Financial Innovation

METHODOLOGY

Open Access

Proposal of an innovative MCDA evaluation methodology: knowledge discovery through rank reversal, standard deviation, and relationship with stock return

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

*Correspondence: mbaydas@erbakan.edu.tr

[1] Faculty of Applied Sciences, Necmettin Erbakan University, Konya, Turkey
[2] Faculty of Transport and Traffic Engineering, University of East Sarajevo, Doboj, Republic of Srpska

Abstract

Financial performance analysis is of vital importance those involved in a business (e.g., shareholders, creditors, partners, and company managers). An accurate and appropriate performance measurement is critical for decision-makers to achieve efficient results. Integrated performance measurement, by its nature, consists of multiple criteria with different levels of importance. Multiple Criteria Decision Analysis (MCDA) methods have become increasingly popular for solving complex problems, especially over the last two decades. There are different evaluation methodologies in the literature for selecting the most appropriate one among over 200 MCDA methods. This study comprehensively analyzed 41 companies traded on the Borsa Istanbul Corporate Governance Index for 10 quarters using SWARA, CRITIC, and SD integrated with eight different MCDA method algorithms to determine the position of Turkey's most transparent companies in terms of financial performance. In this study, we propose "stock returns" as a benchmark in comparing and evaluating MCDA methods. Moreover, we calculate the "rank reversal performance of MCDA methods". Finally, we performed a "standard deviation" analysis to identify the objective and characteristic trends for each method. Interestingly, all these innovative comparison procedures suggest that PROMETHEE II (preference ranking organization method for enrichment of evaluations II) and FUCA (Faire Un Choix Adéquat) are the most suitable MCDA methods. In other words, these methods produce a higher correlation with share price; they have fewer rank reversal problems, the distribution of scores they produce is wider, and the amount of information is higher. Thus, it can be said that these advantages make them preferable. The results show that this innovative methodological procedure based on 'knowledge discovery' is verifiable, robust and efficient when choosing the MCDA method.

Keywords: Financial performance, Share return, Standard deviation, Rank reversal, Capital Markets, MCDA evaluation methodology, Validation sensitivity and robustness analysis

Introduction

As a result of faster access to insights and critical information about companies through digitalization and artificial intelligence (AI) applications, depth dimensions in financial performance calculations have become more important than ever before. Companies need to understand their financial structures more deeply and strengthen their companies to rank higher in their sectors or maintain their positions. The importance of achieving a healthy structure and sustainability is undeniable (Tan et al. 2016). And this requires companies to explore the situation in depth with data analytics, supporting an effective and efficient financial performance analysis process. At this point, after data analytics and data discovery processes, 'knowledge discovery' has finally become more important than ever. As a result of the comprehensive financial performance analysis, important clues can be obtained regarding parameters such as the competitiveness sensitivity of the company, the potential of the projects in hand, and the economic interests of the management. Discovering the company's strengths and weaknesses is critically beneficial to corporate executives, shareholders, investors, lenders, regulators and partners. Financial performance results can also be used as a reference to observe how companies' current policies are effectively implemented (Rao 2000). Thus, companies can better understand their weaknesses and develop policies accordingly. Rankings are vital for companies seeking to determine their respective positions in their sectors, survive, and be successful (Li and Sun 2008). By implementing the financial policies of successful companies in the examined sector, other companies can accelerate their profitability (Rao 2000).

Performance can be defined as a company's efficiency in its area of operation. For stakeholders, financial issues such as the company's ability to meet its short- and long-term obligations, its destocking rate compared to competitors, the efficiency of its receivables policy compared to others in the sector, and the potential economic value of new investment projects are of vital importance. Managers determine how a firm's past financial policies affect the company in the short run and how these policies should be revised in the future using data revealed by financial performance analysis (Uyguntürk and Korkmaz 2012). The financial ratios used for the financial performance analysis were obtained from firms' financial statements. In this way, detailed information can be obtained about companies' potential liquidity problems, growth opportunities, and profitability levels compared with their competitors.

Classical accounting and value-based ratios are used in financial performance evaluations. When the accounting-based ratios preferred in the financial performance literature were examined, it was observed that these ratios were mostly related to profitability. Accounting-based ratios offer capital market stakeholders the opportunity to explore the status of companies with respect to their competitors (Gallizo and Salvador 2003). Reasons such as globalization of companies, tougher competition, an increase in the variety of financial instruments, and acceleration of international capital movement forced companies to adopt more value-based financial management. Along with this development and change, value-based ratios have increased in recent studies measuring the financial performance of companies (Sandoval 2001). In the past, the problem of ranking and choosing alternatives was addressed statistically (Xiao et al. 2023). Multiple criteria decision analysis (MCDA) methods are frequently used in this field because the evaluation of the financial performance of companies through different criteria creates a multidimensional structure (Kou et al. 2021a). In this sense, the use of MCDA methods—which include multiple criteria and decision alternatives—in financial performance studies in a way that includes value- and accounting-based ratios has become more important than before (Kumaraswamy and Ramaswamy 2016).

Corporate governance has increased prominently in capital markets, especially after the Enron scandal in the USA.[1] Corporate governance goals can be achieved by effectively implementing decisions taken in order to manage companies more transparently and avoid misleading investors. The BIST Corporate Governance Index started trading on August 31, 2007, with five competent companies. As of 2023, there were 61 companies on this index. A candidate firm must be rated by companies authorized by the Capital Markets Board (CMB) to obtain a sufficient corporate governance compliance score to be included in this prestigious index (BIST 2023). According to the CMB principles designed in accordance with OECD guidelines, the relevant rating is determined according to four parameters: shareholders, public disclosure and transparency, stakeholders, and the board of directors (SPK 2023). For a company to be included in the BIST Corporate Governance Index, its rating score must be at least 8 out of 10 for all parameters, and at least 7 for each parameter (BIST 2023). Of the companies on this index, including Turkey's most transparent companies, 61% are also traded on the BIST Sustainability Index.

Multi-criteria decision analysis methods continue to be researched with increasing interest among operational research topics, especially in the last two decades. In this field, the objective is to determine the optimal decision under different criteria. It can be said that MCDAs are tools based on creating problem solving methods and procedures so that decision-makers can make more appropriate, consistent and optimal decisions. In the problem-solving process, alternatives are evaluated according to the priorities of the decision-maker, performance is measured, and ranking results are produced (De Almeida et al. 2015). This research area offers various methodologies and solution tools to simplify complex problems and assist in making optimal decisions in times of uncertainty in different fields of science such as engineering, business, and finance. Moreover, a solution to a decision-making problem can sometimes be attributed to a single person. However, in real-life situations, collaborative individuals may also need to make an appropriate choice among alternatives in front of them. In this case, it is also possible to solve the group decision-based problems they encounter with an appropriate methodological system (Li et al. 2022; Kou et al. 2022; Chao et al. 2021).

While each MCDA method has its own set of advantages and disadvantages, it is not possible to determine a single method as the best under all circumstances. Therefore, choosing the most appropriate technique among the MCDA methods for solving

[1] Enron was an energy company founded in 1985 in the United States. Its shares had grown by 311% from the beginning of the 1990s to the end of 1998, but it collapsed in 2001 because it failed to disclose its debts transparently. After this scandal, which has been called the biggest bankruptcy of its time in US history, corporate governance came to the fore and the Sarbanes–Oxley Act of 2002 was enacted by the US Congress.

multi-criteria problems is a paradox in itself (Triantaphyllou 2000). Studies comparing different MCDA methods have been conducted to shed some light on the shortcomings in this field (Buede and Maxwell 1995; Eldrandaly et al. 2009; Athawale and Chakraborty 2011; Guarini et al. 2018; Haddad et al. 2020). In general, MCDA methods are compared based on criteria such as transparency, computation time, simplicity, and data quality (Chatterjee et al. 2011).

In decision analytics, an evaluation system is created to track the causes of a phenomenon, possibilities that will occur in the future, and alternative implementations of the results found by making use of past data (Tavana 2021). This system can be used in current AI applications to provide useful information and insights to users. Thus, in this financial performance study, the results produced by the different methods can be evaluated objectively in accordance with decision analytics.

Success in corporate governance alone is insufficient for investors (Mallin 2007); in fact, it should be supported by high financial performance. This study analyzes non-finance companies in the BIST Corporate Governance Index. Because 20 companies operating in the financial sector should be analyzed with different ratios owing to the specific sector structure, they were excluded from the scope of the study to make a homogeneous assessment. Thus, 41 companies constituting the dataset were examined.

This study investigates the most appropriate method for analyzing financial performance using stock returns (SR) as an external reference. For this purpose, the rank reversal (RR) phenomenon and standard deviation (SD) are also used simultaneously as triple validation, robustness, and sensitivity mechanisms, separating this study from the others. The first section presents an extensive literature review and the second explains the research methodology. In the third section, the application of the findings and results is emphasized, and in the fourth section, the discussion is clarified. Finally, the conclusions are presented in the last section.

Literature review

When examining financial performance studies in the field of social sciences, research is generally conducted with three types of methodologies. These can be summarized as (i) traditional statistical methods; (ii) methods based on machine learning, such as decision trees and artificial neural networks; and (iii) studies based on multi-criteria decision analysis methods (Wu et al. 2010).

In traditional performance studies, the relationship between a company's financial variables and financial performance is analyzed using basic statistical methods. Factor, discriminant, and principal component analyses have been used for this purpose. To illustrate, Altman, who conducted substantial studies on financial failure, used discriminant analysis in his research (Altman 1968; Kou et al. 2021b). Factor analysis is used to measure banks' financial performance in later literature (West 1985). Principal component analysis is preferred to measure financial performance at a higher level (Canbas et al. 2005).

