mathematics

Article

An Alternative Sensitivity Analysis for the Evaluation of MCDA Applications: The Significance of Brand Value in the Comparative Financial Performance Analysis of BIST High-End Companies

Orhan Emre Elma [1], Željko Stević [2,*] and Mahmut Baydaş [1,*]

[1] Faculty of Applied Sciences, Necmettin Erbakan University, Konya 42005, Türkiye; oeelma@erbakan.edu.tr
[2] School of Industrial Management Engineering, Korea University, 145 Anam-Ro, Seongbuk-Gu, Seoul 02841, Republic of Korea
* Correspondence: zeljkostevic88@yahoo.com (Ž.S.); mbaydas@gmail.com (M.B.)

Abstract: Multi-criteria decision analysis (MCDA) applications consist of techniques that enable the decision maker to make clearer decisions in scenarios where there is more than one alternative and criterion. The general approach for sensitivity analysis in MCDA applications implies sensitivity to the weight coefficient. In this study, as an alternative approach, we reinterpret sensitivity by using the statistical relationship between the final ranking produced by an MCDA method and a constant external factor. Thus, we both verify through an anchor and reveal to what extent the change in the weight coefficient changes the external relations of MCDA. The motivation for this study is to propose an alternative sensitivity methodology. On the other hand, brand value is a parameter that contains critical information about the future of the company, which has not integrated into financial performance studies made with MCDAs before. To that end, the financial performance of 31 companies with the highest brand value in Turkey and trading on Borsa Istanbul between 2013 and 2022 was analyzed with seven different MCDA applications via integrating brand value into the criteria for the first time. The study's findings revealed that the proposed innovative sensitivity tests produced similarly robust results as traditional tests. In addition, brand value has been proved to be an advantageous criterion to be implemented into MCDAs for financial performance problems through the sensitivity analysis made.

Keywords: sensitivity; MCDA; capital markets; stock returns; brand value

MSC: 90B50; 91B06; 62C05; 91G15

Citation: Elma, O.E.; Stević, Ž.; Baydaş, M. An Alternative Sensitivity Analysis for the Evaluation of MCDA Applications: The Significance of Brand Value in the Comparative Financial Performance Analysis of BIST High-End Companies. *Mathematics* **2024**, *12*, 520. https://doi.org/10.3390/math12040520

Academic Editor: Maria C. Mariani

Received: 9 January 2024
Revised: 27 January 2024
Accepted: 5 February 2024
Published: 7 February 2024

1. Introduction

Multi-criteria decision analysis (MCDA) applications are used to create a roadmap for the future by evaluating complex real-life scenarios [1,2]. The examined alternatives are put into practice by giving the calculated weights of the predetermined criteria. Ultimately, these alternatives are ranked. All these processes are to ensure that decision makers, who are at the decision-making stage, make more consistent decisions by making use of the past information and data set.

There are more than 200 MCDA methods and it is unclear which of them is the best or most appropriate for the given problem [3–5]. Sensitivity analysis is a methodology used in MCDA evaluations. In general, this analysis measures the sensitivity of an MCDA method to the weight coefficient variation. Although it is not verified, the basic approach of sensitivity analysis states that, if the position or place of the alternatives in the ranking fluctuates too much while the weight coefficients of the criteria change, this may imply the weakness of the method. Because an MCDA method must be consistent and stable to a certain extent against the changes in weight coefficients, it is expected that an MCDA method will not deviate readily [6–10]. In this study, sensitivity to the weight coefficients was interpreted from a different perspective. To illustrate, a deviation in weight coefficients can change the statistical association of MCDA methods with the external factor. Thus, sensitivity can be observed more clearly through an anchor. This approach also demonstrates that an increase or decrease in sensitivity alone may not be a reason for final interpretation. In this case, the increase or decrease in a statistical relationship between two variables is more critical because, if changing an input increases an existing relationship, it can be interpreted as changing the input is more efficient. In other words, an increase in sensitivity is positive if it increases a statistical relationship and vice versa. In this study, the financial performance of enterprises with the highest brand value in an emerging market, Turkey, has been scrutinized, and this new sensitivity analysis has been employed. Seven MCDA methods were used, and brand value was integrated into the criteria for the first time in the financial performance literature. The results obtained were then evaluated with an innovative sensitivity analysis in order to create a clear roadmap for financial stakeholders.

A brand can be defined as a name, design or feature that distinguishes a company's goods or services from other companies in a meaningful way and creates a perception specific to that firm [11]. In an environment where competition has become more difficult with the development of internet technologies, each material or moral feature that will create a company-specific perception is important and valuable in terms of creating and retaining a loyal customer base. Regardless of the form or image, the potential benefits that brands create and add to the company should be evaluated separately from other financial parameters [12]. In modern business literature, the term competitive advantage has now been replaced by brand value. The key distinction here is that ratios and parameters from financial statements focus on historical data, while brand value focuses on the future. Although the ultimate goal of finance is to create shareholder value, brand value management plays a vital role in making this goal sustainable in the long run.

When purchasing the products and services they need, users end up choosing the products that promise the most performance per the price in their income group, taking into account their budgets and the comments of the people around them. While making this decision, the critical factor affecting consumers' preferences is brand perception. The brand power is regarded as the cumulative sum of the right or wrong decisions made by the company during the process of its activities, which includes many sub-parameters such as the expected quality, functionality and design of the product or service that the customer will receive. In fact, in modern competition theory, brands play a pivotal role in the potential success of the firm, as they constitute the first point of differentiation [12]. Through rational co-operation of the marketing and finance departments, a brand value can be created that can carry the company to the top in its sector. Consistent brand value can emerge by providing and maintaining positive customer feedback, as inefficiencies in company returns and financial performance will overcome [13].

Although brand value is a parameter that has been held responsible for market turmoil like the previous 2008 global financial crisis [14], the latest phenomenon created by the pandemic is different [15]. So, this opened up an opportunity for researchers to analyze the hidden relationship between capital markets and investor sentiment [16]. The 2008 global financial crisis severely damaged the economies of various countries globally; on the other hand, COVID period investors reacted faster and increased the value of renowned capital market indexes in a relatively short period of time; even so, there were short-term volatilities. From this point of view, considering brand value as a financial performance parameter during the pandemic process, which constitutes an important stage in the history of financial markets, is of vital importance in terms of being a preliminary preparation for possible crises in the future from the perspective of company managers, creditors and investors who are at the decision stage in uncertainty processes [17].

In the literature, brand value has been evaluated under the title of brand marketing, in particular, with the important factors that can create this value. The motivation for the realization of this study is that the brand value, which also reflects the financial attractiveness and creditworthiness of the company, did not find the necessary place in MCDA studies on financial performance. Although there are several MCDA studies on brand value, the fact that it has not been used in financial performance studies creates an important research gap. It is also aimed that this study, which covers a long period of 10 years, including the uncertainty period of the COVID-19 pandemic, will fill another important gap in the literature in terms of volatility.

Thus, in this study, unlike the previous literature, the potential relationship between brand value and other relevant financial parameters and stock returns will be investigated by MCDA applications. To that end, companies with the highest brand value in Turkey will be analyzed by using FUCA, VIKOR, TOPSIS, SAW, CODAS, RAFSI and GRA methods, and the most appropriate method will be proposed to the decision makers according to the relationship between the method scores produced by financial parameters, including brand values of companies, with the stock returns of the relevant companies. For this purpose, 31 companies that have managed to enter the top 100 consistently in the last 10 years in the 'Türkiye's Most Valuable Companies' reports prepared annually by Brand Finance and also trade in Borsa Istanbul will be analyzed. In order to clearly reveal the scope of the study and the consistency of the results, analyses were performed with seven MCDA methods from different schools.

The remaining sections of this study can be summarized as follows. In Section 2, studies on brand value and MCDAs will be explained. In Section 3, the performance metrics and MCDA methods implemented in the methodology of this study will be clarified. In Section 4, the final outputs and classic and innovative sensitivity analysis performed on seven methods with the criteria including brand value will be presented. In Section 5, the pivotal and critical insights revealed by this study will be unveiled. In Section 6, the results will be expressed and a potential route for future research will be given.

2. Literature Review

Brand value is a topic that is of common interest to marketing and finance fields. In the literature, brand value is defined as the amount of product sold by a company times the product price, minus the amount sold by nonbranded products times the selling price [18]. From this perspective, brand value is closely related to sales. In the same study, it is stated that low-value brands have a price elasticity of -1.195 against a price decrease and -0.921 against a price increase and high-value brands have a price elasticity of -0.747 against a price decrease and -0.183 against a price increase. From this point of view, it has been determined that companies with high brand value experience less revenue loss when they increase the prices of their products. This situation is also experienced in stock markets, and it has been revealed that companies with strong brand value and perception have a more balanced and stable period compared to other companies in markets that are in a downward trend and therefore have intense sales pressure [19].

From the perspective of investors, brands are viewed as assets that can generate potential future cash flows [20]. In support of this, research reveals that companies with high brand value earn more returns with less risk than the market index [21]. It is expected that the managers of low-performing companies will react more quickly to the buy–sell charts, which give an idea about the expectations of the investors about the future of the company, and determine a course that is suitable for both the company's brand perception and financial performance targets [22]. This is especially important in times of financial crisis or increased uncertainty because the reactions of investors in capital markets are different according to various financial crises and country-related determinants [23]. To illustrate, in the Great Depression, a colossal financial crisis in American history, the full recovery of capital markets took approximately 25 years. On the other hand, while the global financial crisis in 2008 affected all world stock markets again, it took approximately 56 months for the S&P 500 Index to fully recover, and the pre-crisis level was broken on 13 September 2012. In BIST100, Türkiye's most popular index, this period lasted only 2 years and the market recovered on 7 January 2010. It can be said that Türkiye is a developing country and the structural reforms implemented in this country at that time were effective.

International valuation companies specializing in the determination of brand value prepare annual reports on a global and national scale and publish the values they calculate for the brands of companies in different markets according to their own methodologies. Among the most popular and globally operating brand valuation companies are Brand Finance, Interbrand, European Brand Institute, BrandZ and Millward Brown. These companies have a national or even global impact, analyze the corporate and transparent companies and publish the national 100 and global 500 lists annually. These rankings are also used as a variable in scientific studies [24]. Among these companies, Brand Finance has focused on copyrights and evaluates the brands based on their market determinants and strength. In addition, only Brand Finance has mostly concentrated on the environmental and social performance values of companies and thus calculated brand value, including sustainability. Sustainability and green finance practices have been attracting investors' attention and indirectly contributing positively to the brand value of firms in the current decade. Sustainability-oriented policies implemented by regulators also explain these shifts in the investment behavior of financial stakeholders [25]. In fact, even in initial public offerings, which are considered risky, investors include sustainability and green finance-oriented company stocks in their portfolios, thereby reducing the risk of underperformance of these shares for both the short and long term [26]. For sustainability reasons, the scores in the annual reports of Brand Finance were implemented in this study.

Interbrand, an international brand valuation company, stated that the stock of a company with a strong brand perception is also strong, such that it will earn between 5% and 7% more from the index during the rise in the markets, while it will experience less loss compared to other stocks when the markets lose power [27]. Again, in a study that analyzed companies in Interbrand's most valuable brands list, it was observed that there was a similar relationship between market-to-book ratios and financial brand value [28]. In a study using variables related to market value, it was concluded that brand power explains 25% of the variance in the market value of firms [29]. In another study, it was found that strong brands provide more returns with less risk, which is the main goal of modern portfolio theory, even when firm size is taken into account [21]. In another study on brand value, it was observed that the strength of brand value positively affects share price and, thus, stock performance [30]. In an analysis using the financial data of 252 companies traded on Equitrend, it has been determined that the stocks of strong brands experience less volatility and, therefore, less risk [31]. Again, in various studies, it was concluded that there is a positive relationship between brand value, market capitalization and financial performance [32–40].

