Memory bandwidth (GB/s), Graphics card power

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

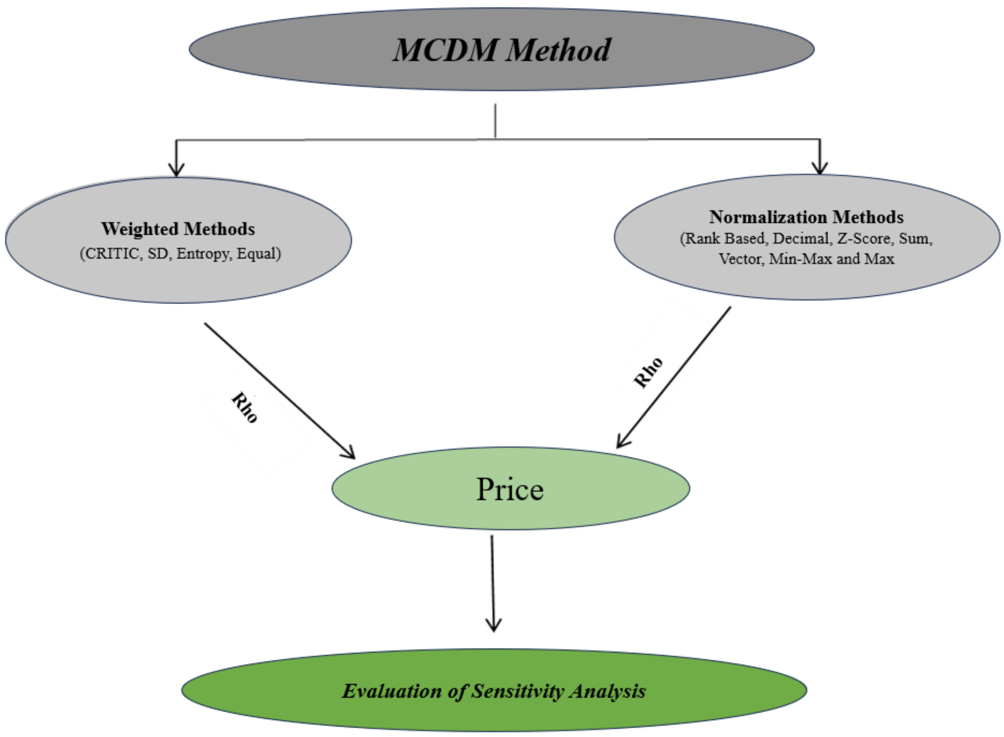

Figure 1. The flow chart of the methodology used in this research

2.1 Performance Criteria

Informative explanations regarding the performance criteria defined for the selection of the graphics card used in this study can be seen below.

Memory size: Memory size pertains to the capacity of a computer or device to retain and access data. This capacity is usually quantified in units such as bytes, kilobytes, megabytes, gigabytes, and terabytes. It dictates the volume of information, encompassing files, documents, images, videos, and applications, that can be accommodated on a device concurrently. Greater memory sizes facilitate the storage and retrieval of more data, thereby enhancing the device's operational speed and effectiveness [19].

Memory speed (MHz): It impacts the performance of the graphics processing unit (GPU). Insufficient memory on the graphics card can restrict the range of options available for resolution, textures, shadows, and various other configurations, effectively placing constraints on the visual quality and performance of your system [20].

GPU cores: The GPU functions as a processor comprised of numerous smaller, specialized cores, each optimized for specific tasks, collectively enabling it to efficiently handle graphics rendering and computational tasks [21]. Cores make up the GPU. During a process, the cores work in coordination with each other, resulting in a smooth and high quality game [22].

Memory interface width (bits): A computer has many memory interfaces. The Memory Interface in a GPU essentially serves as the pathway that allows the GPU to communicate with its memory subsystem. It's like the bridge connecting the GPU's processing power with its memory resources. This interface determines how much data can be transferred between the GPU's processing units and its memory modules at any given time. In simpler terms, it's the width of the pipeline through which data flows between the GPU and its memory, influencing the speed and efficiency of data transfer within the graphics processing unit. Bus width denotes the size of the data path that allows information to flow between components, specifying how many bits can be transmitted concurrently to the CPU [23].