With the development of computer technologies, methodologies based on machine learning have begun to be used to solve real-life problems as they do not require the probabilistic distribution of data, such as basic statistical analysis. The most commonly used methods for this approach are artificial neural networks (ANN) and soft computing. ANNs give more successful results compared to basic statistical methods according to the relevant literature (Brockett et al. 2006; Penpece and Elma 2014). Soft-computing methods are preferred for solving problems in which uncertainty is frequently experienced (Zimmermann 2001).

The MCDA methods, which produce ranking results according to different mathematical backgrounds using more than one criterion, constitute the third group of methodologies used in financial performance studies. These methods, which are based on utility theory, give importance to pairwise comparisons between criteria (Zavadskas and Turskis, 2011). The existence of various MCDA methods with different assumptions and models provides a wealth of solutions to different problems that may arise in different scenarios. In previous studies, a weighting system was created based on objective data and expert opinions. In this study, a financial performance analysis using an MCDA method was preferred.

Performance analysis and MCDA method evaluation

In a study examining 10 agricultural cooperatives working in the food and marketing sector in Greece between 1993 and 1998, the PROMETHEE method was utilized, and the financial performance of 27 companies was ranked according to this method. As a result, the strengths and weaknesses of the firms compared to each other were revealed and the problems related to their financial behavior were determined (Baourakis et al. 2002). In a follow-up study, 20 companies in the agricultural and food sectors were evaluated using the PROMETHEE method with seven accounting-based ratios (Kalogeras et al. 2005). Consequently, the PROMETHEE method has been suggested as a model for guiding companies in their financial decision-making. The research also stated that companies that are less successful can take the financial policies and market behaviors of the more successful ones as an example in light of the MCDA analysis.

In a study that analyzed the financial performance of 33 banks operating in Turkey that extended loans to the agricultural sector, the ANP and ELECTRE methods were preferred based on eight criteria. Among the samples that included public and foreign banks, the values of private banks were found to be the highest. In addition, foreign banks were found to be the highest in terms of performance (Dincer et al. 2016). From this perspective, private and foreign banks contribute more to agricultural activities in the country than public banks. Another study presents a performance analysis that a European investment company can make, when considering the possibility of taking over a company from Turkey (Yucel and Gorener 2016). Four potential companies were examined according to the AHP and ELECTRE methods using six criteria. This study, in which the AHP weighting method was used, proposes choosing between potential investment alternatives.

In a study on the banking sector in Turkey, 13 accounting-based ratios obtained from the financial statements of 2015 were calculated and a financial performance analysis was performed using the DEMATEL weighting technique and the GRA and MOORA methods (Yuksel et al. 2017). An analysis performed on a total of 23 banks, including public, private, and foreign banks, revealed that foreign banks outperformed other types of banks. In a study conducted on eight banks operating in Malaysia, a financial performance analysis was performed using the TOPSIS method and six accounting ratios obtained from financial statements between 2011 and 2015 (Siew et al. 2017). As a result of the study, this method is recommended because it produces successful results in financial performance analysis. In another study examining the pre- and post-offer financial performances of 16 initial public offerings in Borsa Istanbul in 2011, average weight and CRITIC were preferred as the weighting methods, together with the VIKOR method (Yalcin and Unlu 2018). In research where accounting- and value-based ratios were used together, the results obtained with the VIKOR-CRITIC method were more successful.

Using share dynamics as an anchor for MCDA methods

Although many MCDA methods have drawn a roadmap for decision-makers to solve different scenarios, because each method has its own disadvantages, a single method cannot be expected to produce perfect results for each scenario. However, it is critical to determine the results and sequences of different methods and compare them to to make informed decisions (Guitouni and Martel 1998). Stakeholders related to capital markets, such as speculators, managers, partners, investors, and lenders, must be able to make sound decisions regarding which companies are stronger in terms of financial performance. Thus, MCDA methods have emerged as tools in environments with intense uncertainty and variability.

In a study conducted on five automotive companies in Borsa Istanbul, TOPSIS results calculated using accounting ratios were compared with the stock values of the relevant companies (Yurdakul and Ic, 2003). As a result of the study, a consistent and significant relationship was determined between the TOPSIS and the company value rankings. In a study conducted on seven financial leasing and factoring companies trading in Borsa Istanbul, economic value added (EVA) was used as a value-based ratio, along with seven accounting ratios obtained from data between 2005 and 2010 (Ece and Ozdemir 2011). The rankings formed in the financial performance study, in which the TOPSIS method was preferred, were compared with the stock increase. It was observed that the second- and sixth-ranked companies were the same in both rankings. Determining which method outperforms others in terms of output with reference to SRs has become prominent with the strong results obtained in studies conducted in recent years (Baydaş and Elma 2021; Baydaş et al. 2022; Elma 2023).

Rank reversal phenomenon in MCDA applications

While MCDA methods have been extensively studied in the financial performance field, research on the RR problem remains limited and has not been included in the validation process in most studies (Bairagi et al. 2015). Rank reversal (RR) is the situation in which a change occurs in the ranking results after adding or removing alternatives to a predetermined group (Lootsma 1993; Saaty and Sagir 2009). Although the RR problem was first examined in the literature using the AHP method, research on this issue has increased rapidly, and it has been investigated for various other MCDA methods, including TOPSIS and PROMETHEE (Triantaphyllou 2001; Kong 2011; Verly and De Smet 2013). Adding and removing different factors can change the rankings significantly, which raises questions about the efficiency of MCDA methods. This common problem can also be defined as the position of two options being affected by a third option (Brans and De Smet 2016).

Research has shown that this problem occurs as a natural consequence of normalization in almost all MCDA methods (Barzilai and Golany 2017). The fact that the original data changed with normalization was shown to be a factor in the emergence of this problem. Although the existence of different units in the decision-making phase necessitates the use of normalization, if alternatives are selected using traditional methods and improved by pairwise comparison, the problems are somewhat reduced. Another study attempted to solve the RR problem with linear normalization but was unsuccessful because it did not consider the general spread of alternatives (García-cascales and Lamata 2012). In decision-making, if adding or removing new alternatives to the problem does not change the rank, this situation is called the rank preservation axiom. In order for a decision-maker to plan efficiently during uncertainty, the ranking position of alternatives should not change under different conditions (Luce and Raiffa 1957). Therefore, an effective MCDA is expected to have a rank preservation axiom and be free from the RR problem. The RR was evaluated using Spearman's correlation coefficient in a recent study (Mufazzal and Muzakkir 2018). Baydaş et al. (2023) found that the Spearman rank correlation can be used to objectively measure the RR performance of MCDA methods for a given problem.

The RR problem, which led to questions on the effectiveness and efficiency of MCDA methods, was later observed in SAW and TOPSIS (Wang and Luo 2009). Wang and Triantaphyllou (2008) identified this problem in ELECTRE-type MCDAs, whereas Macharis et al. (2004) tracked it in PROMETHEE. As these studies show, almost all MCDA methods have an RR problem to a certain extent.

One of the purposes of this study is to use the RR phenomenon as a validation, robustness, and sensitivity mechanism while identifying MCDA methods that can produce more effective and efficient results in financial performance studies.

Standard deviation in MCDA applications

The use of the standard deviation (SD) as a validation tool for MCDA methods has recently emerged in the literature. Zaidan et al. (2017) conducted the first study to use the SD method for this purpose by normalizing the final MCDA scores and calculating SDs for comparisons. The authors noted that normalization is necessary to draw a strong conclusion on the different scores produced by different criteria. They further recommended that a wider distribution, indicated by a higher SD, should be used to reveal differences between the methods more explicitly.

Table 1 The weighting technique, MCDA methods, decision criteria, and MCDA evaluation methodology used in this study

Weighting method	MCDA methods	Decision criteria	MCDA evaluation methodology
SWARA	COPRAS, CODAS, MOORA, TOPSIS, PROMETHEE II, VIKOR, FUCA, ELECTRE III	ROA, ROE, Altman-Z, MVA, Market-to-Book, EPS, Debt Ratio	Share Return, Standard Deviation, Rank Reversal

In a study of 24 companies traded in Borsa Istanbul, the SD method was used, and consistent results were obtained (Baydaş and Pamucar, 2022). The SD method was previously suggested for determining the objective weights of the criteria (Diakoulaki et al. 1995). The aim is to create a guiding reference point for decision-makers using the SD method. From this perspective, the SD method is suitable for a decision analysis. In this study, which seeks the most appropriate method for financial performance studies, different MCDA methods are also evaluated according to the SD method considering this information. Methods with a higher SD have a wider distribution and contain more information (Diakoulaki et al. 1995).

Material and methods

This study analyzed the period between the last trading day of June 2019 and the last trading day of September 2021 for 41 non-finance companies traded on the BIST Corporate Governance Index. Information about the companies was provided by the FINNET software. Eight MCDA methods from different schools were used to measure financial performance over seven accounting and value-based financial metrics, and companies were listed accordingly for the 10-quarter period examined. The SWARA weighting technique was applied based on the opinions of three experts with at least 10 years of experience in their fields. Excel and Minitab programs were used to calculate the final scores. Accordingly, SRs shaped by the common views of millions of investors were taken as an external reference, and the methods that produced the most sustainable and significant relationships with SRs were determined. Spearman's correlation coefficient was used to determine this relationship. Subsequently, SD, RR, and MCDA rankings based on the SRs were compared to validate the results. In this section, performance criteria, weighting techniques, and MCDA methods are thoroughly discussed. Table 1 lists the metrics used in the study.