Although financial performance is a multi-criteria problem and brand value is an integral part of it, there are hardly any MCDA studies in the literature that include brand value as a criterion or as a result of their evaluation methodology. In a study in which brand power, quality, reputation, loyalty and awareness, which are the sub-parameters of the brand concept, were listed, the AHP method was used and analyzed with financial, institutional, temporal and growth-related criteria [41]. In the study, in which market capitalization was taken as a financial criterion, brand recognition was found as the most important sub-parameter of brand power. In a study analyzing brand image creation, the FANP method was preferred, and the location and atmosphere of the store, the types and prices of the products sold, and sales and services were determined as criteria [42]. As a result of the study, the prices of the products were determined as the most important parameter affecting the brand image. In another study, generating brand value using brand marketing was analyzed with the VIKOR method over the weighting techniques of ANP and DEMATEL [43]. Prices were the parameter that produced the most important result in this study as well. In a study examining brand power in the tourism sector with FDM, DEMATEL and ANP, it was observed that brand power has both direct and indirect effects on tourism [44]. In a recent study, the brand personalities of the businesses operating in the sports shoes industry were analyzed with the FANP method and the most successful company was revealed [45].

Compared to previous studies, this study contributes to the literature in two important areas. First, previous MCDA studies on financial performance have not used brand value as a criterion. In this sense, the use of brand value in this study and the determination that it has a high importance on financial performance according to the two objective weighting techniques integrated into the analyses is critical for future studies. Secondly, previous literature on MCDAs have not used an external anchor in order to perform sensitivity analysis. While the sensitivity analyses in previous studies were conducted by changing the criteria weights and observing the change in the ranking results generated by the methods, in this study, sensitivity analyses were conducted by using an external anchor and correlating the method scores generated with the anchor. The potential change in the relationship between method scores calculated by integrating two objective techniques with different criteria weights and stock returns is the basis of the different sensitivity analyses applied in this study. To that end, future studies may apply this framework to conduct sensitivity analyses for various real-life scenarios.

3. Methodology

In the implementation of this study, 8 performance metrics will be applied on 7 methods according to different weighting techniques, and the performance rankings of the 31 high brand value companies examined between 2013 and 2022 will be created. To that end, in addition to brand value, return on equity (ROE), market-to-book ratio (M-to-B), market value added (MVA), average collection period (ACP), inventory turnover ratio (ITR), equity growth (EG) and earnings per share (EPS) criteria were integrated into the analyses. In the following pages, these performance metrics, as well as the 7 methods used in the analysis of this study, will be explained.

ROE is a classic ratio that measures the efficiency of companies in converting their equity capital into profit. It is used in studies as an indicator of corporate performance: [46] examined companies operating in the UK via using ROE criterion as a financial performance measure, [47] identified the financial performance of Nigerian enterprises, while exercising ROE as a sensitivity criterion, and [48] investigated pharmaceutical companies in Pakistan, integrating ROE as a financial performance indicator among the preferred criteria.

M-to-B is the ratio that shows the change in market value of companies compared to their book value. In other words, this ratio shows the market sensitivity of companies [49]. The authors of [50] revealed that using this metric increases the reliability of the outcomes in performance research. The authors of [51] investigated 146 manufacturing companies traded on the Pakistan Stock Exchange via integrating M-to-B as a financial performance indicator. In some studies, the M-to-B ratio was specified as intellectual capital and the same ratio was integrated into these financial performance studies [52,53].

MVA is the performance criterion that best shows the efficiency with which the managers of a company convert the limited resources of the company into added value [54]. According to the modern literature, the most fundamental purpose of finance is that companies increase value and the wealth of their shareholders. To that end, it is pivotal to integrate not only accounting but also valuation metrics, which can give important ideas about the future, into the applications to be made while performing a financial performance analysis. The authors of [55] examined 173 environmentally friendly firms in terms of their financial performance, and they added MVA into the analysis criteria. The authors of [56] investigated 65 companies traded in FTSE350 and used MVA as a financial performance criterion.

ACP is a measure that demonstrates how long it takes for receivables to turn into liquidity for companies. The authors of [57] investigated Belgian enterprises in terms of their financial performance and profitability via integrating ACP as a criterion into the analysis. The findings of the study demonstrated that the shortening of the ACP increases shareholder value and share prices were gaining momentum with the increasing confidence of investors in stock management.

ITR signalizes the conversion frequency of inventories into liquidity. The authors of [58] examined the performance of manufacturing companies with DEA analysis, and they used ITR as a criterion. Findings of the research revealed that rapid sale of inventory improves performance. In addition, ITR has been used as a criterion in many financial performance studies [59–61].

EG shows the extent to which companies' equity capital grows over time. The authors of [62] scrutinized the financial performance of banks and used EG as a performance metric. They found a positive relationship between the amount of capital of banks and their financial performance. The EG ratio has been preferred as a financial performance indicator in various studies [63–65].

EPS denotes the net profit earned by companies per shareholder. The authors of [66] investigated enterprises listed in Borsa Istanbul in terms of financial performance and integrated EPS as a financial metric into the analysis. The authors of [67] examined the performance of 100 companies traded on the Malaysian Bursa Stock Exchange and used EPS as a financial performance indicator.

3.1. Faire Un Choix Adéquat (FUCA)

FUCA, unlike many MCDA methods, does not normalize the data related to the decision problem that is to be solved [68]. It has been preferred in studies conducted in recent years due to its simplicity and easy calculation. Some of the studies exercised with this method are focused on the selection of the best portfolio alternative in the pharmaceutical industry [68], selection regarding chemical production processes [69] and evaluating financial performance [70].

In the application of this method, first, the values in the decision problem to be solved are ranked. As mentioned above, a normalization process is not applied. Benefit-based criteria are listed from largest to smallest, and cost-based criteria are ranked from smallest to largest, with the best value being 1 and the worst being m.

The ranking values determined above are multiplied by the previously determined criterion weights, as shown in Equation (1) below, and then they are summed for each alternative.

$$v_i = \sum_{j=1}^{n} (r_{ij} \times w_j) \tag{1}$$

Ultimately, the final outputs of the method are obtained. These outputs are sorted from smallest to largest in order to reveal final performance rankings.

3.2. VIekriterijumsko KOmpromisno Rangiranje (VIKOR)

VIKOR method has been developed in order to be exercised in multi-criteria problem solutions that conflict with each other and are difficult to compare [71]. This method is used in various research areas, such as designing new products [72], improving service quality in companies [73], measuring operational performance [74] and developing cloud e-learning strategies [75].

A matrix is created for the complex decision problem to be solved. Then, the best and worst values for each criterion are determined. To that end, Equations (2) and (3) are used.

$$F_j^+ = Max_{i \in m} f_{ij} \text{ and } F_j^- = Min_{i \in m} f_{ij} \textit{ for maximization} \tag{2}$$

$$F_j^+ = Min_{i \in m} f_{ij} \text{ and } F_j^- = Max_{i \in m} f_{ij} \textit{ for minimization} \tag{3}$$

The values of S_i and R_i are calculated for each alternative via Equations (4) and (5), respectively.

$$S_i = \sum_{j=1}^{n} w_j \left(\frac{F_j^+ - f_{ij}}{F_j^+ - F_j^-} \right) \tag{4}$$

$$R_i = Max_{j \in n}\left[w_j\left(\frac{F_j^+ - f_{ij}}{F_j^+ - F_j^-}\right)\right] \quad (5)$$

Finally, Q_i values are identified using Equation (6) given below, where $S^+ = Min_{i \in m} S_i$, $S^- = Max_{i \in m} S_i$, $R^+ = Min_{i \in m} R_i$ and $R^- = Max_{i \in m} R_i$.

$$Q_i = \gamma\left(\frac{S_i - S^+}{S^- - S^+}\right) + (1-\gamma)\left(\frac{R_i - R^+}{R^- - R^+}\right) \quad (6)$$

The outputs obtained with this method are sorted from smallest to largest in order to determine the final performance rankings.

3.3. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS uses positive and negative ideal solutions when establishing the ranking of alternatives. The most successful alternative is closest to the positive ideal solution and farthest from the negative ideal solution [76]. TOPSIS method has been preferred in studies conducted in different areas, such as evaluation of production systems [77], supplier selection [78], personnel selection [79], automotive industry development [80] and bank credit valuation [81].

In order to apply the TOPSIS method, the decision matrix must be created primarily. Afterwards, vector normalization is applied to the values in the relevant matrix with Equation (7) given below.

$$F_{ij} = \frac{f_{ij}}{\sqrt{\sum_{i=1}^{m} f_{ij}^2}} \quad (7)$$

Then, the criteria weights should be calculated according to the previously chosen technique and the weighted and normalized matrix should be created via Equation (8).

$$v_{ij} = F_{ij} \times w_j \quad (8)$$

Positive (A^+) and negative (A^-) ideal solutions, which will be reference points in the ranking of alternatives, should be established by Equations (9) and (10) given below.

$$A^+ = \{(Max_i(v_{ij})|j \in J), (Min_i(v_{ij})|j \in J')|i \in 1, 2, \ldots, m\} = \left\{v_1^+, v_2^+, v_3^+, \ldots, v_j^+, \ldots, v_n^+\right\} \quad (9)$$

$$A^- = \{(Min_i(v_{ij})|j \in J), (Max_i(v_{ij})|j \in J')|i \in 1, 2, \ldots, m\} = \left\{v_1^-, v_2^-, v_3^-, \ldots, v_j^-, \ldots, v_n^-\right\} \quad (10)$$

Right after that, the distance values of negative and positive ideal solutions are calculated with the formulas given below.

$$S_{i+} = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^+\right)^2} \qquad i = 1, 2, 3, \ldots, m \quad (11)$$

$$S_{i-} = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2} \qquad i = 1, 2, 3, \ldots, m \quad (12)$$

Finally, the relative closeness to the ideal solution is computed using Equation (13) given below.

$$C_i = \frac{S_{i-}}{S_{i-} + S_{i+}} \quad (13)$$

Performance rankings are created by sorting the method outputs, calculated according to the above mathematical operations, from largest to smallest.

3.4. Simple Additive Weighting (SAW)

SAW method is known for its simplicity, easy computability and popularity among MCDA methods [82]. SAW method has been preferred in analyses made in various fields, such as market share improvement practices for enterprises [83], knowledge management [84] and valuation of sustainable agricultural practices [85].

Initially, a matrix containing alternative values of the decision problem to be solved is created. Afterwards, among the values in this matrix, benefit-based ones are normalized using Equation (14) and cost-based ones are normalized using Equation (15).

$$F_{ij} = \frac{f_{ij}}{f_j^+} \; for\ maximization,\ where\ f_j^+ = Max_{i \in m} f_{ij} \tag{14}$$

$$F_{ij} = \frac{f_j^-}{f_{ij}} \; for\ minimization, where\ f_j^- = Min_{i \in m} f_{ij} \tag{15}$$

The normalized values calculated above are multiplied by the criterion weights determined by the preferred weighting technique, as seen in Equation (16) below.

$$v_{ij} = F_{ij} \times w_j \tag{16}$$

A_i values, which represent the final method output for each alternative, are calculated as seen in Equation (17) below.

$$A_i = \sum_{j=1}^{n} v_{ij} \tag{17}$$

Ultimately, by ranking the method outputs from largest to smallest, performance rankings are obtained according to the relevant methodology of this method.

3.5. Combinative Distance-Based Assessment (CODAS)

CODAS is an MCDA method which was developed to be sensitive to negative distances. This model, which connects the optimum of an alternative to the rule of being the farthest to the negative distance, calculates this distance according to the Euclidean and taxicab distance [86]. The CODAS method has been applied in studies involving cloud service selection [87], supplier selection [88] and smart health technologies' valuation [89]. The mathematical operations of the given method are as follows [90].