Memory bandwidth (GB/s): Bandwidth relates to the volume of data that can be transferred to or from a given location, and in the context of GPUs, the focus is primarily on global memory bandwidth [24].

2.2 Normalization, Weighting and Statistical Methods Used in this Study

Table 2 demonstrates the normalization, weighting and statistical methods used in this study.

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

Converter/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 Converter	For each criterion, the first rank is fort he best value, while n is for the worst value. Rank is assigned. Hence, the computation of the weighted preference function for each criterion column of the unit cell proceeds as follows: $F_{ij} = r_{ij} \times w_j$ r_{ij} refers the rank of result i for criteria j. Note: Instead of utilizing normalization techniques, it is advisable to utilize the transformator or data converter method, particularly within the FUCA method.
Z-Score	$n_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} = \frac{x_{ij} - \frac{\sum_{i=1}^{m} x_{ij}}{m}}{\sqrt{\frac{\sum_{i=1}^{m} (x_{ij} - \mu_j)^2}{m}}} \quad n_{ij} = -\frac{x_{ij} - \mu_j}{\sigma_j}$ Z-score refers to the measurement of the standard deviation of a value from the mean of a given distribution.
Decimal	This technique involves shifting the decimal point of the values within a series. The specific shift depends on the number of digits present in the maximum value of the series. By employing decimal scaling, the series is transformed into a normalized form, where all values fall within the range of 0 to 1. The number of decimal places shifted is determined by the number of digits in the maximum value (denoted as 'd'): $F_{ij} = f_{ij}/10^d$ $i \in \{1, 2, \ldots, m\}; \; j \in \{1, 2, \ldots, n\}$
Weighted Methods	

Converter/Normalization Method	Equation
Entropy	Normalize the first decision matrix: $F_{ij} = \frac{f_{ij}}{\sum_{k=1}^{m} f_{kj}} \quad i \in \{1,2,\ldots,m\}\,;\ j \in \{1,2,\ldots,n\}$ Compute the Entropy of each criteria's value: $E_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} (F_{ij} \ln F_{ij}) \quad j \in \{1,2,\ldots,n\}$ Define the weight of each criteria: $w_j = \frac{1-E_j}{\sum_{j=1}^{n}(1-E_j)} \quad j \in \{1,2,\ldots,n\}$
SD (Standard Deviation)	for benefit and cost criteria $F_{ij} = \frac{f_{ij} - min_{i\in m} f_{ij}}{max_{i\in m} f_{ij} - min_{i\in m} f_{ij}}$ $F_{ij} = \frac{max_{i\in m} f_{ij} - f_{ij}}{max_{i\in m} f_{ij} - min_{i\in m} f_{ij}}$ Compute the standard deviation of each criteria's value: $\sigma_j = \sqrt{\frac{\sum_{i=1}^{m} (F_{ij} - \overline{F_j})^2}{m}}$ $j \in \{1,2,\ldots,n\}$
CRITIC Weighted Method (Criteria Importance Through Intercriteria Correlation)	Phases 1: "m" is the number of lines and "n" is the number of pillars; $F_{ij} = \frac{f_{ij} - min_{i\in m} f_{ij}}{max_{i\in m} f_{ij} - min_{i\in m} f_{ij}} \quad i \in \{1,2,\ldots,m\}\,;\ j \in \{1,2,\ldots,n\}$ If it is beneficial $F_{ij} = \frac{max_{i\in m} f_{ij} - f_{ij}}{max_{i\in m} f_{ij} - min_{i\in m} f_{ij}} \quad i \in \{1,2,\ldots,m\}\,;\ j \in \{1,2,\ldots,n\}$ If it is cost-oriented Phases 2: A bilateral relations matrix is formulated to assess the association or relationship between the criterias. $\rho_{jk} = \frac{\sum_{i=1}^{m}(F_{ij} - \overline{F_j})(F_{ik} - \overline{F_k})}{\sqrt{\sum_{i=1}^{m}(F_{ij} - \overline{F_j})^2}\sqrt{\sum_{i=1}^{m}(F_{ik} - \overline{F_k})^2}} \quad j,k \in \{1,2,\ldots,n\}$ Phases 3: The standard deviation of the criteria is determined. $\sigma_j = \sqrt{\frac{\sum_{i=1}^{m} (F_{ij} - \overline{F_j})^2}{m}} \quad j \in \{1,2,\ldots,n\}$ Here, $\overline{F_j} = \frac{1}{m} \sum_{i=1}^{m} F_{ij}$ The calculation involves finding the average of the jth normalized neutral measures. Subsequently, The process for determining the weight coefficients of each criterion is as follows. $c_j = \sigma_j \sum_{k=1}^{n} (1 - \rho_{jk}) \quad j \in \{1,2,\ldots,n\}$ $w_j = \frac{c_j}{\sum_{k=1}^{n} c_k} \quad j \in \{1,2,\ldots,n\}$
Equal	Mean/Equal Weighting Method: The equal weighting method assigns uniform weights to each criterion, operating under the assumption that all criteria hold equal significance. Thus, it treats all n criteria with equal importance by assigning them identical weight coefficients: $w_j = 1/n$ j $= \in \{1, 2, \ldots .$n$\}$
Statistical Method Used	
The Spearman rank correlation coefficient evaluates the strength and direction of the relationship between two variables by comparing their rankings rather than their raw data values: $r_s = 1 - \frac{6\sum di^2}{n(n^2-1)}$. Here r_s denotes Spearman's Rho coefficient. di signifies the difference between bilateral sortings. And n stands for the total number of alternatives considered within the formula.	