Decision criteria and Rho coefficient

The solutions to single-criterion problems are simple and optimal. Considering the different sectors and internal dynamics, a financial performance study using a single ratio may not yield reliable results (Hallerbach and Spronk 2002). To measure financial performance effectively and efficiently, many variables must be evaluated, and quantitative and qualitative criteria must be determined (Gomes et al. 2014). This study uses multivariate approaches based on financial ratios. Multiple decision criteria and alternatives in MCDAs have led to the frequent use of these methods for financial performance measurements.

Table 2 Formulas of the financial metrics used in this study

Ratios	Formulas	References
MVA	Total Market Value / Total Capital Employed	Kim et al. (2004)
EPS	Net Income Available to Shareholders / Number of Shares Outstanding	Chen et al. (2007)
Market to Book	Market Capitalization / Net Book Value	Stewart (2013)
Debt Ratio	Total Liabilities / Total Assets	Omurbek and Mercan (2014)
ROE	Net Income / Stockholders' Equity	Livingstone and Grossman (2001)
ROA	Net Income / Total Assets	Moyer et al. (2014)
ALTMAN-Z	1.2 (Working Capital / Total Assets) + 1.4 (Retained Earnings / Total Assets) + 3.3 (EBIT / Total Assets) + 0.6 (Market Value of Equity / Book Value of Total Liabilities) + 1.0 (Sales / Total Assets)	Altman and Hotchkiss (2006)
Share Return	(Closing Share Price – Initial Share Price) / Initial Share Price	Carton and Hofer (2006)

Companies' financial goals, previously identified as profit and wealth maximization, have now been revised to value maximization (Shil 2009). Value-based approaches have become more popular in finance literature, especially since the 1980s. Shareholders invest their earned money in financial instruments to create value. This instinct to create value aligns with the goals of managers and employees. When a country's economy is analyzed as a whole, this value-creation trend increases the country's gross domestic product and positively accelerates the level of development (Camelia and Vasile 2009).

Especially in developed and strong form efficient markets, value-based ratios such as MVA are preferred to measure company values and financial performance since financial information can spread very quickly to the markets. Since financial performance studies have a multi-criteria structure, value-based ratios have been used in recent years, along with accounting-based ratios, in the application of MCDAs.

Table 2 shows the financial ratios and calculation steps used in this study.

Spearman correlation coefficient (ρ or r_s)

Spearman's correlation coefficient, a nonparametric measurement method, measures the degree of dependence of two variables on one another. It is frequently used in MCDA studies owing to its reliability and practicality. The formula for this data analysis tool is as follows (Kou et al. 2012):

$$r_s = 1 - \frac{6\sum d_i^2}{n\left(n^2 - 1\right)} \tag{1}$$

In the above formula, r_s is the Spearman correlation coefficient, d_i is the difference in binary rankings, and n is the number of observations. In this study, the relationship between the MCDA rankings and SRs (and RR performance) was measured using Spearman's correlation coefficient.

MCDA methods

In a scenario involving multiple criteria, rational decisions must be made to obtain the most appropriate result. MCDA methods were developed for this purpose and aimed to provide helpful guidance for decision-makers in complex scenarios. The universe of MCDA methods can be grouped into three classes according to the schools to which they belong: American, European, and blending schools that include the remaining methods. In the first category, the most popular methods of the American school are MAUT and AHP (Behzadian et al. 2012; Opricovic and Tzeng 2007; Zavadskas et al. 2007). When examined thoroughly, it is evident that the American school attaches importance especially to value and use. The methods in this school generally do not consider uncertainties in data or decision-maker preferences.

In contrast, the European school focuses more on bilateral relations and superiority. The PROMETHEE and ELECTRE are the most important methods used in this field (Brans et al. 1986; Hashemi et al. 2016). Different types of ELECTRE methods are generally preferred for solving selection problems (Greco et al. 2016). The PROMETHEE method was used to rank the alternatives. Because it can use real and fake criteria, it not only contains many features of ELECTRE methods, but also enriches these methods by ranking alternatives. While a partial ranking can be created from the input and output preference flows in PROMETHEE I, a clear ranking can be created in PROMETHEE II (Chen 2014).

The school that emerges by combining some of the features of these two is called a blending school (Wątróbski et al. 2019). The blending school includes methods such as COMET, TOPSIS, and VIKOR. In the methods of this school, both quantitative and qualitative criteria can be considered, and because more importance is given to decision rules, variants can be evaluated, and rankings created accordingly (Sałabun 2015). In TOPSIS, which is also one of the most popular methods in this field, the results are ordered according to their distances from the two reference points, called the positive and negative ideal solutions (Rashid et al. 2014).

Complex proportional assessment (COPRAS)

In order to evaluate quantitative and qualitative criteria efficiently, COPRAS as an MCDA method was proposed by academics working at Vilnius Gediminas Technical University (Zavadskas et al. 1994). This method can utilize both benefit and cost criteria and makes use of normalization so that different units can be evaluated and compared.

In this method, the degree and usefulness of alternatives are important, and ranking and evaluations are performed accordingly. The extent to which an alternative is useful or unhelpful compared to other alternatives is described on a percentage basis (Banaitienė et al. 2008). As the priority of the analyzed alternative increases, the degree of benefit also increases. Essentially, the degree of benefit is determined by comparing each alternative with the most efficient one.

Combinative distance-based assessment (CODAS)

In CODAS, a relatively new method, the overall performance of an alternative is measured by its distance from the negative ideal point (Ghorabaee et al. 2016). Therefore, pairs of alternatives must be compared. In this method, the superiority of the alternatives is determined using two measures. The main measure is the Euclidean distance between the considered alternatives and negative ideal. The other measure was taxicab distance. Again, the taxicab distance from the negative ideal was considered. The taxicab distance is preferred when Euclidean distance cannot be used. As this method is calculated according to the distance from the negative ideal, the alternative with the largest distance is preferred.

Multi-objective optimization on the basis of ratio analysis (MOORA)

Another MCDA method used by companies to solve complex problems is MOORA (Brauers and Zavadskas 2006). In this method, a matrix is created based on the responses of the alternatives to the objectives. Subsequently, a ratio system is created in which the alternative response of a target is compared with all alternatives for the same target. This method has been used to solve problems arising in many different scenarios, such as those that may arise in production companies (Chakraborty 2011), and in evaluating a bank's financial performance (Stanujkic et al. 2013).

Technique for order preference by similarity to ideal solution (TOPSIS)

TOPSIS evaluates each criterion and examines whether these criteria have decreasing or increasing utility (Pohekar and Ramachandran 2004). The results were ranked according to two reference points: the positive ideal solution and negative ideal solution; however, pairwise comparisons were avoided.

In the TOPSIS method, it is critical to determine the ideal and non-ideal solutions. The ideal solution maximizes the benefit criteria and minimizes the cost criteria. In contrast, a non-ideal solution minimizes the benefit criteria and maximizes the cost criteria (Wang and Elhag 2006). From this perspective, the most suitable alternative is the closest alternative to the positive ideal solution and the farthest alternative from the negative ideal solution (Benitez et al. 2007).

Preference ranking organization method for enrichment of evaluations II (PROMETHEE II)

PROMETHEE is one method the European school developed for use in complex problem solving (Brans and Vincke 1985). While there was only a partial ranking of alternatives in the first developed PROMETHEE I, a complete ranking of the alternatives became possible in PROMETHEE II. In this method, the preference function is determined according to each criterion. In the binary alternative comparison stage, a comparison was made depending on the preference function. Using the results obtained from pairwise comparisons performed in this manner, a specific or general ranking of alternatives can be made (Dagdeviren 2008).

Viekriterijumsko kompromisno rangiranje (VIKOR)

The VIKOR method, one of the most preferred methods in multi-criteria decision analysis, is based on compromise and ranking systematics (Opricovic 1998). In the presence of contradictions and inconsistencies between criteria, alternatives can be selected and ranked according to their proximity to the ideal solution (Buyukozkan and Ruan 2008).

A compromised solution is considered the closest to the ideal solution. The compromise ranking based on the ideal solution is created based on the determined weights (Opricovic and Tzeng 2004). For this purpose, a multi-criteria ranking index was created for the alternatives, and their closeness to the ideal solution was calculated and compared (Opricovic and Tzeng 2007). This is preferred in situations in which compromised solutions are used to effectively and efficiently solve scenarios and problems in which conflict and incompatibility occur (Ertugrul and Karakasoglu 2008).

Elimination et choix traduisant la realité (ELECTRE III)

ELECTRE can be regarded as a method that uses both satisfaction and dissatisfaction criteria, has both suitability and nonconformity indices, and ranks the relationships between the system in question and alternatives (Roy 1968). Because the lack of normalization in ELECTRE keeps the data reliable, it is a preferred method for decision-makers to solve appropriate problems. In addition, this method's avoidance of compromise and the ability to evaluate uncertain situations constitute other motivations for decision-makers to prefer this method. It has been suggested as an outranking approach, particularly for solving stock portfolio selection problems (Emamat et al. 2022).

Faire un choix adéquat (FUCA)

This method is one of the most effective and straightforward techniques and has become popular in recent years. It is preferred in business studies because of its practicality, capacity to produce results similar to those of PROMETHEE, and ability to provide results from the most appropriate to the most unsuitable alternatives with high consistency (Fernando et al. 2011). In this method, which does not use normalization, the first rank is assigned the best value, and the mth rank is assigned the worst value for each target. The weighted sums were then calculated for each solution to obtain the Pareto-optimal solution. The preferred solution should have the lowest ranking value (Wang et al. 2020).