Max normalization is applied to the matrix created for the decision problem to be solved. For this purpose, Equation (18) is used for benefit-based criteria and Equation (19) is used for cost-based criteria.

$$F_{ij} = \frac{f_{ij}}{max_{i \in m} f_{ij}} \quad i \in \{1, 2, \ldots, m\};\ j \in \{1, 2, \ldots, n\} \quad for\ maximization \tag{18}$$

$$F_{ij} = \frac{min_{i \in m} f_{ij}}{f_{ij}} \quad i \in \{1, 2, \ldots, m\};\ j \in \{1, 2, \ldots, n\} \quad for\ minimization \tag{19}$$

Then, the values in the normalized matrix calculated above are multiplied by the criterion weights, as shown in Equation (20).

$$v_{ij} = F_{ij} \times w_j \quad i \in \{1, 2, \ldots, m\};\ j \in \{1, 2, \ldots, n\} \tag{20}$$

Afterwards, the negative ideal solution (A^-) is determined via Equation (21) given below.

$$A^- = \{ (Min_i(v_{ij}) | i \in 1, 2, \ldots, m \} = \left\{ v_1^-, v_2^-, v_3^-, \ldots, v_j^-, \ldots, v_n^- \right\} \tag{21}$$

The Euclidean distance (E_i) and taxicab distance (T_i) to be used in the next matrix are established using Equations (22) and (23), respectively.

$$E_i = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2} \quad i = 1, 2, 3, \ldots, m \tag{22}$$

$$T_i = \sum_{j=1}^{n}\left|v_{ij} - v_j^-\right| \quad i = 1, 2, 3, \ldots, m \tag{23}$$

Afterwards, the relative assessment matrix is created using Equation (24).

$$h_{ik} = (E_i - E_k) + \psi(E_i - E_k) \times (T_i - T_k) \quad i, k \in \{1, 2, \ldots, m\} \tag{24}$$

Finally, the assessment score of each alternative is calculated through Equation (25).

$$H_i = \sum_{k=1}^{m} h_{ik} \quad i = 1, 2, 3, \ldots, m \tag{25}$$

The outputs produced by the method are sorted from largest to smallest to obtain final performance rankings.

3.6. Ranking of Alternatives through Functional Mapping of Criterion Sub-Intervals into a Single Interval (RAFSI)

Order changes may actualize when new alternatives are added or removed from analyses performed using MCDA methods, and this problem is called rank reversal. In order to prevent this phenomenon, a new method has been developed that uses the technique of placing values within a certain limit [91]. The newly established RAFSI method has been used in studies in different areas, such as determination of the optimal location for emergency services [92], selection of the industrial mechanical equipment [93] and valuation of the potential dock [94].

Initially, a decision matrix is created regarding the decision problem to be solved. Ideal (a_{Ij}) and non-ideal values (a_{Nj}) are determined for each criterion.

$$N = \begin{array}{c} \\ A_1 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccc} C_1 & \ldots & C_n \end{array} \\ \begin{bmatrix} n_{11} & \cdots & n_{1n} \\ \vdots & \ddots & \vdots \\ n_{m1} & \cdots & n_{mn} \end{bmatrix} \end{array}$$

Values are placed within a specified interval according to the types of criteria. The process shown in Figure 1 is applied based on maximization in benefit-based criteria and minimization in cost-based criteria.

$$C_j \in \left[a_{Nj}, a_{Ij}\right] \textit{ for maximization} \tag{26}$$

$$C_j \in \left[a_{Ij}, a_{Nj}\right] \textit{ for minimization} \tag{27}$$

According to this method, the ideal values should be at least 6 times larger than the non-ideal. Taking this as a reference, the n_1 and n_{2k} values seen in the figure above are established by Equation (28).

$$f_s(x) = \frac{n_{2k} - n_1}{a_{Ij} - a_{Nj}} x + \frac{a_{Ij}.n_1 - a_{Nj}.n_{2k}}{a_{Ij} - a_{Nj}} \tag{28}$$

Thus, the matrix S shown below is obtained.

$$S = \begin{array}{c} \\ A_1 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccc} C_1 & \ldots & C_n \end{array} \\ \begin{bmatrix} S_{11} & \cdots & S_{1n} \\ \vdots & \ddots & \vdots \\ S_{m1} & \cdots & S_{mn} \end{bmatrix} \end{array}$$

Right after establishing the S matrix, arithmetic (A) and harmonic (H) averages are calculated, where the arithmetic average is used for benefit-based criteria and the harmonic average is used for cost-based criteria.

$$A = \frac{n_1 + n_{2k}}{2} \tag{29}$$

$$H = \frac{2}{\frac{1}{n_1} + \frac{1}{n_{2k}}} \tag{30}$$

Afterwards, the maximization of benefit-based criteria is performed as shown in Equation (31) and the minimization of cost-based criteria is performed as shown in Equation (32).

$$\hat{s}_{ij} = \frac{s_{ij}}{2A} \tag{31}$$

$$\hat{s}_{ij} = \frac{H}{2s_{ij}} \tag{32}$$

Thus, the $\hat{S}$ matrix is created, which will be used to calculate the final scores of this method.

$$\hat{S} = \begin{array}{c} \\ A_1 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccc} C_1 & \dots & C_n \end{array} \\ \begin{bmatrix} \hat{S}_{11} & \cdots & \hat{S}_{1n} \\ \vdots & \ddots & \vdots \\ \hat{S}_{m1} & \cdots & \hat{S}_{mn} \end{bmatrix} \end{array}$$

V values are calculated from the data of the aforementioned matrix using Equation (33) given below.

$$V(A_i) = w_1\hat{s}_{i1} + w_2\hat{s}_{i2} + \ldots + w_n\hat{s}_{in} \tag{33}$$

The outputs produced by RAFSI regarding the relevant problem are sorted from largest to smallest and the final performance rankings are determined.

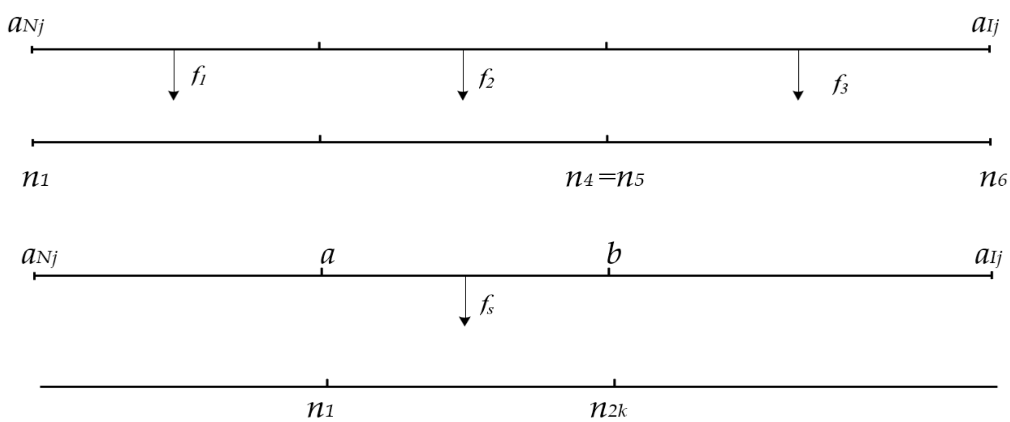

Figure 1. The process of putting the criteria into the specified intervals.

3.7. Grey Relational Analysis (GRA)

The GRA method appears as a method developed from the concept of grey theory, which helps solve complex problems through incomplete and uncertain data [95]. In the application of this method, all alternative values are first converted into a comparability sequence and a reference sequence is created from this. Afterwards, the alternatives are ranked using the difference between these two sequences. This method has been exercised in various studies, such as the evaluation and development of customer satisfaction in transportation [96], company valuation through corporate social responsibility [97], and evaluation and comparison of companies' performance in the financial crisis environment [98].

After the decision matrix for the problem to be solved is created, normalization is applied to the decision matrix values through Equations (34) and (35).

$$F_{ij} = \frac{f_{ij} - min_{i \in m} f_{ij}}{max_{i \in m} f_{ij} - min_{i \in m} f_{ij}} \quad (34)$$

$$F_{ij} = \frac{max_{i \in m} f_{ij} - f_{ij}}{max_{i \in m} f_{ij} - min_{i \in m} f_{ij}} \quad (35)$$

Then, the reference sequences are obtained using Equation (36) shown below.

$$F_j^+ = max_{i \in m} F_{ij} \quad (36)$$

Equation (37) is used to obtain the difference between the reference indexes and the comparability indexes.

$$\Delta I_{ij} = \left| F_j^+ - F_{ij} \right| \quad (37)$$

Afterwards, the grey relational coefficients are established with Equation (38) shown below.

$$GRC_i = \frac{1}{m} \sum_{j=1}^{n} \frac{\Delta min + \Delta max}{\Delta I_{ij} + \Delta max} \quad (38)$$

Consequently, GRC_i values indicating the method outputs are sorted from largest to smallest and final performance rankings are revealed.

3.8. CRiteria Importance through Intercriteria Correlation (CRITIC)

The CRITIC technique evaluates all information about the criteria and determines the criterion weights through standard deviation and correlation processes [99–101]. This technique provides a more comprehensive result since it takes other criteria into account; thus, this advantage has enabled this technique to be integrated into studies more popularly than other objective techniques.

In order to apply the CRITIC technique, a decision matrix is firstly organized that contains alternative values for the complex problem to be solved. Afterwards, the values related to the alternatives are normalized with the aid of Equation (39).

$$r_{ij} = \frac{x_{ij} - x_j min}{x_j max - x_j min} \quad (39)$$

Then, correlation densities are computed for each criterion included in the analysis. In order to perform this mathematical process, first, the correlations between the criteria are determined by Spearman's coefficient. Afterwards, the standard deviation of the values of each criterion in the normalized decision matrix is established. Consequently, correlation densities are determined by using these aforementioned values as shown in Equation (40) below.

$$C_j = \sigma_j \sum_{i=1}^{m} (1 - r_{ij}) \quad (40)$$

Finally, the correlation densities calculated above are normalized. For this, Equation (41) shown below is applied so that the sum of the criterion weights equals 1.

$$w_j = \frac{C_j}{\sum_{i=1}^{m} C_i} \quad (41)$$

Thus, the weights for each criterion are calculated by applying only mathematical operations. In the analysis made regarding the decision problem to be solved, the operations given above in Equations (39) to (41) are repeated for each period.

3.9. Standard Deviation Weighting Method (SD)

The standard deviation weighting technique determines the criterion weights mathematically by calculating the change in the values determined for the alternatives. This technique establishes criterion weights by taking into account the change in data in the decision matrix [102].

In order to apply this technique, a decision matrix containing alternative values related to the complex problem to be solved is created initially. Min–max normalization process is applied to the relevant values by using Equation (42) for benefit-based criteria and (43) for cost-based criteria.

$$F_{ij} = \frac{f_{ij} - min_{i \in m} f_{ij}}{max_{i \in m} f_{ij} - min_{i \in m} f_{ij}} \; for\ maximization \tag{42}$$

$$F_{ij} = \frac{max_{i \in m} f_{ij} - f_{ij}}{max_{i \in m} f_{ij} - min_{i \in m} f_{ij}} \; for\ minimization \tag{43}$$

Standard deviation calculations for the alternative values obtained as an outcome of the above computation processes exercised are performed by applying Equation (44) below.

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m} \left(F_{ij} - \overline{F_j}\right)^2}{m}} \quad j \in \{1, 2, \ldots, n\} \tag{44}$$

Finally, Equation (45) is used to establish the criterion weights of the alternatives.

$$w_j = \frac{\sigma_j}{\sum_{k=1}^{n} \sigma_k} \quad j \in \{1, 2, \ldots, n\} \tag{45}$$

Thus, the weight of each criterion in the relevant period is calculated. Depending on how many periods will be examined in the analysis, the above processes are applied separately to the decision matrix of each period.

4. Application

In this study, the 31 most valuable companies of the last 10 years in Türkiye were evaluated with seven different MCDA methods based on eight criteria, including brand value. To that end, stock returns and financial statement data were obtained from the FINNET program. Annual brand value data were taken from Brand Finance's annual 100 most valuable company reports. In order to make a homogeneous 10-year evaluation, the parameter that all of these companies should be trading in the capital markets during the entire analyzed period was taken as a basis. Application steps of the analysis employed in this study are shown in Figure 2 below.