Source: [25–29]

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

The study utilized Multi-Criteria Decision Making (MCDM) methods, specifically focusing on PROBID. Wang et al. [30] devised the PROBID approach, employing a methodology similar to distance-based methods. Below are the equations of the PROBID method:

Phase 1. Using the Vector normalization method, the raw data is converted into a decision matrix with m lines and n pillars.

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

Phase 2. The weighted decision matrix is derived by multiplying each column by a specific weight coefficient:

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

Phase 3. The maximum figure PIS is defined $(A_{(1)})$, 2nd PIS $\left(A_{(2)}\right)$, 3rd PIS $(A_{(3)}), \ldots$, and $m \ldots \ldots th$ PIS $(A_{(m)})$ (i.e., the most NIS).

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

where, $k\ \in \{1, 2, \ldots, m\}$, 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 largest figure in the jth weighted normalized neutral pillar (i.e., v_j) and $Small\,(v_j, k)$ means the k^{th} smallest figure in the jth weighted normalized neutral pillar (i.e., v_j). After that, calculate the mean figure of each neutral pillar.

$$\bar{v}_j = \frac{\sum_{k=1}^{m} v_{(k)j}}{m} \quad \text{for } j \in \{1, 2, \ldots, n\} \quad (4)$$

The mean result is then:

$$\bar{A} = \{\bar{v}_1,\ \bar{v}_2,\ \bar{v}_3, \ldots, \bar{v}_j,\ \ \ldots,\ \ \bar{v}_n\ \} \quad (5)$$

Phase 4. Compute the Euclidean range of every result to every optimal results as well as to the mean result:

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

Afterwards, the range to mean result is calculated as:

$$S_{i(avg)} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - \bar{v}_j\right)^2}\, i \in \{1, 2, \ldots, m\} \quad (7)$$

Phase 5. In this phase, the overall positive-optimal range weighted total range of a result to the first half of the optimal results, is found:

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

And, define the general NIS, which is actually the weighted total range of one result to the second half of optimal results.

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

Here, weight is rising with the optimal result figure (i.e., k increasing to m). Therefore, general positive-optimal and negative-optimal ranges of each result (i = 1, 2, ..., m) are computed by Eqs. (8) and (9) in sequence.

Phase 6. Compute the PIS/NIS ratio (R_i) and then performance figure (P_i) of each result is below:

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

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

The further a result is from NIS and the nearer it is from PIS, the higher the performance figure P_i. The result with the highest P_i is advised to the decider.