Step-wise weight assessment ratio analysis (SWARA)

Determining the weights of multiple criteria is an important step in MCDAs, which is a substantial branch in the field of operations research (Pamučar et al. 2018). Weights can be determined by subjective methods, such as AHP, SMART, SWARA, or the swing method. It can also be specified by objective methods, such as mean weight, SD, entropy, and CRITIC. In addition, incompatibilities between criteria and preference dependence can affect the results of different MCDA methods used to solve multi-criteria problems. In this study, the SWARA method was preferred owing to its practical advantages.

The SWARA method is a subjective weighting method that is used in MCDA studies. Although the AHP is a subjective weighting method, SWARA is preferred in MCDA studies because it has much fewer pairwise comparisons and is easy to use and apply. It was developed in 2010 and is applied as a subjective weighting method in different areas such as personnel selection, product design, investment selection, and corporate social responsibility (Kersuliene et al. 2010; Kersuliene and Turskis 2011; Zolfani et al. 2013;

Karabašević et al. 2016; Stević et al. 2022). In this method, experts in the field prioritize each criterion for risk assessment, placing the most important criterion first and the least important criterion last. The compensatory nature and independence of the criteria are among the advantages of this method (Salamai 2021).

Criteria importance through intercriteria correlation (CRITIC)

Another popular objective weighting method used in multi-criteria decision-making problems is CRITIC. This method is based on the contrast within the decision problem when calculating the weights for each criterion (Diakoulaki et al. 1995). It uses correlation analysis and standard deviation for this purpose. While evaluating the decision matrix, separate criterion weights are calculated for each period as a result of the standard deviation of the normalized criterion values and the correlation of the criterion values with each other (Madić and Radovanović, 2015).

Standard deviation weighting method (SD)

Standard deviation, which plays a pivotal role in risk calculations in finance, can also be used to find the weights of all criteria for each period, considering the distribution among alternatives. Thus, weights are determined based on the distribution of criteria within the alternatives (Diakoulaki et al. 1995). A matrix is created by applying min–max normalization according to whether the criteria are cost, or benefit oriented. The weights are determined by calculating the standard deviation of each criterion in the matrix. This weighting method is preferred in complicated and ambiguous scenarios where experts cannot be used (Xu and Da 2008).

The studies based on the MCDA methods and weighting techniques described above and preferred for this financial performance study are shown in Table 3.

The formulation steps of the methods used in the studies mentioned in table above are shown in Appendix 1 this study.

Table 3 Research in which the formulations of respective MCDAs and weighting techniques used in this study

MCDA methods	References
PROMETHEE II	Behzadian et al. (2010)
COPRAS	Wang and Rangaiah (2017)
VIKOR	Opricovic and Tzeng (2004)
CODAS	Ghorabaee et al. (2016)
FUCA	Wang et al. (2020)
ELECTRE	Roy (1968)
MOORA	Wang and Rangaiah (2017)
TOPSIS	Wang and Rangaiah (2017)
Weighting technique	**Reference**
SWARA	Kersuliene et al. (2010)

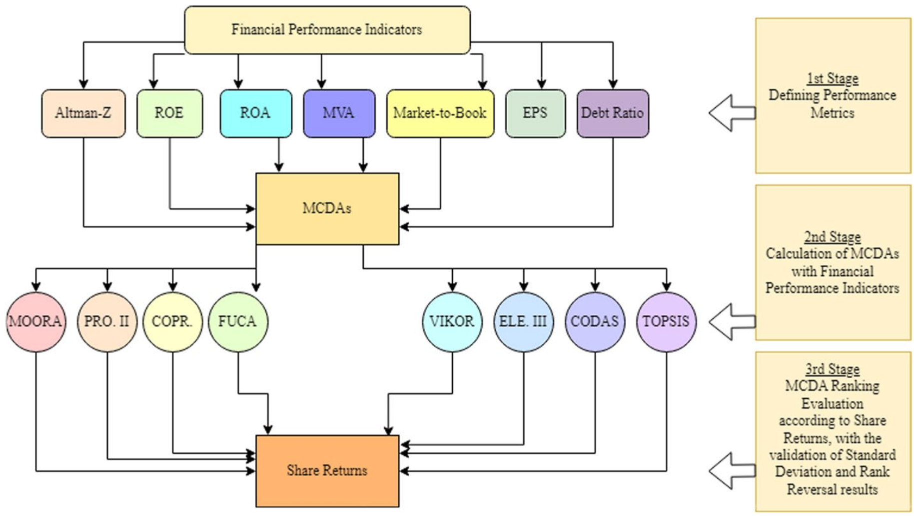

Fig. 1 The flow chart of the methodology used in this research

Application

In this study, based on financial performance analysis, the rankings created by MCDA methods are compared with SRs that represent real life and are validated with SD and RR, and the most appropriate methods are suggested for this field of research. The methodological approach used in this study is summarized as follows:

Step 1. Determination of financial performance measures: The SRs and ratios of the 41 companies examined in this study were obtained using FINNET. These criteria are preferred because they are frequently used in financial performance literature. A decision matrix was created using these financial performance metrics for eight related MCDA methods. Based on the opinions of the three experts, the weights related to these metrics were calculated using the SWARA method.

Step 2. Determining the ranking results of the MCDA methods: The ranking results of 41 companies traded on the BIST Corporate Governance Index, covering 10 quarters, were calculated using eight MCDA methods from different schools. SANNA Excel extensions were used with the application preferred by Wang and developed specifically for MCDA studies (Wang et al. 2020). In the study using the general preference function for PROMETHEE II, all the methods were calculated in Excel.

Step 3. Comparison of SR and MCDA ranking results in order to find the most appropriate method for financial performance analysis: Rankings calculated separately for 10 quarters using seven financial metrics with eight MCDA models were compared with SR rankings for the relevant quarter. In this study, in which only the SWARA weighting method was preferred, the strength of the relationships between the rankings was determined using Spearman's correlation coefficient. The most stable, powerful and high-result-producing methods have been proposed to financial decision-makers. A diagram of the methodology applied in this study is shown in Fig. 1.

After the analysis, the SD and RR rankings were used as validation mechanisms to confirm the accuracy of the results, as explained in the following section. Finally, the

Table 4 The decision matrix used in this financial performance analysis

Firms	ALTMAN-Z	ROE	ROA	MVA	M-to-b ratio	EPS	Debt R	Share ret
AEFES	0.21	0.02	0.02	0.07	0.11	1.04	14.71	*0.136*
AGHOL	0.13	0.02	0.01	− 0.35	− 0.06	1.5	315.85	*− 0.111*
AKSA	0.27	0.06	0.01	0.11	0.11	0.39	11.14	*0.008*
AKSGY	0.09	0.08	0.04	− 0.02	− 0.04	0.63	1.5	*− 0.099*
ALARK	0.61	0.11	0.06	0.14	0.14	0.42	− 24.17	*0.256*
ARCLK	0.29	0.02	0	0.15	0.15	0.35	8.13	*0.151*
ASELS	− 0.16	0.06	0.03	− 0.34	− 0.43	0.62	− 0.91	*− 0.154*
AYGAZ	0.69	0.06	0.03	− 0.25	− 0.21	0.41	− 22.1	*− 0.088*
BTCIM	− 0.04	− 0.08	− 0.02	− 0.1	− 0.01	− 0.35	5.37	*− 0.093*
CCOLA	0.26	0.06	0.02	0.05	− 0.01	1.54	11.04	*− 0.015*
CRDFA	0.1	0.03	0.01	− 0.06	− 0.06	0.06	− 1.28	*− 0.055*
DGGYO	0.05	− 0.03	− 0.01	− 0.04	0.07	− 0.06	3.97	*0.051*
DOAS	0.44	0.02	0	0.17	0.15	0.11	30.44	*0.221*
DOHOL	0.44	0.03	0.02	0.01	− 0.02	0.08	− 12.53	*0.000*
ENJSA	0.2	0.02	0.01	0.3	0.04	0.14	− 23.09	*0.068*
ENKAI	0.52	0.03	0.02	0.09	0.09	0.21	− 1.72	*0.192*
GARFA	0.14	0.05	0.01	− 0.16	− 0.16	0.12	− 340.62	*− 0.061*
GLYHO	0.04	− 0.01	0	− 0.12	− 0.2	− 0.05	− 37.31	*− 0.075*
HLGYO	0.07	0	0.01	0.03	0.03	0.02	0.8	*0.027*
HURGZ	− 0.1	− 0.03	− 0.02	− 0.06	− 0.05	− 0.03	0.46	*− 0.110*
IHEVA	0.34	0	0	0.19	0.22	0	4.18	*0.275*
IHLAS	− 0.01	− 0.05	− 0.01	− 0.05	0.08	− 0.05	19.08	*0.105*
ISFIN	− 0.14	0.05	0	− 2.44	− 2.57	0.09	− 46.12	*− 0.560*
LIDFA	0.05	0	0	− 0.08	− 0.08	0	0.53	*− 0.126*
LOGO	0.25	0.06	0.03	− 0.02	− 0.06	0.88	− 1.11	*0.064*
MGROS	0.35	− 0.88	− 0.01	− 5.8	3.29	− 0.84	2,090.13	*− 0.002*
OTKAR	0.65	0.44	0.07	− 1.95	− 2.81	8.6	− 292.48	*0.087*
PETUN	0.31	0.03	0.02	− 0.08	− 0.09	0.26	− 4.37	*− 0.131*
PINSU	0.1	− 0.22	− 0.02	0	0.16	− 0.19	130.53	*− 0.023*
PNSUT	0.3	0	0	0.01	0.01	0.01	− 0.34	*0.027*
PRKAB	0.41	0.02	0.01	− 0.14	− 0.12	0.04	8.88	*− 0.120*
SEKFK	0.05	− 0.01	0	0.38	0.38	− 0.02	0.67	*0.200*
SISE	− 0.01	0.03	0.02	− 0.01	− 0.16	0.32	6.95	*− 0.110*
TATGD	0.14	0.03	0.01	− 0.25	− 0.06	0.14	18.46	*− 0.019*
TAVHL	0.03	0.04	0.01	0.15	0.15	0.72	− 0.98	*0.157*
TOASO	0.52	0.11	0.02	0.28	0.01	0.82	− 27.31	*0.128*
TRCAS	0.02	0.01	0.01	0.05	− 0.02	0.02	− 5.59	*− 0.036*
TTKOM	0.23	0.05	0.01	0.52	0.26	0.12	− 42.99	*0.145*
TTRAK	0.22	0.02	0.01	0.43	0.03	0.26	− 9.67	*0.031*
TUPRS	0.39	0.07	0.02	− 0.28	− 0.43	3.54	− 21.85	*− 0.079*
VKGYO	0	0	0	− 0.03	0	− 0.01	2.13	*− 0.017*

Table 5 Weights calculated according to the SWARA technique for this study

Objectives	Types (Max or Min)	Weightage
ΔALTMAN-Z	Max	0.132295
ΔROE	Max	0.077821
ΔROA	Max	0.048638
ΔMVA	Max	0.45245
ΔMarket-to-Book	Max	0.238132
ΔEPS	Max	0.030399
ΔDebt Ratio	Min	0.020266

three ranking results were compared at the end of the study to find the most suitable method for financial performance analysis among the eight MCDA techniques.