Findings and Results

The analysis results are of critical importance as brand value is integrated for the first time in financial performance studies conducted with MCDA methods. In order to use the methods and weighting techniques explained above, decision matrices were created for each year to be examined. In this sense, the decision matrix consisting of dynamic performance metrics used for 2013 is given in Table 1 below.

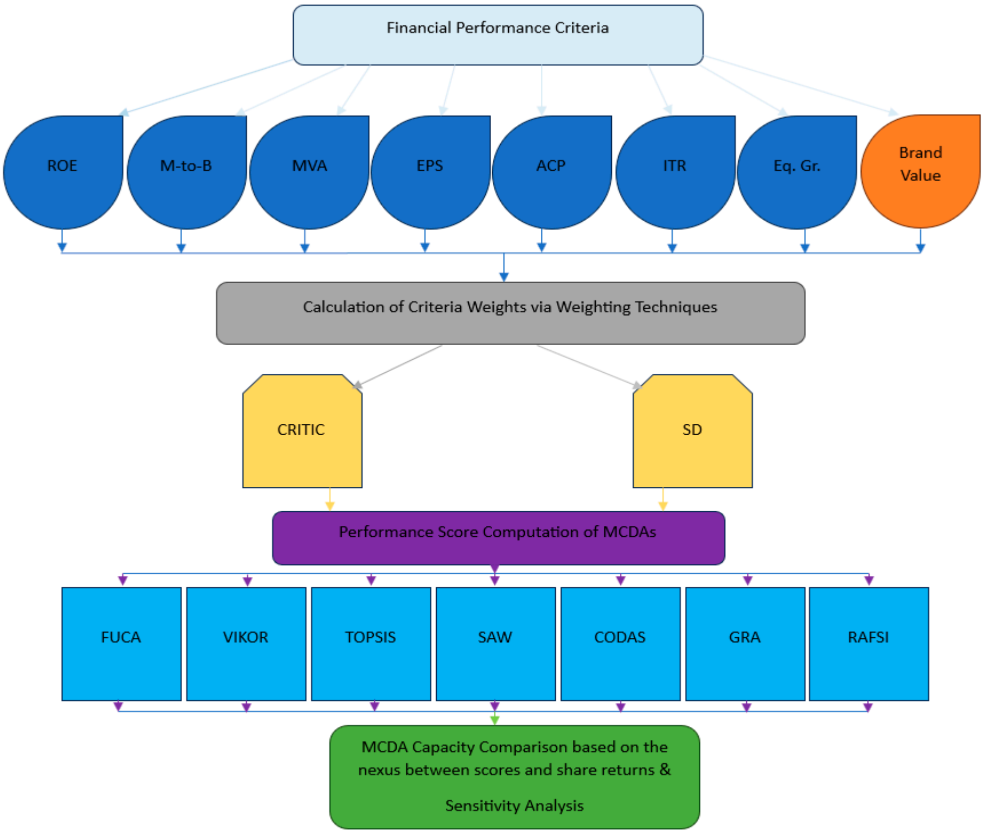

Figure 2. Application steps of the analysis.

Table 1. Decision matrix of the analyzed scenario for the year 2013.

Alt.	ROE	M-to-B	MVA	EPS	ACP	ITR	Equity Gr.	Brand V.
THYAO	−0.38985	1.30879	0.17641	−0.23971	−0.16799	0.27497	0.08207	0.08208
TTKOM	−0.35906	−0.03721	0.02883	−0.30677	0.04473	−0.27344	−2.67076	0.19123
TCELL	−0.06322	0.13328	0.53846	0.10124	0.14325	−0.20728	0.23103	−0.06694
ARCLK	−0.01335	0.52599	1.56183	0.05595	−0.00636	0.01642	1.37760	0.14335
FROTO	−0.03150	0.43222	0.75913	0.05860	−0.17119	−0.09113	0.26791	0.06169
ULKER	0.08626	2.84171	7.43865	−0.31568	−0.15613	0.07329	−0.29444	0.46887
AEFES	17.60169	−0.14392	0.02790	24.74303	−0.11130	0.08622	−0.68890	−0.14817
BIMAS	−0.14767	0.04279	0.31512	0.07165	−0.06846	−0.03007	0.14473	0.46084
TOASO	0.06624	0.68814	1.26481	0.08168	−0.15252	−0.02046	−0.88760	−0.10458
VESTL	−0.90681	−0.25963	1.01020	−0.88711	0.04775	−0.16049	6.06656	0.28899
SISE	−0.16646	−0.08811	−1.57737	−0.15602	−0.02332	−0.05533	−0.48660	0.05755
MGROS	−0.45326	0.34437	0.66563	−0.43313	−0.09577	−0.04389	0.25537	0.05233
DOAS	−0.23320	0.93863	5.23865	−0.11120	−0.06126	0.58774	−0.32136	0.12171
TBORG	−3.45470	0.52828	1.93347	−2.28400	−0.23862	0.27930	−10.50624	0.22108
ENKAI	−0.18443	0.02365	0.15587	−0.20607	0.04928	0.06466	−0.64949	−0.03563
ASELS	−0.31246	0.78927	1.81930	−0.61574	0.62515	0.02477	−0.22461	0.18055
TTRAK	0.18450	1.10936	1.12898	−0.05895	−0.14057	−0.03879	−1.30076	0.26318
TAVHL	0.35220	0.28834	0.57834	0.47743	−0.06194	1.95324	−0.55553	0.23755
AYGAZ	−0.59634	0.09995	0.66838	−0.56532	−0.00246	−0.22991	0.07785	−0.00524
OTKAR	2.48948	0.66923	1.23329	3.12687	−0.19223	0.57545	6.69234	0.09594
BRISA	1.20898	0.51570	0.01608	−0.95043	0.42147	0.17257	−1.47886	0.29786
KENT	52.71864	−0.29734	−0.30952	53.54116	−0.12607	0.37850	−0.76315	0.08904
TATGD	0.08256	−0.09211	−0.19518	0.12056	0.03423	−0.13934	−0.08408	0.21581
BANVT	−1.25975	0.15975	0.16101	−1.23161	0.01224	−0.08127	−0.50445	0.04770
INDES	−0.54600	0.43875	2.02165	−0.52559	−0.06412	−0.00041	−0.62093	0.12604
VAKKO	−1.94398	−0.15150	−0.32434	−1.91337	0.17950	0.06298	−1.43805	0.10834
TKNSA	−0.24406	0.08528	0.46574	0.00246	−0.31382	−0.06471	1.80881	0.73006
NETAS	−0.85230	−0.18154	−0.32078	−0.98617	0.73890	−0.15812	−1.90712	0.31371
DYOBY	−0.67163	−0.22555	−0.15117	−0.58621	0.20142	0.05421	−2.56665	0.21266
BOSSA	−0.33074	−0.40931	2.22938	−0.16758	−0.10684	0.04490	1.22430	0.01055
RYSAS	−0.50210	−0.46431	−6.59149	−0.40640	1.71472	−0.45968	−2.56678	0.09971

In order to perform the analysis, the weights of the performance metrics must be determined beforehand. CRITIC, one of the objective weighting techniques, was preferred because it does not require expert opinion, can only be calculated using mathematical operations, and thus appeals to more financial stakeholders. Regarding the analysis in which eight different criteria were determined, the criterion weights determined for the entire period as a result of the CRITIC technique calculations are given in Table 2 below. The seven criteria exercised are benefit-based, while ACP is cost-based. Calculating a superior weight for a criterion indicates the relative importance of that criterion compared to other criteria in the relevant period. As can be seen below, brand value stood out as the most important criterion in almost all periods examined. For this purpose, the pivot function of brand value in explaining financial performance has been revealed.

Table 2. CRITIC weights calculated for the entire period.

Criteria	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
ROE	0.1234	0.1143	0.0981	0.1038	0.1039	0.1105	0.1281	0.1180	0.1203	0.1046
M-to-B	0.1374	0.1337	0.1207	0.1030	0.1004	0.1136	0.1099	0.1105	0.1346	0.0795
MVA	0.0959	0.1144	0.1262	0.0928	0.0975	0.0824	0.0983	0.1131	0.1034	0.1194
EPS	0.1320	0.1179	0.0966	0.1056	0.0971	0.1021	0.1391	0.1091	0.1029	0.1055
ACP	0.1150	0.1108	0.1510	0.1481	0.1448	0.1467	0.1327	0.1439	0.1107	0.1500
ITR	0.1159	0.1340	0.1418	0.1804	0.1542	0.1784	0.1202	0.1216	0.1447	0.1610
Equity Gr.	0.1211	0.1371	0.1019	0.1151	0.1088	0.1063	0.1100	0.1286	0.1211	0.1172
Brand V.	0.1593	0.1379	0.1639	0.1511	0.1933	0.1600	0.1618	0.1552	0.1623	0.1627

After establishing the criterion weights, the financial performance of each enterprise was calculated annually for seven methods, using Equations (1)–(38). Performance scores calculated using 2013 data are shown in Table 3 below. While the company with the highest brand value in 2013 was Türk Telekom, no method found the performance of the relevant company at the highest level. As a result of integrating dynamic brand value data with seven other criteria, the company providing the highest performance according to the FUCA method was revealed as Otokar Automotive (OTKAR). The top-performing companies according to all analyzed methods for the year 2013 are shown in italics in the table below.

For all methods, 10-year performance calculations were made using the criterion weights determined by the CRITIC weighting technique. Afterwards, the relationship between the performance outcomes determined by the methods for each company and the dynamic stock returns of the relevant companies was examined. The association of all methods with stock returns throughout the analyzed period is shown in Table 4 below. FUCA method provided the highest association in 7 of the 10 years examined. In 2015 and 2017, RAFSI and, in 2019, TOPSIS methods were the methods that provided the highest correlation. FUCA stood out as the method that provided superior results when the association levels of all periods were analyzed. Additionally, this relationship was statistically significant ($p < 0.10$). According to the comparative analysis results, the second-ranked method was determined as RAFSI, in terms of performance.

Table 3. MCDA outputs generated with CRITIC weights for the year 2013.

	FUCA	VIKOR	TOPSIS	SAW	CODAS	GRA	RAFSI
THYAO	12.7589	0.2901	0.4190	0.3147	−25.7755	0.6482	0.4197
TTKOM	21.3909	0.3977	0.3377	−0.8331	−93.0579	0.6062	0.3585
TCELL	17.7154	0.6313	0.3483	−0.2613	−58.0893	0.6052	0.3651
ARCLK	10.9856	0.3068	0.4052	5.7810	312.89	0.6382	0.4063
FROTO	12.8179	0.3377	0.3876	0.2545	−27.5372	0.6317	0.3916
ULKER	7.3521	*0.1018*	0.5198	0.5653	−17.7427	*0.7496*	0.5054
AEFES	15.5723	0.7156	0.4197	0.3803	−20.3890	0.6409	0.4249

Table 3. *Cont.*

	FUCA	VIKOR	TOPSIS	SAW	CODAS	GRA	RAFSI
BIMAS	12.1460	0.2826	0.4072	0.6347	−6.1406	0.6452	0.4009
TOASO	13.9659	0.6727	0.3775	0.2465	−26.8655	0.6263	0.3868
VESTL	18.7615	0.3286	0.4274	−0.5966	−83.7666	0.6540	0.4064
SISE	19.4660	0.4009	0.3468	1.5232	52.8956	0.6070	0.3609
MGROS	16.9846	0.3635	0.3801	0.4135	−17.7084	0.6261	0.3863
DOAS	10.8689	0.2494	0.4477	0.7571	−0.4014	0.6691	0.4403
TBORG	15.4920	0.4360	0.3504	0.0628	−35.6991	0.6243	0.3602
ENKAI	19.5264	0.5497	0.3507	−0.7462	−87.8551	0.6083	0.3670
ASELS	15.3872	0.3594	0.3675	0.0384	−42.8293	0.6151	0.3965
TTRAK	10.8394	0.2776	0.4113	0.3569	−22.9632	0.6472	0.4145
TAVHL	9.8021	0.2000	0.4724	0.7640	−0.3981	0.6875	0.4480
AYGAZ	20.8831	0.4761	0.3578	*14.6849*	*868.13*	0.6126	0.3683
OTKAR	*6.4316*	0.1244	0.4836	0.4258	−23.1349	0.6889	0.4599
BRISA	15.7102	0.3582	0.3647	−0.0116	−45.2086	0.6158	0.3907
KENT	14.1774	0.1399	*0.5621*	0.5515	−16.0980	0.7442	*0.5373*
TATGD	15.6601	0.3541	0.3663	−1.0238	−106.48	0.6177	0.3752
BANVT	22.3926	0.4191	0.3559	−2.9498	−218.87	0.6121	0.3694
INDES	15.9151	0.3437	0.3884	0.6240	−5.4279	0.6324	0.3949
VAKKO	23.8782	0.4587	0.3347	−0.2205	−55.3090	0.6008	0.3570
TKNSA	10.8403	0.2010	0.4571	0.3128	−28.7024	0.6952	0.4321
NETAS	23.6558	0.4370	0.3111	−0.0416	−44.9538	0.5901	0.3547
DYOBY	22.1222	0.4047	0.3347	−0.1919	−53.7617	0.6031	0.3598
BOSSA	16.2524	0.4738	0.3851	0.3728	−20.1267	0.6290	0.3805
RYSAS	26.2479	0.7264	0.1889	−0.1826	−48.6389	0.5318	0.2894

Table 4. The level of association between MCDA outputs and share returns based on CRITIC weighting.