3 Application

This study aims to test with an innovative sensitivity analysis whether it is possible to understand the confirmability and robustness of choosing the best graphics card among the alternatives with the MCDM method. As it is known, "sensitivity analysis" is frequently used in the evaluation of MCDM methods. And in this study, we questioned the "stability" approach of the sensitivity analysis methodology. Moreover, while classical sensitivity analysis focuses too much on whether the ranking position of the "best" alternative has changed, we thought it was more convincing to focus on the sentiment of the entire ranking. We thought that choosing to work with many alternatives was more useful in understanding sentiment. In this study, we focused on the selection of a graphics card consisting of 50 alternatives and 6 criteria. We used some methods whose formulas and information are given in the methods and materials section. In this study, an MCDM method, four weight coefficient assignments, and 7 normalization methods are adopted to capture the impact of MCDM components in a comprehensive view for sensitivity analysis. Thus, when we changed an input parameter, we determined the degree to which the results were affected through Spearman Rank Correlation, a statistical method. So, we calculated a rank correlation between MCDM results and graphics card price rankings. We accessed the performance criteria data about the graphics card from "https://www.epey.com" [31], an open-access commercial website. In this study, we wanted to see statistically how much the overall final ranking could change by changing an input parameter, to provide more solid evidence for sensitivity. In other words, we tried to determine the sensitivity analysis of the entire ranking by comparing it with a fixed reference ranking. The basis of the innovative sentiment model here is the comparison of the rankings produced by an MCDM with a fixed "price" ranking.

In Table 3 below, you can see the Spearman correlation results between PROBID, an MCDM method, and the price of graphics card alternatives. Thus, the effect or sensitivity of both weighting and normalization methods on the PROBID method can be seen at the same time. First of all, when examining the analysis, the analysis can be interpreted by keeping the weighting method along the column or the normalization technique along the row constant. Numerical values in the table are Spearman rank correlation values, which express the relationship of different MCDM ranks with price. On the other hand, the first of the two rows and columns written in bold is the standard deviation of the values and expresses the effect of the sensitivity proposed in this study. The second is the arithmetic average of the correlation values, which gives an idea about the strength of the produced ranking. The first criterion measures sensitivity based on standard deviation. The second criterion provides information about the level of relationship between performance-based MCDM and price, which indicates whether the external relationships of an MCDM ranking are broken.

In Table 3 below, the weight coefficients assigned to the criteria according to the methods can be seen.

Table 3. Weight coefficients of criteria assigned according to methods

Criteria	Benefit or Cost	Entropy	SD	CRITIC	Equal
Memory Size	Max	0.212866	0.126864	0.121205	0.166667
Memory Speed (Mhz)	Max	0.036408	0.143549	0.307620	0.166667
Gpu Cores	Max	0.351013	0.178710	0.168489	0.166667
Memory Interface Width (Bits)	Max	0.056924	0.197264	0.146601	0.166667
Memory Bandwidth (Gb/S)	Max	0.204516	0.181304	0.121677	0.166667
Graphics Card Power	Max	0.138273	0.172310	0.134408	0.166667

In Table 4 below, the impact of normalization and weighting techniques on PROBID's external relations and the general sensitivity (standard deviation) level of PROBID in different scenarios can be clearly seen.

Table 4. Effect of normalization and weighting methods on PROBID MCDM method

	Entropy	Equal	SD	CRITIC	StDv	Mean
Sum	0.879	0.883	0.885	0.856	**0.011605**	**0.875750**
Vector	0.876	0.875	0.877	0.850	**0.011281**	**0.869500**
Min-Max	0.867	0.870	0.868	0.741	**0.055148**	**0.836500**
Max	0.861	0.857	0.868	0.793	**0.030136**	**0.844750**
Rank Based	0.421	0.514	0.524	0.413	**0.051201**	**0.468**
Decimal	0.870	0.860	0.853	0.805	**0.024990**	**0.847**
Z-Score	0.647	0.617	0.648	0.452	**0.081213**	**0.591**
Stdv	**0.16370**	**0.14007**	**0.1329**	**0.17404**		
Mean	**0.77442**	**0.78228**	**0.7890**	**0.70142**		