Findings and results

Consistent with the methodology explained above, the MCDA performance points and rankings of 41 companies traded on the Borsa Istanbul Corporate Governance Index are calculated first, and then the comparison procedures are applied. The decision matrix forming the financial performance rankings of the MCDA methods over the seven preferred criteria is presented in Table 4 below. In addition, share returns parameter, which is used as a proxy for the study as explained above, is also added to the table and shown in italics.

During the examined period, criterion weights were calculated for the SWARA technique based on the opinions of the three experts for the entire period. The criteria covering all the periods were evaluated by experts with experience in their respective fields. Accordingly, the highest weights were given to MVA and the market-to-book ratio, which are valuation-based ratios. According to this technique, the debt ratio, which is cost-based, has the lowest weight. The criteria weights calculated using this method are listed in Table 5.

Table 6 presents the weights calculated for each period using the CRITIC weighting method. Because no experts were involved in this objective weighting method, the weighting of the valuation-based ratios was drastically reduced. The following paragraphs comparatively analyze the impact of this situation on the final results of the MCDA methods and their relationship with stocks.

The weights calculated according to standard deviation weighting, another objective weighting method, are listed in Table 7. With this weighting method, there are significant decreases in valuation-based ratios, which play a vital role in the financial evaluation of businesses.

The calculation steps of FUCA, which stood out as the most successful of the methods analyzed in this study, for the second quarter of 2019 are shown in the Appendix. Appendix 2 provides the ranking of all 41 companies in the sample for each criterion.

The highest criterion in benefit-based criteria and the smallest criterion in cost-based criteria are ranked in a hierarchy that will come in higher ranks in Appendix 2. Accordingly, Aygaz ranked first in Altman Z-scores. Otkar ranked first in terms of both ROE and ROA ratios. Turk Telekom ranked first in the MVA ratio. Migros was listed as the first company in terms of market-to-book ratio. Otkar again ranked first in terms of

Table 6 Weights calculated according to the CRITIC technique for this study

Objectives	2021/09	2021/06	2021/03	2020/12	2020/09	2020/06	2020/03	2019/12	2019/09	2019/06
ΔALT.-Z	.13	0.13	0.15	0.17	0.14	0.17	0.13	0.14	0.13	0.21
ΔROE	0.11	0.10	0.15	0.14	0.09	0.13	0.11	0.11	0.10	0.08
ΔROA	0.13	0.19	0.14	0.14	0.15	0.17	0.18	0.14	0.13	0.15
ΔMVA	0.09	0.11	0.14	0.14	0.17	0.15	0.13	0.15	0.11	0.13
ΔM-t-B	0.11	0.11	0.15	0.15	0.17	0.15	0.15	0.21	0.23	0.19
ΔEPS	0.22	0.14	0.12	0.11	0.15	0.10	0.14	0.13	0.19	0.13
ΔDebt	0.21	0.21	0.15	0.15	0.13	0.14	0.16	0.12	0.11	0.11

Table 7 Weights calculated according to the SD technique for this study

Objectives	2021/09	2021/06	2021/03	2020/12	2020/09	2020/06	2020/03	2019/12	2019/09	2019/06
ΔALT.-Z	0.14	0.15	0.18	0.20	0.16	0.19	0.14	0.14	0.14	0.21
ΔROE	0.13	0.12	0.14	0.13	0.10	0.12	0.12	0.13	0.13	0.11
ΔROA	0.14	0.21	0.18	0.17	0.17	0.20	0.21	0.16	0.14	0.17
ΔMVA	0.11	0.12	0.12	0.12	0.17	0.12	0.11	0.17	0.13	0.14
ΔM-t-B	0.12	0.13	0.13	0.12	0.12	0.13	0.12	0.13	0.15	0.11
ΔEPS	0.23	0.15	0.13	0.13	0.16	0.11	0.16	0.14	0.18	0.13
ΔDebt	0.13	0.13	0.14	0.13	0.12	0.13	0.13	0.13	0.13	0.12

Table 8 Spearman's Rho coefficients showing the relationship between SRs and financial performance scores generated by MCDAs

MCDAs	2021 III	2021 II	2021 I	2020 IV	2020 III	2020 II	2020 I	2019 IV	2019 III	2019 II	Mean
PRO. II	0.80	0.82	0.75	0.80	0.85	0.69	0.77	0.60	0.77	0.81	0.77
FUCA	0.80	0.82	0.75	0.80	0.85	0.69	0,77	0,60	0.77	0.81	0.76
TOPSIS	0.71	0.67	0.64	0.76	0.84	0.47	0.74	0.59	0.80	0.77	0.70
VIKOR	0.68	0.68	0.50	0.70	0.79	0.53	0.58	0.60	0.78	0.61	0.64
MOORA	0.68	0.67	0.45	0.67	0.73	0.47	0.63	0.58	0.80	0.65	0.63
ELEC. III	0.66	0.48	0.30**	0.65	0.55	0.28**	0.22***	0.53	0.69	0.38*	0.47*
COPRAS	-0.43	0.68	0.71	0.72	0.67	0.56	0.64	0.49	0.81	0.64	0.28
CODAS	0.32*	0.39*	0.22***	0.09***	0.20***	0.29**	0.17***	0.25***	0.21***	0.24***	0.09***

[*] $p < .05$

[**] $p < .10$

[***] $p > .10$

Remaining coefficients, $p < .01$

Table 9 The SD values of firms' MCDA based financial performance scores

MCDAs	2021 III	2021 II	2021 I	2020 IV	2020 III	2020 II	2020 I	2019 IV	2019 III	2019 II	Mean
PRO. II	0.30	0.26	0.26	0.26	0.27	0.28	0.25	0.27	0.25	0.27	0.27
FUCA	0.30	0.26	0.26	0.26	0.27	0.28	0.25	0.27	0.25	0.27	0.27
ELEC. III	0.22	0.16	0.16	0.18	0.19	0.21	0.15	0.19	0.20	0.17	0.18
TOPSIS	0.13	0.15	0.13	0.15	0.23	0.15	0.14	0.21	0.14	0.22	0.17
MOORA	0.13	0.14	0.13	0.14	0.20	0.15	0.16	0.19	0.15	0.19	0.16
VIKOR	0.13	0.15	0.13	0.14	0.22	0.15	0.14	0.18	0.14	0.17	0.16
CODAS	0.17	0.19	0.18	0.14	0.15	0.11	0.16	0.14	0.16	0.15	0.16
COPRAS	0.14	0.15	0.13	0.14	0.14	0.15	0.15	0.15	0.14	0.14	0.14

earnings per share ratio. Lastly, Garfa ranked first as the most efficient debt-managing firm when it comes to the sole cost-based ratio in this analysis, the debt ratio.

Subsequently, the values determined in Appendix 2 were multiplied by the SWARA criteria weights to obtain the second-stage matrix, which is given in Appendix 3. As can be seen, Turk Telekom, a communications company, had the minimum value for the quarter, and as a result, became the most suitable company to invest in this financial quarter.

Finally, the results for each alternative were summed, and a ranking list was created with the smallest value at the top. Accordingly, Turk Telekom was the first to produce the most successful scores in the second quarter of 2019, as Appendix 4 shows.

As seen in Table 8, the FUCA and PROMETHEE II methods were the most successful in seven out of the 10 quarters examined in this study. Both methods produced the highest Spearman's correlation coefficient. It has been determined that the FUCA method, which is independent of normalization, and PROMETHEE II, which uses the general preference function, should be recommended to financial decision-makers.

In addition, a strong correlation was determined using TOPSIS, along with the VIKOR and MOORA results. The ELECTRE III, COPRAS, and CODAS methods also produced the lowest correlations.