	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Avrg.	R
FUCA	64.8%	58.6%	45.7%	32.6%	29.1%	54.4%	16.1%	46.0%	67.0%	27.7%	44.2%	1
	0.00	0.00	0.01	0.07	0.11	0.00	0.39	0.01	0.00	0.13	0.07	
VIKOR	36.5%	44.5%	29.1%	17.5%	12.4%	32.5%	2.0%	1.0%	46.0%	4.0%	22.6%	5
	0.04	0.01	0.11	0.35	0.51	0.08	0.93	0.96	0.01	0.85	0.39	
TOPSIS	41.2%	45.0%	27.9%	17.3%	31.0%	27.0%	25.0%	19.0%	58.6%	14.0%	30.6%	4
	0.02	0.01	0.13	0.35	0.09	0.14	0.17	0.30	0.00	0.45	0.17	
SAW	36.0%	3.0%	38.8%	3.0%	21.0%	3.0%	11.0%	10.0%	39.0%	2.0%	16.7%	6
	0.05	0.88	0.03	0.86	0.25	0.87	0.56	0.62	0.03	0.91	0.51	
CODAS	32.9%	2.0%	37.4%	4.0%	21.0%	2.0%	13.0%	10.0%	41.0%	3.0%	16.6%	7
	0.07	0.92	0.04	0.81	0.26	0.93	0.50	0.59	0.02	0.88	0.50	
GRA	45.2%	42.5%	46.4%	16.5%	29.0%	27.3%	24.0%	17.0%	59.3%	14.0%	32.1%	3
	0.01	0.02	0.01	0.38	0.12	0.14	0.19	0.37	0.00	0.44	0.17	
RAFSI	43.5%	54.5%	50.6%	24.4%	33.4%	29.4%	16.0%	11.0%	62.6%	18.0%	34.3%	2
	0.01	0.00	0.00	0.19	0.07	0.11	0.40	0.55	0.00	0.32	0.17	

In order for the classic and innovative sensitivity analysis about the research results above, all calculations have been conducted from scratch according to the standard deviation weighting technique. For this purpose, the weights of the eight criteria integrated into the analyses of this study were calculated according to the standard deviation weighting technique. To that end, Equations (42) to (45) were applied to the decision matrices established for each year. The criterion weights of each criterion computed according to the standard deviation weighting technique are given in Table 5 below. It has been observed that, in some years, M-to-B, EPS, ACP and ITR ratios stand out. But, despite this, the importance weight of brand value is either in second or third place in the relevant years. In this weighting technique, just like in CRITIC, it has been determined that the brand value criterion plays the pivotal role in almost all years. Thus, it has been established that the criterion that has maintained a stable importance in all years is brand value.

Table 5. Standard deviation weights calculated for the entire period.

Criteria	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
ROE	0.1234	0.1215	0.1063	0.1132	0.1093	0.1107	0.1320	0.1236	0.1215	0.1081
M-to-B	0.1360	0.1422	0.1257	0.1130	0.1086	0.1317	0.1187	0.1199	0.1354	0.0992
MVA	0.1067	0.1202	0.1292	0.1069	0.1120	0.1055	0.1031	0.1197	0.1134	0.1214
EPS	0.1312	0.1296	0.1006	0.1178	0.1076	0.1269	0.1418	0.1228	0.1093	0.0991
ACP	0.1311	0.1145	0.1546	0.1354	0.1434	0.1215	0.1413	0.1383	0.1138	0.1574
ITR	0.1186	0.1237	0.1394	0.1542	0.1423	0.1529	0.1223	0.1210	0.1541	0.1626
Equity Gr.	0.1110	0.1234	0.0886	0.1074	0.1029	0.1230	0.0931	0.1132	0.1140	0.1065
Brand V.	0.1420	0.1249	0.1556	0.1522	0.1739	0.1278	0.1478	0.1414	0.1385	0.1457

Performance outputs were computed yearly for every analyzed method by applying Equations (1)–(38) above according to the standard deviation weighting technique. The outputs of the methods calculated based on the criterion weights determined by the standard deviation weighting technique for 2013 are given in Table 6 below. When the relevant results are compared with Table 3, it is observed that the FUCA method again signified Otokar Automotive (OTKAR) as the company with the highest performance. The highest-performing companies calculated based on the criterion weights of the standard deviation technique are given in italics in the table below for all methods.

Table 6. MCDA outputs generated with standard deviation weights for the year 2013.

	FUCA	VIKOR	TOPSIS	SAW	CODAS	GRA	RAFSI
THYAO	12.5802	0.3513	0.4320	0.3426	−29.5264	0.6482	0.4160
TTKOM	21.5093	0.4586	0.3522	−0.9468	−105.5833	0.6062	0.3543
TCELL	17.7547	0.5218	0.3608	−0.2949	−65.7307	0.6052	0.3614
ARCLK	11.0874	0.3632	0.4154	6.5717	356.5503	0.6382	0.4018
FROTO	12.6101	0.3898	0.4022	0.2829	−31.2588	0.6317	0.3882
ULKER	7.2915	0.1752	0.5296	0.5965	−21.0854	*0.7496*	0.5026
AEFES	15.2205	0.7019	0.4366	0.4301	−22.9355	0.6409	0.4226
BIMAS	12.4224	0.3459	0.4123	0.6977	−7.4202	0.6452	0.3946
TOASO	13.4451	0.6048	0.3966	0.2849	−30.2152	0.6263	0.3850
VESTL	19.1384	0.4094	0.4266	−0.7169	−96.3870	0.6540	0.3988
SISE	19.5188	0.4574	0.3592	1.7367	60.7421	0.6070	0.3562
MGROS	16.8611	0.4257	0.3941	0.4654	−19.9676	0.6261	0.3827
DOAS	10.7095	0.3063	0.4656	0.8450	−0.6200	0.6691	0.4390
TBORG	15.0885	0.5298	0.3771	0.0974	−39.4298	0.6243	0.3613
ENKAI	19.4399	0.4570	0.3658	−0.8465	−99.6725	0.6083	0.3637
ASELS	15.5731	0.4333	0.3715	0.0287	−48.8918	0.6151	0.3911
TTRAK	10.7503	0.3381	0.4238	0.3896	−26.5459	0.6472	0.4105
TAVHL	9.8665	0.2503	0.4837	0.8440	−0.8877	0.6875	0.4446
AYGAZ	20.7858	0.4710	0.3719	*16.7396*	*990.0514*	0.6126	0.3648
OTKAR	*6.2339*	*0.1218*	0.4888	0.4419	−27.2795	0.6889	0.4544
BRISA	16.0561	0.4406	0.3689	−0.0284	−51.6075	0.6158	0.3846
KENT	14.0167	0.2261	*0.5709*	0.5900	−19.1803	0.7442	*0.5334*
TATGD	16.0156	0.4096	0.3755	−1.1768	−121.3346	0.6177	0.3699
BANVT	22.3438	0.4971	0.3696	−3.3627	−250.2010	0.6121	0.3656
INDES	15.7423	0.4088	0.4038	0.7034	−6.0172	0.6324	0.3917
VAKKO	24.0354	0.5521	0.3468	−0.2494	−62.5712	0.6008	0.3526
TKNSA	11.0172	0.2737	0.4573	0.3094	−33.8819	0.6952	0.4246
NETAS	24.1113	0.5201	0.3101	−0.0536	−51.0367	0.5901	0.3479
DYOBY	22.3306	0.4730	0.3465	−0.2182	−60.8459	0.6031	0.3552
BOSSA	15.9422	0.5862	0.4000	0.4215	−22.6581	0.6290	0.3779
RYSAS	26.5019	0.8723	0.1719	−0.1941	−54.5722	0.5318	0.2799

The association between the method outputs calculated using the criteria weights of the companies determined by the standard deviation weighting technique and the stock returns of the relevant companies are shown in Table 7 below. The RAFSI method in 2015, the TOPSIS method in 2017 and 2019, and the VIKOR method in 2018 provided the highest correlation. In the other six periods, FUCA stood out as the method providing the highest association. When looking at the entire 10-year analysis period, the highest relationship was achieved by the FUCA method with 44.5% level. Additionally, this relationship was statistically significant ($p < 0.10$). Thus, the analysis results proved that the FUCA method was the most successful method in this performance analysis. In the calculations where weighting according to the standard deviation technique was exercised, the RAFSI method ranked second in performance ranking.

Table 7. The level of association between MCDA outputs and share returns based on standard deviation weighting.

	2013	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**Avrg.**	**R**
FUCA	65.6%	59.0%	45.0%	32.0%	33.0%	55.0%	12.4%	47.0%	67.0%	29.3%	44.5%	1
	0.00	0.00	0.01	0.08	0.07	0.00	0.51	0.01	0.00	0.11	0.08	
VIKOR	44.0%	58.0%	30.0%	24.0%	21.0%	60.0%	5.0%	18.4%	58.0%	4.0%	32.2%	5
	0.01	0.00	0.10	0.20	0.26	0.00	0.81	0.32	0.00	0.85	0.26	
TOPSIS	46.0%	44.0%	32.0%	20.0%	37.4%	28.0%	25.0%	24.0%	64.0%	15.0%	33.5%	3
	0.01	0.01	0.08	0.30	0.04	0.13	0.18	0.20	0.00	0.43	0.14	
SAW	37.0%	2.0%	38.0%	4.0%	20.0%	5.0%	9.0%	8.0%	40.0%	1.0%	16.4%	7
	0.04	0.93	0.04	0.85	0.28	0.80	0.62	0.67	0.03	0.97	0.52	
CODAS	34.0%	2.0%	37.0%	5.0%	21.0%	3.0%	12.0%	10.0%	42.0%	3.0%	16.9%	6
	0.07	0.92	0.04	0.81	0.26	0.89	0.54	0.58	0.02	0.89	0.50	
GRA	45.0%	43.0%	46.0%	17.0%	29.0%	27.0%	24.0%	17.0%	59.0%	14.0%	32.1%	4
	0.01	0.02	0.01	0.38	0.12	0.14	0.19	0.37	0.00	0.44	0.17	
RAFSI	45.2%	53.0%	52.0%	27.0%	34.0%	34.0%	14.0%	14.0%	63.2%	20.0%	35.6%	2
	0.01	0.00	0.00	0.14	0.06	0.07	0.45	0.45	0.00	0.29	0.15	

The analyses conducted in this study showed that FUCA has the most capacity, in terms of financial performance, for the analysis where brand value was integrated as a criterion. In addition, a new sensitivity analysis was conducted to observe which criteria have the most impact on the results solely for this method. For this purpose, calculations were performed for eight different scenarios where one criterion has a weightage of 30% and the others have a weightage of 10% for ROE, M-to-B, MVA, EPS, ACP, ITR, EG and BV, respectively. To illustrate, for the first scenario, ROE's weightage has been set to 30%, while the rest has been set to 10%. The results of this new sensitivity analysis are given in Table 8 below. The criterion which has a higher weightage (30%) for the scenario is indicated at the first column in the avorementioned table.