According to the table above, the top line is interpreted as follows. "Sum normalization" was preferred for PROBID, where Entropy, Equal, CRITIC and SD weighting methods were applied separately, and when kept constant, the obtained correlations were 87.9%, 88.3%, 88.5% and 85.6%, respectively. Their standard deviation is 0.011605 and their mean is 0.87575. When we apply the same procedure for each row, we obtain different rankings and correlations. When looking at the correlation values with fixed price over all lines, it can be seen that Sum and Vector techniques have low standard deviation values while simultaneously producing high correlation. This is the first evidence that a low sensitivity MCDM ranking also correlates well with price. In fact, this situation (low sensitivity and high correlation with price) also shows a situation similar to pattern matching based on data analytics. On the other hand, if we look at the upper left column of Table 3 with the same approach, this time we will see the effects of normalization on the MCDM method. By keeping the "entropy weighting method" constant, the extent to which other normalization types affect the relationship with price can be understood with the correlation results 87.9, 87.6, 86.7, 86.1, 42.1, 87 and 64.7%. So, this evaluation is repeated for all columns. When we finally evaluate the results, we see that the standard deviation values are 0.163707, 0.140077, 0.132904 and 0.174048. Moreover, it can be seen that the average correlation values are 0.774429, 0.782286, 0.789 and 0.701429. In other words, the best normalization technique is the SD method, which reduces MCDM sensitivity, which can be understood with the correlation value of 0.789.

According to Table 3, it is understood that under conditions where sensitivity is high, the relationship with price decreases and vice versa. On the other hand, the efficient ecosystem situation in which the highest correlation in the matrix (88.5%) is obtained is the situation with the Sum/SD-PROBID compatible combination. In other words, the two techniques that showed the best normalization and weighting performance were combined with PROBID to produce the best correlation. It can be said that this is a result in line with expectations. Moreover, according to Table 3, the CRITIC method, which has the highest sensitivity, produced the lowest correlation on the overall average. As we said above, the SD method produced the highest relationship on average but was the method with the lowest sensitivity. Rank Based and Z-Score (interestingly, Min-Max and Z-score are almost indispensable technical choices in artificial intelligence applications) produced the lowest correlation and highest sensitivity among the MCDM rankings.

The "*Gigabyte GeForce RTX 4090 Gaming*" alternative, which produces the highest correlation, stands out as the best alternative to the SD-Sum-PROBID combination, which is the MCDM ranking that produces the best correlation (89%) among MCDM rankings (Table 5).

In many MCDM problems, we see that sensitivity analysis results are incorrectly generalized. For example, authors introducing a new MCDM method perform sensitivity analysis to demonstrate the robustness of this method. However, it is ignored that these sensitivity analysis results are valid only for a specific problem. Although the basic equation of an MCDM method used is fixed, the weighting method, normalization type, and other parameters vary in different data and problems. With this change, the sensitivity of the MCDM method also changes. For example, if you use CRITIC on one data type, precision may increase, and if you use Entropy on another data type, precision may decrease. On the other hand, sensitivity may also decrease or increase depending on the type of normalization. So, in fact, the basic equation of an MCDM is not the sole determinant of sensitivity. In fact, the chosen combination-equation of an MCDM is not the sole determinant of sensitivity. Combinations of MCDM can be many, and normalization, weighting, and MCDM basic equation components are the key parameters that determine sensitivity. Although our main goal is to choose a graphics card, in this study we will also test our matching pattern model on a completely different problem and data type. Below, we have determined which year is the best year using the PROBID method, based on the 10-year economic performance criteria of the Turkiye economy. The sensitivity analysis results below can be better examined by following the basic procedure for the graphics card above.

The analysis findings in Table 6 are parallel to the previous analysis findings. It can be said that the low standard deviation and high correlation performance results of Sum and Vector normalization types are symptoms of low sensitivity and strong MCDM. On the other hand, it can be seen that Min-Max and Rank-Based converters produce high standard deviation and low average correlation with price. This situation also shows that these data converters negatively affect the sensitivity of MCDM and therefore the price relationship performance in general. On the other hand, we can look at how weight coefficient assignment methods affect sensitivity and performance. In general, we see that the Entropy method provides the lowest standard deviation and the highest correlation generation performance. The CRITIC method seems to have negatively affected the performance of the PROBID method by producing the highest standard deviation and the lowest correlation with price, showing a similar trend as in the previous data and problem. On the other hand, the highest performance among the 28 PROBID rankings belongs to the Rank-Based-Entropy-PROBID combination. Although we propose the low sensitivity-high correlation theorem here, it should be noted that this is a general clustering rule. A good ranking arises from a good combination, but the best alternative may not arise from this combination. While the best ranking combination is Sum or Vector-Entropy-PROBID, the ranking combination with the best alternative belongs to the Rank Based-Entropy-PROBID combination. In the previous problem, the ecosystem with the best ranking was SD-PROBID and the alternative that produced the best correlation emerged from this ranking. This situation shows us that the best ranking and the best alternative are located very close to each other, but there is no guarantee that they will be in the same position.