Table 10 RR Performance of the First Group of 21 Firms MCDA based Financial Performance Scores

MCDAs	2021 III	2021 II	2021 I	2020 IV	2020 III	2020 II	2020 I	2019 IV	2019 III	2019 II	Mean
PRO. II	1.00	1.00	0.99	1.00	0.98	0.99	0.99	0.99	0.99	0.99	0.99
FUCA	1.00	1.00	0.99	1.00	0.98	0.99	0.99	0.99	0.99	0.99	0.99
TOPSIS	0.87	0.81	0.95	0.83	1.00	0.58	0.99	0.99	0.93	0.97	0.89
MOORA	0.82	0.89	0.96	0.78	0.94	0.73	0.87	1.00	0.94	0.87	0.88
VIKOR	0.74	0.83	0.93	0.75	0.97	0.73	0.79	1.00	0.89	0.73	0.83
CODAS	0.99	0.72	0.92	0.52*	0.81	0.56	0.40**	0.99	0.87	0.88	0.76
ELEC. III	0.68	0.85	0.91	0.69	0.93	0.65	0.35***	0.97	0.81	0.76	0.76*
COPRAS	0.44*	0.97	0.16***	0.76	0.63	0.92	0.44*	0.40**	0.96	0.74	0.24**

* $p < .05$

** $p < .10$

*** $p > .10$

Remaining coefficients, $p < .01$

Table 11 RR Performance of the Second Group of 20 Firms in the MCDA based Financial Performance Scores

MCDAs	Mean	Rank	MCDAs	Mean	Rank	MCDAs	Mean	Rank
PRO. II	0.9871	1	TOPSIS	0.9756	4	COPRAS	0.799**	7
FUCA	0.9856	2	VIKOR	0.9671	5	CODAS	0.4537*	8
MOORA	0.9814	3	ELECTRE III	0.9044*	6			

* $p < .05$

** $p < .10$

Remaining coefficients, $p < .01$

MCDA evaluation methodology

The MCDA rankings, which were calculated over the financial ratios mentioned above in this financial performance study, were compared with the rankings based on SRs, the SD method, and RR problem. The simultaneous use of these methodologies is exceptional in this field of study. The RR phenomenon was also used as a validation tool in this study because different types of normalization may affect the ranking results.

In accordance with the literature mentioned above, the SD results are consistent with the findings of the financial performance scores generated by the MCDA methods, as shown in Table 9. The FUCA and PROMETHEE II methods yielded the highest SD scores, suggesting that these methods are more successful for this financial performance analysis. The TOPSIS, MOORA, and VIKOR results also yielded strong SD results, following FUCA and PROMETHEE II. Alternatively, CODAS and COPRAS methods stand out as those that gave the lowest SD range.

The RR phenomenon was another validation tool used in this study. With the occurrence of RR, the rank determined by the MCDA method becomes unstable, affecting the results. Although each of the more than 200 MCDM methods is a research topic of its own, the issue of which method most commonly contains RR and to what extent it affects the best alternative is an important topic in the literature. While many studies recommend revisions for MCDA models, chronic problems may occur in these revised models that affect the overall performance of MCDAs. In this study, the RR results of the MCDA methods, which were examined specifically for financial performance analysis,

Table 12 Performance rankings of the methods according to their SR Rhos, SD and RR Benchmarks

MCDA Methods	Rho	Rank	SD	Rank	Rank Rev	Rank	Mean
PROMETHEE II	0.7670	1	0.2670	1	0.9904	2	1
FUCA	0.7633	2	0,2670	1	0.9914	1	1
TOPSIS	0.6991	3	0.1650	4	0.8903	3	3
MOORA	0.6309	5	0.1581	5	0.8804	4	4.67
VIKOR	0.6438	4	0.1553	6	0.8349	5	5
ELECTRE III	0.474*	6	0.1811	3	0.7599*	7	5.67
CODAS	0.0855***	8	0.1550	7	0.7636	6	7.67
COPRAS	0.2789	7	0.1429	8	0.2394**	8	8.67

* $p < .05$

** $p < .10$

*** $p > .10$

Remaining coefficients, $p < .01$

were scrutinized using Spearman's correlation coefficient to determine which method remained at the same rank when adding and removing alternatives (Mufazzal and Muzakkir 2018). If RR equals 1, there is no rank reversal problem.

The consistency of these results was investigated by determining the RR sensitivities of the methods used in this study. Accordingly, the 41 companies in this study was reduced to 21 to create a more rigorous test and changes in the ranking were observed. In other words, the MCDA methods were recalculated by removing the first 20 companies from the list in alphabetical order. The MCDA rankings of the 21 companies on the first list and those of the 20 companies in the second list were compared using Spearman's correlation. It was assumed that the RR problem decreased as the ratio approached 1.00. A comparison of MCDA methods according to the RR criterion was performed in this study. While most of the studies mentioned in the literature generally followed a methodology of addition or subtraction of an alternative, in this study, 20 alternatives were removed, and validation was performed according to these criteria. In addition, unlike other studies that performed observational comparisons, this study used statistical comparisons.

In accordance with the above results, the PROMETHEE II and FUCA methods showed the highest performance with the lowest observed RR, as shown in Table 10. The TOPSIS, MOORA, and VIKOR methods were found to have minor RRs. In contrast, the COPRAS method had the highest RR.

In addition, the RR of the 20 companies in the second cluster were compared, and the results are presented in Table 11. The second group of companies had similar rankings but with slight differences. PROMETHEE II and FUCA retained their positions in the top two places for both clusters, while the MOORA method ranked third for the companies in the second cluster.

As shown in Table 12, the PROMETHEE II and FUCA methods were suggested as the most appropriate for financial performance analysis among the methods examined in this research. The TOPSIS, MOORA, and VIKOR methods stand out as the other methods that produce strong results. It is also important to note that the ELECTRE III, COPRAS, and CODAS methods stood out consistently with the lowest performance and the highest RR, in this financial performance study.

Table 13 Correlation performances of weighting techniques with SR

Rank	SWARA		SD		CRITIC	
	Method	**RHO Mean**	**Method**	**RHO Mean**	**Method**	**Rho Mean**
1	PROMETHEE II	0.7670	FUCA	0.4417*	FUCA	0.4815*
2	FUCA	0.7633	PRO. II	0.4403*	PRO. II	0.4815*
3	TOPSIS	0.6991	TOPSIS	0.3322***	VIKOR	0.4223*
4	VIKOR	0.6438	VIKOR	0.3319***	TOPSIS	0.3984**
5	MOORA	0.6309	MOORA	0.3277***	MOORA	0.3581**
6	ELECTRE III	0.4740*	ELECTRE III	0.3166***	ELECTRE III	0.3310***
7	COPRAS	0.2789	COPRAS	0.2891***	COPRAS	0.2982***
8	CODAS	0.0855***	CODAS	0.1488***	CODAS	0.1127***

* $p < .05$

** $p < .10$

*** $p > .10$

Remaining coefficients, $p < .01$

When the general preference function is used in the first step of PROMETHEE II, a decision matrix is created with deviances regarding pairwise comparisons that have only 0 or 1 value. If the deviance value was greater than 0, it was assumed to be 1. Otherwise, according to the methodology, if the deviance value is equal to or smaller than 0, it should be assumed to be 0. Thus, a hierarchy is formed among all alternatives depending on the order of preference. The FUCA exhibited similar characteristics. The alternatives are hierarchically ordered according to their ranking positions. This explains why PROMETHEE II and FUCA yielded nearly identical results. These slight differences can be explained by the effect of the next formulation steps of PROMETHEE II, which are presented in Appendix 1.

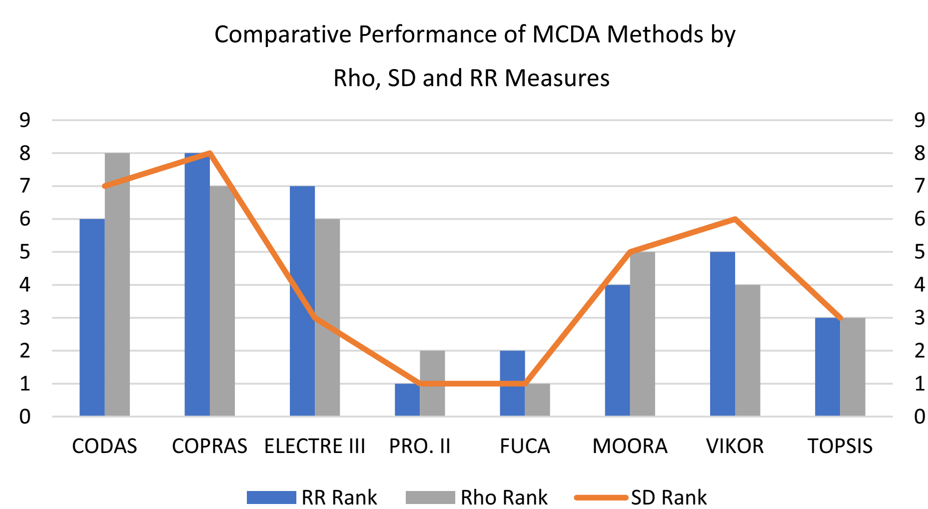

Fig. 2 Comparative performance of MCDA methods by various metrics

Finally, information demonstrating the relationship between the calculations made for the eight MCDA methods according to all weighting techniques and stock returns is provided in Table 13. Of all the weighting techniques, FUCA and PROMETHEE II produced the most stable and significant relationships with share returns; thus, they were recommended to financial decision-makers as a result of this financial performance study.

Discussion

MCDA methods can address problems with different approaches, such as distance-based, value, utility, or ordering. Additionally, MCDA methods may require the user to use different assumptions or thresholds. For example, the PROMETHEE II method recommends that the decision-maker use one of the different preference functions.

In this study, assisting decision-makers in real-life problems through eight different MCDA models was examined in terms of financial performance. In addition, triple validation, sensitivity, and robustness analyses of the MCDA assessment methodology were performed, including SR, SD, and RR. The results of all the three analyses were largely consistent. As shown in Fig. 2, the PROMETHEE II and FUCA methods were established as the most suitable for financial performance analysis among the methods examined in this study. While the TOPSIS method consistently ranked third, the CODAS and COPRAS methods consistently ranked last.