Accordingly, FUCA method realized the highest capacity in the second scenario where M-to-B criterion's weightage was set as 30%. This was followed by the third scenario where MVA is weighted higher. On the other hand, the FUCA method realized the lowest capacity in the first scenario where ROE is weighted as 30%. The eighth scenario, in which the brand value criterion, which is applied for the first time in this study, is weighted higher, provided a higher capacity than ROE, which is a popular and classical ratio. Thus, it can be concluded that FUCA method responded more positively to market-based ratios, while its success decreased for accounting-based ratios.

This study revealed that FUCA produced superior results for financial stakeholders compared to other methods examined. The results of this study are consistent with the previous literature [70]. In addition, the companies with the highest performance for each year according to all weighting techniques and methods applied are given in Table 9 below. Considering the 10-year period examined, findings indicated that the financial performance of automotive, defense, airport management and technology companies before the pandemic and agricultural machinery and logistics companies after the pandemic were higher. This finding demonstrated that the direction of consumer perception has changed with the pandemic and the interest shown by financial stakeholders to agricultural and logistics companies has increased.

Table 8. Deviations in the association between FUCA outputs and stock returns according to 8 different scenarios where criterion weights are changed.

FUCA	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Avg.
Scenario 1 (ROE)	51.60%	49.20%	28.80%	28.40%	28.80%	46.10%	6.90%	39.70%	59.30%	22.40%	36.12%
	0.003	0.005	0.116	0.122	0.117	0.009	0.714	0.027	0.000	0.226	0.134
Scenario 2 (M-t-B)	77.70%	53.70%	56.80%	34.50%	58.10%	56.80%	32.70%	63.30%	71.70%	45.40%	55.07%
	0.000	0.002	0.001	0.057	0.001	0.001	0.073	0.000	0.000	0.010	0.015
Scenario 3 (MVA)	71.10%	65.80%	55.40%	45.70%	46.90%	58.30%	19.10%	47.30%	69.80%	30.60%	51.00%
	0.000	0.000	0.001	0.010	0.008	0.001	0.302	0.007	0.000	0.094	0.042
Scenario 4 (EPS)	56.30%	47.30%	27.40%	29.90%	27.10%	49.60%	8.80%	39.20%	60.20%	20.80%	36.66%
	0.001	0.007	0.135	0.103	0.141	0.005	0.638	0.029	0.000	0.262	0.132
Scenario 5 (ACP)	67.20%	42.90%	36.70%	29%	34.70%	44.70%	4.70%	53.80%	61.60%	20.30%	39.56%
	0.000	0.016	0.042	0.113	0.056	0.012	0.800	0.002	0.000	0.274	0.132
Scenario 6 (ITR)	58.40%	45.90%	35.80%	36.80%	32.60%	55.20%	18%	51.20%	61.70%	28.50%	42.41%
	0.001	0.009	0.048	0.042	0.074	0.001	0.333	0.003	0.000	0.120	0.063
Scenario 7 (EG)	62.20%	57.40%	37.50%	34.90%	45.80%	46.20%	14.30%	32.50%	67.30%	27.50%	42.56%
	0.000	0.001	0.038	0.055	0.010	0.009	0.442	0.075	0.000	0.135	0.077
Scenario 8 (BV)	54.90%	59.20%	38.40%	23.60%	26.50%	43.40%	20.90%	35.70%	56.90%	28.30%	38.78%
	0.001	0.000	0.033	0.202	0.150	0.015	0.259	0.048	0.001	0.123	0.083

Table 9. Top-performing enterprises for different weighting techniques implemented into the 7 MCDAs analyzed.

Method	W	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
FUCA	C	OTKAR	TAVHL	DOAS	INDES	ASELS	FROTO	VESTL	TTRAK	TTRAK	THYAO
	S	OTKAR	TAVHL	DOAS	INDES	ASELS	FROTO	VESTL	TTRAK	TTRAK	THYAO
VIKOR	C	*ULKER*	VESTL	DOAS	INDES	*ASELS*	*TOASO*	VESTL	RYSAS	*BRISA*	*THYAO*
	S	*OTKAR*	VESTL	DOAS	INDES	*VAKKO*	*BOSSA*	VESTL	RYSAS	*KENT*	*NETAS*
TOPSIS	C	KENT	VESTL	DOAS	INDES	*ASELS*	BOSSA	VESTL	*TTRAK*	TBORG	*VAKKO*
	S	KENT	VESTL	DOAS	INDES	*BANVT*	BOSSA	VESTL	*RYSAS*	TBORG	*NETAS*
SAW	C	AYGAZ	VAKKO	THYAO	*INDES*	TATGD	INDES	TTRAK	ARCLK	DOAS	TCELL
	S	AYGAZ	VAKKO	THYAO	*NETAS*	TATGD	INDES	TTRAK	ARCLK	DOAS	TCELL
CODAS	C	AYGAZ	VAKKO	THYAO	*INDES*	TATGD	INDES	TTRAK	ARCLK	DOAS	TCELL
	S	AYGAZ	VAKKO	THYAO	*NETAS*	TATGD	INDES	TTRAK	ARCLK	DOAS	TCELL
GRA	C	ULKER	VESTL	DOAS	INDES	BANVT	BOSSA	VESTL	TTRAK	TBORG	NETAS
	S	ULKER	VESTL	DOAS	INDES	BANVT	BOSSA	VESTL	TTRAK	TBORG	NETAS
RAFSI	C	KENT	VESTL	DOAS	TTKOM	*ASELS*	BOSSA	VESTL	RYSAS	*TBORG*	VAKKO
	S	KENT	VESTL	DOAS	TTKOM	*BANVT*	BOSSA	VESTL	RYSAS	*KENT*	VAKKO

Enterprises in italics show the shift in top-performing companies identified for a method when the weighting technique applied is changed.

Although the weighting technique has changed, the top-performing companies have not deviated in the FUCA method. The relevant method has consistently placed the same companies at the top of the performance rankings. This result reveals the superiority of FUCA over other methods as a result of both classical and innovative sensitivity analysis. Consequently, based on the analysis findings above, FUCA is recommended to financial stakeholders. In addition, this study revealed that brand value is a vital criterion that can be used in financial research performed with MCDAs.

5. Discussion

The act of decision making is one of the indispensable parts of human life. MCDA methods are used with increasing frequency in making important decisions where there are many alternatives and criteria. Since the results of complex problems that need to be solved affect human life, choosing the method that will produce the most efficient results is of critical importance. In this study, financial performance analysis of 31 companies listed on BIST, which are among the most valuable companies in Turkey consistently in the last decade, was carried out. Important insights regarding the analyses performed are listed as follows:

- A comparative study in which brand value is considered as a performance criterion has been conducted for the first time in financial performance literature based on MCDAs, to the best of the authors' knowledge. Since brand value has the capacity to show the future and credibility of the company, its application in financial performance studies carried out with MCDA applications is of critical importance. In this sense, this study makes important contributions to the literature.
- It is also noteworthy that this study was conducted specifically for Borsa Istanbul, as it is a developing market and the volatility brought by high inflation after the pandemic affected companies with low and high brand values.
- In this study, sensitivity analysis has been approached from a different perspective and ultimately inferred that a change in criteria weights changed the association between MCDA method outputs and stock returns. In this respect, an original dimension has been added to sensitivity analyses by taking into account an external factor.
- Remarkably, the FUCA method stood out as the most efficient method for both innovative and classical sensitivity analysis because, although the weight coefficient changed, FUCA still produced a better statistical relationship with the external factor and did not change the order of the best alternatives.
- Comparative analysis was performed according to the criterion weights determined by CRITIC objective weighting technique. To that end, the use of seven different methods for a 10-year period is noteworthy as it signalizes the broad scope of the study. Thus, the performance before and after the pandemic was measured together.
- Sensitivity analyses were exercised using the standard deviation weighting technique as opposed to CRITIC. As a result of all these analyses, it has been clearly established that FUCA method scores provided the highest association with stock returns. More importantly, brand value has become the most pivotal criterion for both weighting techniques.
- In both FUCA-CRITIC and FUCA-SD techniques, the highest-performing companies in the financial performance rankings did not change. In addition, in the scenario where two different weighting techniques were used, the association between FUCA outputs and stock returns was statistically significant and robust.
- The RAFSI method, which eliminates the rank reversal problem, ranked second among all methods in scenarios where two different weighting techniques were used. However, the associations between the outputs of this method and stock returns were statistically insignificant.
- Earlier studies in the literature have not integrated brand value as a criterion for the analysis performed via various methods from different schools, so have not pointed out the importance of this criterion in financial studies exercised with MCDAs. This study measured the weight of brand value with two different weighting techniques and revealed its prominence in performance studies carried out with MCDAs.
- In the innovative sensitivity analyses including eight scenarios and conducted for the FUCA method, the highest capacity was realized in the scenario where the M-to-B criterion was weighted highly. This was followed by the scenario which set a higher weighting for MVA. The lowest capacity was realized in the scenario where ROE was weighted dominantly. FUCA's success in the scenario where brand value was superiorly weighted was higher than in the scenario where a well-established and frequently used ratio such as ROE was weighted substantially more. This finding is an indication that market-based ratios are more critical than accounting-based ratios for FUCA. According to these findings, brand value is recommended to be integrated as a criterion in future financial performance studies with MCDAs.
- The capacity obtained by FUCA in the relevant scenario where the lowest capacity is provided (36.2%) is still higher than the capacities of all other methods calculated according to CRITIC and standard deviation weighting techniques, as shown in Tables 4 and 7. This finding signified the success of FUCA in financial performance studies compared to the other analyzed methods. For this purpose, FUCA

method is recommended to financial stakeholders at their vitally important decision-making stages.

6. Conclusions

With the comprehensive analysis conducted in this study, the importance of brand value in financial performance studies was revealed. In addition, from a method set containing hundreds of MCDA methods, seven methods were integrated into the financial performance analyses and the most successful method was determined to be FUCA. Of course, one method cannot be the most effective in solving all problems in different fields of science. But, in solving the financial problem in this study, FUCA method was able to produce statistically strong and significant results. For this reason, FUCA method is recommended to financial stakeholders regarding the financial problems they will solve.

In this study, sensitivity analysis was approached from a different perspective. It is interesting that a deviation in MCDA inputs changed the relationship between MCDA outputs and an external factor. The sensitivity was interpreted through this innovative point of nuance. Accordingly, FUCA method stood out as the most efficient method for both innovative sensitivity analysis and classical sensitivity analysis because, although the weight coefficient changed, FUCA method still produced the best statistical relationship with an external factor and did not change the order of the best alternatives.

The findings of this comparative analysis are beneficial for investors concerning to diversify their portfolios, for managers attending to outperform their rivals and for creditors scrutinizing to reveal the credibility of their debtors. To that end, it can be said that using brand value as a performance measure in financial performance analysis provides additional advantages to decision makers who want to correctly position the company's future as well as its present.

This study offers important contributions to the academic literature, financial participants and those who are interested in the subject. With the presented framework, the effect of brand value on financial performance studies is revealed. Having a flexible methodology has increased the computability and the ability to use the systematics in the study for different methods in the future.

Limitations of the Study

A major limitation of this study is that it only includes companies with the highest brand value listed on Borsa Istanbul. Companies that are traded in developed as well as developing markets and have the highest brand value can be included in an analysis within different clusters in the future. Thus, the results obtained according to different methods in MCDA studies that consider brand value as a criterion can be observed for different country markets, comprehensively. In addition, the performance scores produced by brand valuation results determined according to different valuation methods can be compared in future studies. Another study limitation is the number of methods used in this study. There are over 200 methods with different mathematical backgrounds in the MCDA literature. Future studies can be carried out using different methods to expand the most appropriate method set to assist financial stakeholders in their challenging decisions. In addition, more comprehensive and comparative analyses can be made on a sample of companies operating in the same sector in developed and developing countries, including enterprises with low brand value.