Table 5. The scores and rankings of the alternatives

Alternatives	Score	Rank	Alternatives	Score	Rank
Afox GeForce GTX 1660	0.048679	39	MSI GeForce RTX 4090 Ventus 3X 24G OC	0.907442	3
ASRock Radeon RX 6700 XT Challenger D 12GB OC	0.157482	28	MSI Radeon RX 6750 XT Mech 2X 12G OC	0.198831	27
Asus Cerberus GeForce GTX 1050 Ti OC 4G (1341 MHz)	0.023327	42	MSI Radeon RX 7900 XT Gaming Trio Classic 20G	0.628142	19
Asus Dual GeForce GTX 1660 Super OC Edition 6GB GDDR6 EVO	0.058592	38	NVIDIA Quadro P1000	0.012070	45
Asus Phoenix GeForce GTX 1050 Ti	0.023327	43	NVIDIA Quadro RTX 4000	0.118828	32
Asus ROG Strix GeForce RTX 4080 16GB GDDR6X White	0.699804	13	Palit GeForce RTX 4090 GameRock	0.907353	6
Asus ROG Strix Radeon RX 570 OC 8G	0.077457	37	PNY GeForce RTX 3080 10GB XLR8 Gaming Revel Epic-X RGB Triple Fan LHR	0.678167	16
Colorful GeForce RTX 4070 Ti NB EX-V	0.426456	22	PNY GeForce RTX 4070 Verto	0.276108	26
Colorful GeForce RTX 4080 16GB NB EX-V	0.699804	14	PNY GeForce RTX 4080 16GB TF Verto Edition	0.705477	12
Gainward GeForce RTX 4070 Ti Panther	0.426456	23	PNY Quadro P2000	0.026082	41
Gainward GeForce RTX 4080 Phantom	0.708727	11	PNY RTX A5500	0.792270	9
Galax GeForce RTX 4090 SG 1-Click OC	0.907353	5	PNY RTX A6000	0.847710	8
Gigabyte GeForce RTX 4080 16GB Aero	0.699804	15	PNY Tesla K20	0.128552	31
Gigabyte GeForce RTX 4090 Gaming	0.907442	1	PowerColor Red Devil Radeon RX 580 8GB GDDR5 Golden	0.107690	34
HP Radeon Pro W6800	0.456869	21	PowerColor Red Devil Radeon RX 7900 XT 20GB GDDR6	0.628142	20
HP RTX A2000 12GB	0.081063	36	Quadro GeForce GT 730 4G D3L	0.009510	47
HP RTX A6000	0.847710	7	Quadro GeForce GTX 1050 Ti	0.022962	44
iGame GeForce RTX 4070 Ti Ultra W OC-V	0.276108	25	Quadro Radeon R7 240 2GD5	0.010188	46
Inno3D GeForce RTX 2060 Super Twin x2 OC	0.136650	30	Sapphire Nitro+ Radeon RX 580 8GD5 Special Edition (8 GB / 1430 MHz)	0.146087	29
Intel Arc A770	0.331523	24	Sapphire Nitro+ Radeon RX 7900 XT Vapor-X	0.651587	17
Lenovo Quadro K420 2GB	0.008938	49	Sapphire Pulse Radeon RX 6700	0.114952	33
Lenovo RTX A5000	0.727075	10	Sapphire Pulse Radeon RX 7900 XT 20G	0.635927	18
MSI GeForce GTX 1660 Ti Ventus XS OC (1830 MHz)	0.043116	40	Seclife GeForce GT 730 2GB	0.007957	50
MSI GeForce RTX 2060 Gaming Z	0.081317	35	Seclife GeForce GT 730 4GB	0.009270	48
MSI GeForce RTX 4090 Suprim 24G	0.907442	2	Zotac Gamıng GeForce RTX 4090 Trinity	0.907442	4