There is a lack of research in the literature to determine how to match the most suitable MCDA method to the relevant problem. The comparison reference for this study is simple and shaped by three benchmarks: SR, RR, and SD. Some MCDA methods, such as PROMETHEE II and FUCA, provided better results than the other methods used in this study. This study shows that some methods model real life better or have a special capacity to address a given financial performance problem.

Conclusion

Financial performance analysis is one of the most widely studied areas in finance. In capital markets, where uncertainty is at the forefront, the parties related to the firm (investors, lenders, partners, company managers, etc.) must evaluate many criteria and draw an appropriate roadmap to make critical decisions. In such a situation, when a decision-maker are faced with many alternatives, it makes sense to use an appropriate MCDA method with multiple criteria. The focus of this study is to propose an appropriate MCDA selection and evaluation methodology for the financial performance analysis of firms.

Choosing a suitable MCDA method is difficult and has been a problem for years. According to the results they produce, it is difficult to determine the capacity or capabilities of each of more than 200 MCDA methods. Unlike previous studies based on the theoretical background, in this study, 'knowledge discovery' was made by going through data analytics and data discovery analysis processes and it was aimed to determine the hidden capacity, tendencies, and properties of MCDA methods. To provide a broader perspective on the research topic, eight MCDA methods were compared based on the association of generating power with SRs, SD distribution, and RR performance.

MCDA methods may use different data structures, normalization types, weighting methods, calculation equations, assumptions, and thresholds. Undoubtedly, this makes a fair comparison difficult. It is unclear which of these MCDA elements is better and which should be used as MCDA inputs. In the MCDA literature, comparisons often result in ambiguity; therefore, the solution is ambiguous. This study reveals a transparent and objective result compared with the literature, in which the MCDA method has a higher capacity in terms of financial performance. For example, PROMETHEE II and FUCA were found to be the most appropriate MCDA methods for financial performance problems compared to the other six methods examined in this study. However, under different scenarios, different MCDA methods may be more appropriate than the model proposed in this study.

A reasonable and objective comparison framework is required to determine the capacity or capabilities of the MCDA methods. Among MCDA techniques, we suggest that an MCDA method that captures real life, reasonable SD distribution, and RR performance in a sustained and consistent manner may be more appropriate. The implication of this study is to find and propose objective benchmarks to compare MCDA methods and find a suitable method that can model real-life scenarios more comprehensively than others in the field of financial performance.

The results of this study are critical in many ways and may be encouraging for future studies. This study indicates that different benchmarks can be generated and used in MCDA techniques. In future studies, using the methodology employed in this study, different methods can be compared, and more detailed information can be provided to determine which method is most appropriate, especially in the field of financial performance.

Limitations of this study

Although the results of this study were validated within a 10 quarter-period, it should be noted that some parameters were kept constant. These include the MCDA type, normalization type, threshold value for some, and the preference function. However, the relative success of the MCDA method in terms of ranking was not absolute. Although CODAS and COPRAS are at the bottom of the rankings, these methods can perform relatively better after appropriate normalization or the use of threshold values. It should be noted that the SD and RR benchmarks are applicable in all fields of science. The use of the Rho criterion depends on generating a suitable real-life ranking for each field. In this study, the share price was accepted as a real-life reference. While choosing the eight MCDA methods, criteria such as popularity, wide adoption, and being from different schools (value, outranking, etc.) were considered.

Appendix 1: The Steps to Implement MCDA Techniques and SWARA Method in this Study

St	PROMETHEE	TOPSIS	ELECTRE III
1	Designate the deviances as regards to the binary comparisons: $d_j(a,b) = g_j(a) - g_j(b)$	Creating a normalized decision matrix: $F_{ij} = \frac{f_{ij}}{\sqrt{\sum_{i=1}^{m} f_{ij}^2}}$	Modify the objective matrix as in ELECTRE II
2	Computation of the preference function: $P_j(a,b) = F_j\left[d_j(a,b)\right] \quad j = 1,\ldots,k$	Obtaining the weighted normalized matrix: $v_{ij} = F_{ij} \times w_j$	An element of the concordance matrix of m rows and columns is computed by: $C(a,b) = \sum_{j=1}^{n} w_j C_j(a,b)$ Where $C_j(a,b) = \left\{ \begin{array}{ll} 1 & if\ \ F_j(b) - F_j(a) \le Q_j \\ 0 & if\ \ F_j(b) - F_j(a) > P_j \\ \frac{P_j - [F_j(b) - F_j(a)]}{P_j - Q_j} & if\ \ Q_j < F_j(b) - F_j(a) \le P_j \end{array} \right\}$
3	Computation of a preference index: $\forall a,b \in A, \pi(a,b) = \sum_{j=1}^{k} P_j(a,b) w_j$	Finding positive (A^+) and negative (A^-) ideal solutions: $A^+ = \left\{ \left(Max_i(v_{ij}) \| j \in J\right), \left(Min_i(v_{ij}) \| j \in J'\right) \| i \in 1,2,\ldots,m \right\}$ $= \left\{ v_1^+, v_2^+, v_3^+, \ldots, v_j^+, \ldots, v_n^+ \right\}$ $A^- = \left\{ \left(Min_i(v_{ij}) \| j \in J\right), \left(Max_i(v_{ij}) \| j \in J'\right) \| i \in 1,2,\ldots,m \right\}$ $= \left\{ v_1^-, v_2^-, v_3^-, \ldots, v_j^-, \ldots, v_n^- \right\}$	Construct elements of discordance matrix by: $D_j(a,b) = \left\{ \begin{array}{ll} 1 & if\ \ F_j(b) - F_j(a) > V_j \\ 0 & if\ \ F_j(b) - F_j(a) \le P_j \\ \frac{F_j(b) - F_j(a) - P_j}{V_j - P_j} & if\ \ P_j < F_j(b) - F_j(a) \le V_j \end{array} \right\}$
4	Computation of positive and negative outranking flows: $\phi^+(a) = \frac{1}{n-1} \sum_{x \in A} \pi(a,x)$ $\phi^-(a) = \frac{1}{n-1} \sum_{x \in A} \pi(x,a)$	Computing the positive and negative ideals' distance values: $S_{i+} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \quad i = 1,2,3,\ldots,m$ $S_{i-} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \quad i = 1,2,3,\ldots,m$	The credibility matrix of m rows and columns is given by: $S(a,b) = \left\{ \begin{array}{ll} C(a,b) & \text{if } D_j(a,b) \le C(a,b) \forall j \\ C(a,b) \prod_{j \in J(a,b)} \frac{1 - D_j(a,b)}{1 - C(a,b)} & \text{otherwise} \end{array} \right.$
5	Computation of the complete ranking: $\phi(a) = \phi^+(a) - \phi^-(a)$	Computing relative proximity to ideal solution: $C_i = \frac{S_{i-}}{S_{i-} + S_{i+}}$	Finally, make the selection based on credibility matrix by calculating difference between the strength (sum of row) and weakness (sum of column) of each solution, with or without cut-off values

St	SD Method	CODAS	SWARA	CRITIC
1	Normalize the objective matrix: for benefit objective $F_{ij} = \frac{f_{ij} - min_{i \in m} f_{ij}}{max_{i \in m} f_{ij} - min_{i \in m} f_{ij}}$ for cost objective $F_{ij} = \frac{max_{i \in m} f_{ij} - f_{ij}}{max_{i \in m} f_{ij} - min_{i \in m} f_{ij}}$	Construct normalized objective matrix with max normalization $F_{ij} = \frac{f_{ij}}{max_{i \in m} f_{ij}} \quad i \in \{1, 2, \ldots, m\};\ j \in \{1, 2, \ldots, n\}\ for\ benefit$ $F_{ij} = \frac{min_{i \in m} f_{ij}}{f_{ij}} \quad i \in \{1, 2, \ldots, m\};\ j \in \{1, 2, \ldots, n\}\ for\ cost$	Objectives are sorted in descending order based on their importance decided by the decision maker. The first objective is the most important and last objective is the least important. Next, the decision maker needs to give the relative importance *Sj* value (≥ 0 and ≤ 1), which is the objective *j* over the previous objective (j-1), starting from the second objective (i.e., j = 2, 3, …, n)	First, a decision matrix is created and then normalized $r_{ij} = \frac{x_{ij} - x_j min}{x_j max - x_j min}$
2	Calculate the standard deviation of values of each objective: $\sigma_j = \sqrt{\frac{\sum_{i=1}^{m} (F_{ij} - \overline{F}_j)^2}{m}}$ $j \in \{1, 2, \ldots, n\}$	Construct weighted normalized objective matrix $v_{ij} = F_{ij} \times w_j \quad i \in \{1, 2, \ldots, m\};$ $j \in \{1, 2, \ldots, n\}$ And determine the negative-ideal solution, A^- $A^- = \{(Min_i(v_{ij}) \mid i \in 1, 2, \ldots, m\}$ $= \{v_1^-, v_2^-, v_3^-, \ldots, v_j^-, \ldots, v_n^-\}$	Compute K_j and Q_j $K_j = \begin{cases} 1 & if\ j = 1 \\ S_j + 1 & if\ j > 1 \end{cases}$ $Q_j = \begin{cases} 1 & if\ j = 1 \\ \frac{Q_{j-1}}{K_j} & if\ j > 1 \end{cases}$	After calculating the standard deviation and multiple correlations for each criterion, the correlation density is computed $C_j = \sigma_j \sum_{i=1}^{m} (1 - r_{ij})$
3	Determine the weight for each objective: $w_j = \frac{\sigma_j}{\sum_{k=1}^{n} \sigma_k}$ $j \in \{1, 2, \ldots, n\}$	Calculate the Euclidean and Taxicab distances $E_i = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \quad i = 1, 2, 3, \ldots, m$ $T_i = \sum_{j=1}^{n} \lvert v_{ij} - v_j^- \rvert \quad i = 1, 2, 3, \ldots, m$	Ultimately the weight for each objective is determined as $w_j = \frac{Q_j}{\sum_{k=1}^{n} Q_j}$ $j \in \{1, 2, \ldots, n\}$	Finally, this calculated correlation density is normalized and weights are computed for each criterion $w_j = \frac{C_j}{\sum_{i=1}^{m} C_i}$
4		Construct the relative assessment matrix $h_{ik} = (E_i - E_k) + \psi(E_i - E_k)$ $\times (T_i - T_k) \quad i, k \in \{1, 2, \ldots, m\}$ And calculate the assessment score of each solution $H_i = \sum_{k=1}^{m} h_{ik} \quad i = 1, 2, 3, \ldots, m$		