Author Contributions: Conceptualization, O.E.E.; methodology, O.E.E. and M.B.; software, O.E.E.; validation, Ž.S. and M.B.; formal analysis, O.E.E.; investigation, M.B.; resources, O.E.E., Ž.S. and M.B.; data curation, O.E.E.; writing—original draft preparation, O.E.E.; writing—review and editing, O.E.E., Ž.S. and M.B.; visualization, M.B.; supervision, Ž.S.; project administration, Ž.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Elma, O.E. A Comparative MCDA Application on The Long-Term Performance of IPOs During the Pandemic on Borsa Istanbul. *J. Econ. Bus. Political Res.* **2023**, *8*, 269–293. [CrossRef]
2. Baydaş, M.; Elma, O.E. An objective criteria proposal for the comparison of MCDM and weighting methods in financial performance measurement: An application in Borsa Istanbul. *Decis. Mak. Appl. Manag. Eng.* **2021**, *4*, 257–279. [CrossRef]
3. Cinelli, M.; Kadziński, M.; Gonzalez, M.; Słowiński, R. How to support the application of multiple criteria decision analysis? Let us start with a comprehensive taxonomy. *Omega* **2020**, *96*, 102261. [CrossRef]
4. Baydaş, M.; Eren, T.; Stević, Ž.; Starčević, V.; Parlakkaya, R. Proposal for an objective binary benchmarking framework that validates each other for comparing MCDM methods through data analytics. *PeerJ Comput. Sci.* **2023**, *9*, e1350. [CrossRef] [PubMed]
5. Wang, Z.; Baydaş, M.; Stević, Ž.; Özçil, A.; Irfan, S.A.; Wu, Z.; Rangaiah, G.P. Comparison of fuzzy and crisp decision matrices: An evaluation on PROBID and sPROBID multi-criteria decision-making methods. *Demonstr. Math.* **2023**, *56*, 20230117. [CrossRef]
6. Antunes, C.H.; Clímaco, J.N. Sensitivity analysis in MCDM using the weight space. *Oper. Res. Lett.* **1992**, *12*, 187–196. [CrossRef]
7. Wolters, W.T.M.; Mareschal, B. Novel types of sensitivity analysis for additive MCDM methods. *Eur. J. Oper. Res.* **1995**, *81*, 281–290. [CrossRef]
8. Bakhtavar, E.; Yousefi, S. Assessment of workplace accident risks in underground collieries by integrating a multi-goal cause-and-effect analysis method with MCDM sensitivity analysis. *Stoch. Environ. Res. Risk Assess.* **2018**, *32*, 3317–3332. [CrossRef]
9. Mukhametzyanov, I.; Pamucar, D. A sensitivity analysis in MCDM problems: A statistical approach. *Decis. Mak. Appl. Manag. Eng.* **2018**, *1*, 51–80. [CrossRef]
10. da Silva, L.B.L.; Alencar, M.H.; de Almeida, A.T. Exploring global sensitivity analysis on a risk-based MCDM: A model to support urban adaptation policies against floods. *Int. J. Disaster Risk Reduct.* **2022**, *73*, 102898. [CrossRef]
11. Koontz, C.M. *Glossary of Marketing Definitions*; NTC Publishing Group: Lincolnwood, IL, USA, 2001.
12. Wood, L. Brands and brand equity: Definition and management. *Manag. Decis.* **2000**, *38*, 662–669. [CrossRef]
13. Herremans, I.M.; Ryans, J.K., Jr.; Aggarwal, R. Linking advertising and brand value. *Bus. Horiz.* **2000**, *43*, 19–26. [CrossRef]
14. Voss, K.; Mohan, M. Good times, bad times: The stock market performance of firms that own high value brands. *Eur. J. Mark.* **2016**, *50*, 670–694. [CrossRef]
15. Verma, S.; Gustafsson, A. Investigating the emerging COVID-19 research trends in the field of business and management: A bibliometric analysis approach. *J. Bus. Res.* **2020**, *118*, 253–261. [CrossRef] [PubMed]
16. Roland Berger. This Crisis Is Different—Comparing the Coronavirus Crisis with the Financial Crash. Available online: https://www.rolandberger.com/en/Insights/Publications/This-crisis-is-different-Comparing-the-coronavirus-crisis-with-the-financial.html (accessed on 5 September 2023).
17. Salinas, G. Managing Your Brand in Times of Crisis: Lessons from the Past. Available online: https://brandfinance.com/insights/managing-your-brand-in-times-of-crisis (accessed on 30 August 2023).
18. Ailawadi, K.L.; Lehmann, D.R.; Neslin, S.A. Revenue premium as an outcome measure of brand equity. *J. Mark.* **2003**, *67*, 1–17. [CrossRef]
19. Srinivasan, R.; Lilien, G.L.; Sridhar, S. Should firms spend more on research and development and advertising during recessions? *J. Mark.* **2011**, *75*, 49–65. [CrossRef]
20. Rao, V.R.; Agarwal, M.K.; Dahlhoff, D. How is manifest branding strategy related to the intangible value of a corporation? *J. Mark.* **2004**, *68*, 126–141. [CrossRef]
21. Madden, T.J.; Fehle, F.; Fournier, S. Brands matter: An empirical demonstration of the creation of shareholder value through branding. *J. Acad. Mark. Sci.* **2006**, *34*, 224–235. [CrossRef]
22. Markovitch, D.G.; Steckel, J.H.; Yeung, B. Using capital markets as market intelligence: Evidence from the pharmaceutical industry. *Manag. Sci.* **2005**, *51*, 1467–1480. [CrossRef]
23. Borio, C. The Covid-19 economic crisis: Dangerously unique. *Bus. Econ.* **2020**, *55*, 181–190. [CrossRef]
24. Bagna, E.; Dicuonzo, G.; Perrone, A.; Dell'Atti, V. The value relevance of brand valuation. *Appl. Econ.* **2017**, *49*, 5865–5876. [CrossRef]
25. Li, Z.; Huang, Z.; Su, Y. New media environment, environmental regulation and corporate green technology innovation: Evidence from China. *Energy Econ.* **2023**, *119*, 106545. [CrossRef]
26. Mumtaz, M.Z.; Yoshino, N. Aftermarket performance of green IPOs and portfolio allocation. *Green Financ.* **2023**, *5*, 321–342. [CrossRef]
27. Parkhurst, J. *Leveraging Brand to Generate Value. From Ideas to Assets: Investing Wisely in Intellectual Property*; John Wiley & Sons: Hoboken, NJ, USA, 2002; pp. 395–420.
28. Kerin, R.A.; Sethuraman, R. Exploring the brand value-shareholder value nexus for consumer goods companies. *J. Acad. Mark. Sci.* **1998**, *26*, 260–273. [CrossRef]

29. Knowles, J. Value-based brand measurement and management. *Interact. Mark.* **2003**, *5*, 40–50. [CrossRef]
30. Yeung, M.; Ramasamy, B. Brand value and firm performance nexus: Further empirical evidence. *J. Brand Manag.* **2008**, *15*, 322–335. [CrossRef]
31. Rego, L.L.; Billett, M.T.; Morgan, N.A. Consumer-based brand equity and firm risk. *J. Mark.* **2009**, *73*, 47–60. [CrossRef]
32. Aaker, D.A.; Jacobson, R. The value relevance of brand attitude in high-technology markets. *J. Mark. Res.* **2001**, *38*, 485–493. [CrossRef]
33. Krasnikov, A.; Mishra, S.; Orozco, D. Evaluating the financial impact of branding using trademarks: A framework and empirical evidence. *J. Mark.* **2009**, *73*, 154–166. [CrossRef]
34. Bharadwaj, S.G.; Tuli, K.R.; Bonfrer, A. The impact of brand quality on shareholder wealth. *J. Mark.* **2011**, *75*, 88–104. [CrossRef]
35. Hsu, F.J.; Wang, T.Y.; Chen, M.Y. The impact of brand value on financial performance. *Adv. Manag. Appl. Econ.* **2013**, *3*, 129.
36. Mizik, N. Assessing the total financial performance impact of brand equity with limited time-series data. *J. Mark. Res.* **2014**, *51*, 691–706. [CrossRef]
37. Malshe, A.; Agarwal, M.K. From finance to marketing: The impact of financial leverage on customer satisfaction. *J. Mark.* **2015**, *79*, 21–38. [CrossRef]
38. Chehab, A.; Liu, J.; Xiao, Y. More on intangibles: Do stockholders benefit from brand values? *Glob. Financ. J.* **2016**, *30*, 1–9. [CrossRef]
39. Ha, K.C.; Song, R.; Erickson, G. Multidimensional brand equity and asymmetric risk. *Int. J. Res. Mark.* **2021**, *38*, 593–614. [CrossRef]
40. Rahman, M.; Faroque, A.R.; Sakka, G.; Ahmed, Z.U. The impact of negative customer engagement on market-based assets and financial performance. *J. Bus. Res.* **2022**, *138*, 422–435. [CrossRef]
41. Costa, R.; Evangelista, S. An AHP approach to assess brand intangible assets. *Meas. Bus. Excell.* **2008**, *12*, 68–78. [CrossRef]
42. Lin, L.Z.; Hsu, T.H. Designing a model of FANP in brand image decision-making. *Appl. Soft Comput.* **2011**, *11*, 561–573. [CrossRef]
43. Wang, Y.L.; Tzeng, G.H. Brand marketing for creating brand value based on a MCDM model combining DEMATEL with ANP and VIKOR methods. *Expert Syst. Appl.* **2012**, *39*, 5600–5615. [CrossRef]
44. Liu, C.H.S.; Chou, S.F. Tourism strategy development and facilitation of integrative processes among brand equity, marketing and motivation. *Tour. Manag.* **2016**, *54*, 298–308. [CrossRef]
45. Pool, J.K.; Arabzad, S.M.; Asian, S.; Fahimi, M.; Kazemi, R.V. Employing fuzzy ANP for ranking the personality of international brands in the sports shoe industry. *J. Model. Manag.* **2018**, *13*, 137–155. [CrossRef]
46. Moore, G.; Robson, A. The UK supermarket industry: An analysis of corporate social and financial performance. *Bus. Ethics A Eur. Rev.* **2002**, *11*, 25–39. [CrossRef]
47. Uwuigbe, U.; Egbide, B.C. Corporate social responsibility disclosures in Nigeria: A study of listed financial and non-financial firms. *J. Manag. Sustain.* **2012**, *2*, 160. [CrossRef]
48. Malik, M.S.; Kanwal, L. Impact of corporate social responsibility disclosure on financial performance: Case study of listed pharmaceutical firms of Pakistan. *J. Bus. Ethics* **2018**, *150*, 69–78. [CrossRef]
49. Abdi, Y.; Li, X.; Càmara-Turull, X. Exploring the impact of sustainability (ESG) disclosure on firm value and financial performance (FP) in airline industry: The moderating role of size and age. *Environ. Dev. Sustain.* **2022**, *24*, 5052–5079. [CrossRef]
50. Xie, X.; Huo, J.; Zou, H. Green process innovation, green product innovation, and corporate financial performance: A content analysis method. *J. Bus. Res.* **2019**, *101*, 697–706. [CrossRef]
51. Din, S.U.; Khan, M.A.; Khan, M.J.; Khan, M.Y. Ownership structure and corporate financial performance in an emerging market: A dynamic panel data analysis. *Int. J. Emerg. Mark.* **2021**, *17*, 1973–1997. [CrossRef]
52. Forte, W.; Tucker, J.; Matonti, G.; Nicolò, G. Measuring the intellectual capital of Italian listed companies. *J. Intellect. Cap.* **2017**, *18*, 710–732. [CrossRef]
53. Xu, J.; Liu, F. The impact of intellectual capital on firm performance: A modified and extended VAIC model. *J. Compet.* **2020**, *12*, 161–176. [CrossRef]
54. Prasad, H.; Shrimal, K. An empirical study on relationship between selected financial measures and market value added of infrastructural companies in India. *Pac. Bus. Rev. Int.* **2015**, *8*, 19–23.
55. Lee, J.; Kwon, H.B. The synergistic effect of environmental sustainability and corporate reputation on market value added (MVA) in manufacturing firms. *Int. J. Prod. Res.* **2019**, *57*, 7123–7141. [CrossRef]
56. Gómez-Bezares, F.; Przychodzen, W.; Przychodzen, J. Bridging the gap: How sustainable development can help companies create shareholder value and improve financial performance. *Bus. Ethics A Eur. Rev.* **2017**, *26*, 1–17. [CrossRef]
57. Deloof, M. Does working capital management affect profitability of Belgian firms? *J. Bus. Financ. Account.* **2003**, *30*, 573–588. [CrossRef]
58. Leachman, C.; Pegels, C.C.; Shin, S.K. Manufacturing performance: Evaluation and determinants. *Int. J. Oper. Prod. Manag.* **2005**, *25*, 851–874. [CrossRef]
59. Chang, D.; Lee, S.M. Impact of JIT on organizational performance of US firms. *Int. J. Prod. Res.* **1995**, *33*, 3053–3068. [CrossRef]
60. Huson, M.; Nanda, D. The impact of just-in-time manufacturing on firm performance in the US. *J. Oper. Manag.* **1995**, *12*, 297–310. [CrossRef]
61. Gaur, V.; Kesavan, S. The effects of firm size and sales growth rate on inventory turnover performance in the US retail sector. In *Retail Supply Chain Management*; Springer: Boston, MA, USA, 2015; pp. 25–52. [CrossRef]