Table 6. The effect of normalization and weighting methods on the PROBID MCDM method for the Turkiye's economic performance according to years

	Entropy	**Equal**	**SD**	**CRITIC**	**StDv**	**Mean**
Sum	0.745	0.782	0.782	0.806	**0.02181**	**0.77870**
Vector	0.745	0.794	0.782	0.806	**0.02285**	**0.78170**
Min-Max	0.697	0.067	0.067	0.176	**0.26088**	**0.25170**
Max	0.697	0.685	0.685	0.636	**0.02346**	**0.67570**
Rank Based	0.890	0.345	0.333	0.139	**0.28506**	**0.43000**
Decimal	0.794	0.794	0.709	0.673	**0.05305**	**0.74250**
Z-Score	0.879	0.782	0.806	0.152	**0.29245**	**0.65470**
StDv	**0.07686**	**0.26659**	**0.26267**	**0.29039**		
Mean	**0.78000**	**0.60700**	**0.59485**	**0.48400**		

Note: This MCDM problem includes 6 economic criteria and 10 alternative years. The criteria are as follows: Exports of goods and services (US$), Imports of goods and services (US$), Inflation, consumer prices (annual %) Interest payments (% of expense), Total reserves (includes gold, current US$), Unemployment, total (% of total labor force) (national estimate). On the other hand, we calculated the country's economic performance with MCDM and chose GDP per capita as the fixed reference point in this study. The above results show the correlations between the country's economy performance and GDP per capita.

Source: World Bank datas (https://data.worldbank.org/) [32]

4 Discussion

The sensitivity analysis application procedure of our study is different and innovative from other classical sensitivity analyses measuring the stability of MCDM methods:

• A key point in all our work was undoubtedly the "price", which we used as a fixed reference point. We produced a total of 56 different MCDM sequences for two different problems. We obtained correlations between these rankings and price. We understood from the standard deviation results that the sensitivity of the MCDM rankings, which produce the best relationship with price, is also low. As it is known, there is no reference point for MCDM results in classical sensitivity analysis, and this may cause problems in terms of the direction of sensitivity. The claim that all kinds of sensitivity are negative is not true in an absolute sense.

• Classical sensitivity analysis is not based on the degree to which the entire ranking is affected and is more concerned with the position of a single alternative. The statistical approach we propose here is more convincing.

• Another issue is that we think that all MCDM components determine sensitivity. It is difficult to understand the sensitivity just by the weight coefficient. In this study, the effects of normalization and data type on sensitivity were also investigated.

• This study discovers that low sensitivity and high correlation are reasonable and general pattern matching for understanding the location of the best MCDM rankings. However, although the MCDM methods that produce the best rankings are methods with low sensitivity and high correlation with price, the best alternative may not be in an identical position with the best rankings.

• Results from data analytics showed that for PROBID variants, the SD-Sum/PROBID combination produced the best relationship available. It is no coincidence that the Best alternative appears in the combination of SD and Sum that produces the best rankings. While CRITIC increases the sensitivity in weighting, SD and Entropy decrease it. It is understood that the Z-score method, which is frequently used in artificial intelligence studies, shows a mediocre performance. 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.

Figure 2 and Figure 3 show the levels of precision created through the impact of normalization and weighting methods on MCDM final results. While the Sum and Vector method had low sensitivity, it produced a high correlation with price. Although the SD weighting method had low sensitivity, it produced high correlation with price. The converse is also linearly true. These results provide strong evidence that there are pattern matches in terms of sensitivity and performance.

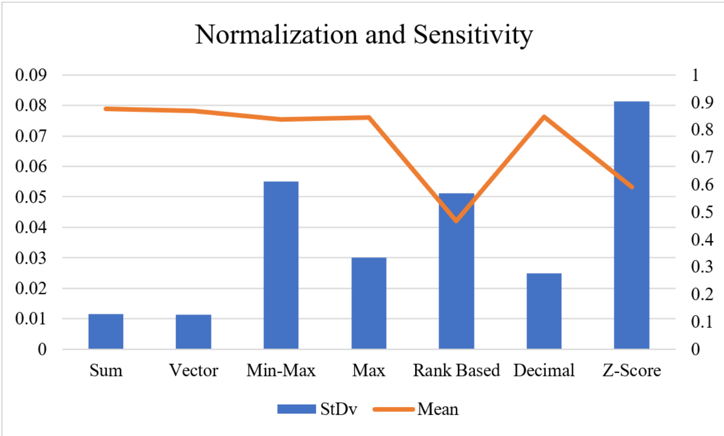

Figure 2. Sensitivity production levels of PROBID according to normalization methods

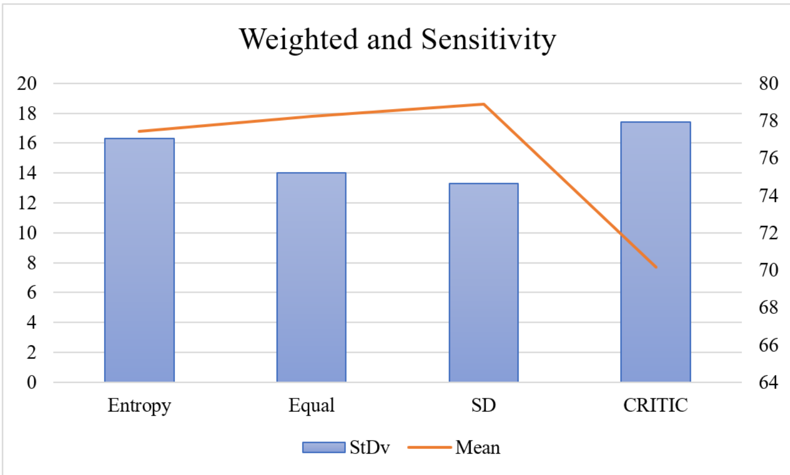

Figure 3. Sensitivity production levels of PROBID according to weight coefficient assignment methods

5 Conclusions

When you change any input parameter of a system, this may affect the final results of the system to a certain extent, that is, it may change the results. If this happens excessively, it causes inefficiency. So in general, over-influence also reduces the quality of any metric. For this purpose, sensitivity analyses have been used after study results as an important criterion for MCDM methods in recent years to understand the extent of the influence. Sensitivity analysis, often used in the sense of stability or confirmation, actually suggests and desires low sensitivity. However, since there is no reference point and direction for sensitivity, there is also confusion about which MCDM method is better, more robust, or more reliable. In this context, in this study focusing on the choice of the video card, which is a computer card, MCDM final results were compared with fixed "price" rankings of the same products, which is a fixed external reference. In other words, while the price order was kept constant, the change in MCDM rankings was observed. In the study, we focused on the entire sequence and approached sensitivity holistically. We tested 28 modified combinations of PROBID with 50 alternative e-display card alternatives and 6 decision criteria. We observed the degree of sensitivity with different input parameters (4 different weighting methods and 7 data transformation methods). In total, we examined the correlation relationships of 28 different MCDM rankings with changing prices. All the resulting MCDM rankings told us the same thing: In general, MCDM rankings produced a good relationship with the price if they had low sensitivity. And the opposite was also true linearly. We tested our model again with a completely different data type and a different problem. The results once again confirmed this pattern match. Moreover, we obtained strong evidence that the location of the best alternative should also be sought in clusters with low sensitivity and high correlation with price. These results are the unique discovery of our study.

Research Suggestions: Although sensitivity is considered negative, there are many positive examples of sensitivity in today's world. Positive and smart sensitivity solutions (like sensor technologies) for the MCDM methodology may also be developed in the future.

Author Contributions

Conceptualization, M.B. and M.K.; methodology, M.B., and Z.W.; validation, M.B., and Z.W.; formal analysis, M.B., and M.K.; investigation, M.B.; resources, M.B.; data curation, M.B.; writing—original draft preparation, M.B., and M.K.; writing—review and editing, M.B., Z.W., and M.K.; visualization and M.B. and M.K.; supervision, M.B., and Z.W. All authors have read and agreed to the published version of the manuscript. The relevant terms are explained in the CRediT taxonomy.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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