62. Adesina, J.B.; Nwidobie, B.M.; Adesina, O.O. Capital structure and financial performance in Nigeria. *Int. J. Bus. Soc. Res.* **2015**, *5*, 21–31.
63. Detthamrong, U.; Chancharat, N.; Vithessonthi, C. Corporate governance, capital structure and firm performance: Evidence from Thailand. *Res. Int. Bus. Financ.* **2017**, *42*, 689–709. [CrossRef]
64. Vo, X.V. Determinants of capital structure in emerging markets: Evidence from Vietnam. *Res. Int. Bus. Financ.* **2017**, *40*, 105–113. [CrossRef]
65. Fosu, S. Capital structure, product market competition and firm performance: Evidence from South Africa. *Q. Rev. Econ. Financ.* **2013**, *53*, 140–151. [CrossRef]
66. Nassar, S. The impact of capital structure on Financial Performance of the firms: Evidence from Borsa Istanbul. *J. Bus. Financ. Aff.* **2016**, *5*, 1000173.
67. Nor, N.M.; Bahari, N.A.S.; Adnan, N.A.; Kamal, S.M.Q.A.S.; Ali, I.M. The effects of environmental disclosure on financial performance in Malaysia. *Procedia Econ. Financ.* **2016**, *35*, 117–126. [CrossRef]
68. Fernando, M.M.L.; Escobedo, J.L.P.; Azzaro-Pantel, C.; Pibouleau, L.; Domenech, S.; Aguilar-Lasserre, A. Selecting the best portfolio alternative from a hybrid multi-objective GA-MCDM approach for New Product Development in the pharmaceutical industry. In Proceedings of the IEEE Symposium on Computational Intelligence in MDCM, Paris, France, 11–15 April 2011; pp. 159–166. [CrossRef]
69. Ouattara, A.; Pibouleau, L.; Azzaro-Pantel, C.; Domenech, S.; Baudet, P.; Yao, B. Economic and environmental strategies for process design. *Comput. Chem. Eng.* **2012**, *36*, 174–188. [CrossRef]
70. Baydaş, M.; Elma, O.E.; Pamučar, D. Exploring the specific capacity of different multi criteria decision making approaches under uncertainty using data from financial markets. *Expert Syst. Appl.* **2022**, *197*, 116755. [CrossRef]
71. Opricovic, S. *Multicriteria Optimization of Civil Engineering Systems*; Faculty of Civil Engineering, University of Belgrade: Belgrade, Serbia, 1998.
72. Mousavi, S.M.; Torabi, S.A.; Tavakkoli-Moghaddam, R. A hierarchical group decision-making approach for new product selection in a fuzzy environment. *Arab. J. Sci. Eng.* **2013**, *38*, 3233–3248. [CrossRef]
73. Saqlain, M. Sustainable hydrogen production: A decision-making approach using VIKOR and intuitionistic hypersoft sets. *J. Intell. Manag. Decis.* **2023**, *2*, 130–138. [CrossRef]
74. Lee, Z.Y.; Pai, C.C. Applying improved DEA & VIKOR methods to evaluate the operation performance for world's major TFT–LCD manufacturers. *Asia-Pac. J. Oper. Res.* **2015**, *32*, 1550020. [CrossRef]
75. Su, C.H.; Tzeng, G.H.; Hu, S.K. Cloud e-learning service strategies for improving e-learning innovation performance in a fuzzy environment by using a new hybrid fuzzy multiple attribute decision-making model. *Interact. Learn. Environ.* **2016**, *24*, 1812–1835. [CrossRef]
76. Hwang, C.L.; Yoon, K. Methods for multiple attribute decision making. In *Multiple Attribute Decision Making*; Springer: Berlin/Heidelberg, Germany, 1981; pp. 58–191.
77. Dabić-Miletić, S.; Raković, K. Ranking of autonomous alternatives for the realization of intralogistics activities in sustainable warehouse systems using the TOPSIS method. *Spectr. Eng. Manag. Sci.* **2023**, *1*, 48–57. [CrossRef]
78. Boran, F.E.; Genç, S.; Kurt, M.; Akay, D. A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method. *Expert Syst. Appl.* **2009**, *36*, 11363–11368. [CrossRef]
79. Chen, S.M.; Lee, L.W. Fuzzy multiple attributes group decision-making based on the interval type-2 TOPSIS method. *Expert Syst. Appl.* **2010**, *37*, 2790–2798. [CrossRef]
80. Petrović, N.; Živanović, T.; Mihajlović, J. Evaluating the annual operational efficiency of passenger and freight road transport in Serbia through entropy and TOPSIS methods. *J. Eng. Manag. Syst. Eng.* **2023**, *2*, 204–211. [CrossRef]
81. Kou, G.; Peng, Y.; Lu, C. MCDM approach to evaluating bank loan default models. *Technol. Econ. Dev. Econ.* **2014**, *20*, 292–311. [CrossRef]
82. Serrai, W.; Abdelli, A.; Mokdad, L.; Hammal, Y. Towards an efficient and a more accurate web service selection using MCDM methods. *J. Comput. Sci.* **2017**, *22*, 253–267. [CrossRef]
83. Ginevicius, R.; Podvezko, V.; Bruzge, Š. Evaluating the effect of state aid to business by multicriteria methods. *J. Bus. Econ. Manag.* **2008**, *9*, 167–180. [CrossRef]
84. Chu, M.T.; Shyu, J.; Tzeng, G.H.; Khosla, R. Comparison among three analytical methods for knowledge-communities group-decision analysis. *Expert Syst. Appl.* **2007**, *33*, 1011–1024. [CrossRef]
85. Puška, A.; Stojanović, I.; Štilić, A. The influence of objective weight determination methods on electric vehicle selection in urban logistics. *J. Intell. Manag. Decis.* **2023**, *2*, 117–129. [CrossRef]
86. Ghorabaee, M.K.; Zavadskas, E.K.; Turskis, Z.; Antucheviciene, J. A New Combinative Distance-Based Assessment (CODAS) Method for Multi-Criteria Decision-Making. *Econ. Comput. Econ. Cybern. Stud. Res.* **2016**, *50*, 25–44.
87. Ilieva, G.; Yankova, T.; Hadjieva, V.; Doneva, R.; Totkov, G. Cloud service selection as a fuzzy multi-criteria problem. *TEM J.* **2020**, *9*, 484–495. [CrossRef]
88. Boltürk, E. Pythagorean fuzzy CODAS and its application to supplier selection in a manufacturing firm. *J. Enterp. Inf. Manag.* **2018**, *31*, 551–564. [CrossRef]
89. Büyüközkan, G.; Mukul, E. Evaluation of smart health technologies with hesitant fuzzy linguistic MCDM methods. *J. Intell. Fuzzy Syst.* **2020**, *39*, 6363–6375. [CrossRef]

90. Wang, Z.; Rangaiah, G.P. Application and analysis of methods for selecting an optimal solution from the pareto-optimal front obtained by multi-objective optimization. *Ind. Eng. Chem. Res.* **2017**, *56*, 560–574. [CrossRef]
91. Žižović, M.; Pamučar, D.; Albijanić, M.; Chatterjee, P.; Pribićević, I. Eliminating rank reversal problem using a new multi-attribute model—The RAFSI method. *Mathematics* **2020**, *8*, 1015. [CrossRef]
92. Alosta, A.; Elmansuri, O.; Badi, I. Resolving a location selection problem by means of an integrated AHP-RAFSI approach. *Rep. Mech. Eng.* **2021**, *2*, 135–142. [CrossRef]
93. Bozanic, D.; Milic, A.; Tesic, D.; Salabun, W.; Pamucar, D. D numbers–FUCOM–fuzzy RAFSI model for selecting the group of construction machines for enabling mobility. *Facta Univ. Ser. Mech. Eng.* **2021**, *19*, 447–471. [CrossRef]
94. Pamucar, D.; Badi, I.; Stevic, Z. An integrated FUCOM-RAFSI model for assessing the potential of a new gateway port in Libya for some African landlocked countries. *Int. J. Qual. Res.* **2022**, *16*, 613–624. [CrossRef]
95. Kuo, Y.; Yang, T.; Huang, G.W. The use of grey relational analysis in solving multiple attribute decision-making problems. *Comput. Ind. Eng.* **2008**, *55*, 80–93. [CrossRef]
96. Çelik, E.; Bilisik, O.N.; Erdogan, M.; Gumus, A.T.; Baracli, H. An integrated novel interval type-2 fuzzy MCDM method to improve customer satisfaction in public transportation for Istanbul. *Transp. Res. Part E Logist. Transp. Rev.* **2013**, *58*, 28–51. [CrossRef]
97. Wang, Q.; Wu, C.; Sun, Y. Evaluating corporate social responsibility of airlines using entropy weight and grey relation analysis. *J. Air Transp. Manag.* **2015**, *42*, 55–62. [CrossRef]
98. Lee, P.T.W.; Lin, C.W.; Shin, S.H. A comparative study on financial positions of shipping companies in Taiwan and Korea using entropy and grey relation analysis. *Expert Syst. Appl.* **2012**, *39*, 5649–5657. [CrossRef]
99. Diakoulaki, D.; Mavrotas, G.; Papayannakis, L. Determining objective weights in multiple criteria problems: The CRITIC method. *Comput. Oper. Res.* **1995**, *22*, 763–770. [CrossRef]
100. Hadžikadunić, A.; Stević, Ž.; Badi, I.; Roso, V. Evaluating the logistics performance index of European Union Countries: An integrated multi-criteria decision-making approach utilizing the Bonferroni Operator. *Int. J. Knowl. Innov. Stud.* **2023**, *1*, 44–59. [CrossRef]
101. Huskanović, E.; Stević, Ž.; Simić, S. Objective-subjective CRITIC-MARCOS model for selection forklift in internal transport technology processes. *Mechatron. Intell Transp. Syst.* **2023**, *2*, 20–31. [CrossRef]
102. Sałabun, W.; Wątróbski, J.; Shekhovtsov, A. Are MCDA methods benchmarkable? A comparative study of TOPSIS, VIKOR, COPRAS, and PROMETHEE II methods. *Symmetry* **2020**, *12*, 1549. [CrossRef]