St	MOORA	COPRAS	VIKOR
1	Construct normalized objective matrix applying vector normalization: $F_{ij} = \frac{f_{ij}}{\sqrt{\sum_{k=1}^{m} {f_{kj}}^2}}$ $i \in \{1, 2, \ldots, m\}$; $j \in \{1, 2, \ldots, n\}$	Construct normalized objective matrix: $F_{ij} = \frac{f_{ij}}{\sum_{k=1}^{m} f_{kj}}$ $i \in \{1, 2, \ldots, m\}$; $j \in \{1, 2, \ldots, n\}$	For each objective, determine the best and worst values: $F_j^+ = Max_{i \in m} f_{ij}$ and $F_j^- = Min_{i \in m} f_{ij}$ for maximization objectives $F_j^+ = Min_{i \in m} f_{ij}$ and $F_j^- = Max_{i \in m} f_{ij}$ for minimization objectives
2	Construct weighted normalized objective matrix: $v_{ij} = F_{ij} \times w_j$ $i \in \{1, 2, \ldots, m\}$; $j \in \{1, 2, \ldots, n\}$	Construct weighted normalized objective matrix: $v_{ij} = F_{ij} \times w_j$ $i \in \{1, 2, \ldots, m\}$; $j \in \{1, 2, \ldots, n\}$	Compute S_i and R_i for each solution: $S_i = \sum_{j=1}^{n} w_j \left(\frac{F_j^+ - f_{ij}}{F_j^+ - F_j^-} \right)$ $R_i = Max_{j \in n} \left[w_j \left(\frac{F_j^+ - f_{ij}}{F_j^+ - F_j^-} \right) \right]$
3	Calculate the performance scores for each solution: $P_i = \sum_{j=1}^{g} v_{ij} - \sum_{j=g+1}^{n} v_{ij}$ $i \in \{1, 2, \ldots, m\}$	For each solution, calculate the sums of weighted normalized values for both benefit and cost objectives: $S_{i+} = \sum_{j=1}^{g} v_{ij}$ $i \in \{1, 2, \ldots, m\}$ $S_{i-} = \sum_{j=g+1}^{n} v_{ij}$ $i \in \{1, 2, \ldots, m\}$	Compute Q_i $Q_i = \gamma \left(\frac{S_i - S^+}{S^- - S^+} \right) + (1 - \gamma) \left(\frac{R_i - R^+}{R^- - R^+} \right)$ where $S^+ = Min_{i \in m} S_i, S^- = Max_{i \in m} S_i,$ $R^+ = Min_{i \in m} R_i R^- = Max_{i \in m} R_i$
4		Determine the relative importance of each solution: $Q_i = \begin{cases} S_{i+} + \frac{\sum_{i=1}^{m} S_{i-}}{S_{i-} \sum_{i=1}^{m} \frac{1}{S_{i-}}} & \textit{for both benefit and cost} \\ S_{i+} & \textit{for only benefit} \\ \frac{\sum_{i=1}^{m} S_{i-}}{S_{i-} \sum_{i=1}^{m} \frac{1}{S_{i-}}} & \textit{for only cost} \end{cases}$	Rank Pareto-optimal solutions, sorting by the value of $Q_i \| i = 1, 2, \ldots, m$ in decreasing order. Propose a compromise solution $A^{(1)}$ by the measure $Min_{i \in m} Q_i$ if acceptable advantage and acceptable stability in decision-making is met

St	FUCA
1	For each of the objectives, rank 1 is assigned to the best value, and rank m is assigned to the worst value
2	A weighted summation for each optimal solution i is computed as: $v_i = \sum_{j=1}^{n} (r_{ij} \times w_j)$

Appendix 2: FUCA methods' first stage ranking matrix

	ALTMAN-Z	ROE	ROA	MVA	M-to-B	EPS	Debt Ratio
AEFES	20	25	8	13	11	5	35
AGHOL	24	26	15	38	28	4	40
AKSA	15	6	24	11	10	13	34
AKSGY	27	4	3	21	25	9	25
ALARK	3	2	2	10	9	11	7
ARCLK	14	21	27	9	7	14	31
ASELS	41	9	4	37	39	10	19
AYGAZ	1	9	4	35	37	12	9
BTCIM	38	39	40	30	21	40	29
CCOLA	16	6	8	14	21	3	33
CRDFA	25	17	24	26	29	26	16
DGGYO	29	37	36	24	14	38	27
DOAS	6	21	27	7	7	23	38
DOHOL	7	17	8	17	23	25	11
ENJSA	21	21	15	4	15	19	8
ENKAI	4	16	8	12	12	18	15
GARFA	23	11	15	33	34	21	1
GLYHO	32	34	27	31	36	36	5
HLGYO	28	29	15	16	16	29	24
HURGZ	39	36	39	26	26	35	21
IHEVA	11	29	27	6	4	31	28
IHLAS	36	38	38	25	13	37	37
ISFIN	40	12	27	40	40	24	3
LIDFA	31	29	27	29	31	31	22
LOGO	17	6	4	21	29	6	17
MGROS	10	41	36	41	1	41	41
OTKAR	2	1	1	39	41	1	2
PETUN	12	17	8	28	32	16	14
PINSU	26	40	40	19	5	39	39
PNSUT	13	29	27	17	18	30	20
PRKAB	8	21	15	32	33	27	32
SEKFK	29	35	27	3	2	34	23
SISE	36	15	8	20	35	15	30
TATGD	22	17	24	34	27	20	36
TAVHL	33	14	15	8	6	8	18
TOASO	5	3	7	5	19	7	6
TRCAS	34	28	15	14	23	28	13
TTKOM	18	13	15	1	3	21	4
TTRAK	19	26	15	2	17	16	12
TUPRS	9	5	8	36	38	2	10
VKGYO	35	29	27	23	20	33	26

Appendix 3: FUCA methods' second stage matrix

	ALTMAN-Z	ROE	ROA	MVA	M-to-B	EPS	Debt Ratio
AEFES	2.65	1.95	0.39	5.88	2.62	0.15	0.71
AGHOL	3.18	2.02	0.73	17.19	6.67	0.12	0.81
AKSA	1.98	0.47	1.17	4.98	2.38	0.40	0.69
AKSGY	3.57	0.31	0.15	9.50	5.95	0.27	0.51
ALARK	0.40	0.16	0.10	4.52	2.14	0.33	0.14
ARCLK	1.85	1.63	1.31	4.07	1.67	0.43	0.63
ASELS	5.42	0.70	0.19	16.74	9.29	0.30	0.39
AYGAZ	0.13	0.70	0.19	15.84	8.81	0.36	0.18
BTCIM	5.03	3.04	1.95	13.57	5.00	1.22	0.59
CCOLA	2.12	0.47	0.39	6.33	5.00	0.09	0.67
CRDFA	3.31	1.32	1.17	11.76	6.91	0.79	0.32
DGGYO	3.84	2.88	1.75	10.86	3.33	1.16	0.55
DOAS	0.79	1.63	1.31	3.17	1.67	0.70	0.77
DOHOL	0.93	1.32	0.39	7.69	5.48	0.76	0.22
ENJSA	2.78	1.63	0.73	1.81	3.57	0.58	0.16
ENKAI	0.53	1.25	0.39	5.43	2.86	0.55	0.30
GARFA	3.04	0.86	0.73	1493	8.10	0.64	0.02
GLYHO	4.23	2.65	1.31	14.03	8.57	1.09	0.10
HLGYO	3.70	2.26	0.73	7.24	3.81	0.88	0.49
HURGZ	5.16	2.80	1.90	11.76	6.19	1.06	0.43
IHEVA	1.46	2.26	1.31	2.71	0.95	0.94	0.57
IHLAS	4.76	2.96	1.85	11.31	3.10	1.12	0.75
ISFIN	5.29	0.93	1.31	18.10	9.53	0.73	0.06
LIDFA	4.10	2.26	1.31	13.12	7.38	0.94	0.45
LOGO	2.25	0.47	0.19	9.50	6.91	0.18	0.34
MGROS	1.32	3.19	1.75	18.55	0.24	1.25	0.83
OTKAR	0.26	0.08	0.05	17.65	9.76	0.03	0.04
PETUN	1.59	1.32	0.39	12.67	7.62	0.49	0.28
PINSU	3.44	3.11	1.95	8.60	1.19	1.19	0.79
PNSUT	1.72	2.26	1.31	7.69	4.29	0.91	0.41
PRKAB	1.06	1.63	0.73	14.48	7.86	0.82	0.65
SEKFK	3.84	2.72	1.31	1.36	0.48	1.03	0.47
SISE	4.76	1.17	0.39	9.05	8.33	0.46	0.61
TATGD	2.91	1.32	1.17	15.38	6.43	0.61	0.73
TAVHL	4.37	1.09	0.73	3.62	1.43	0.24	0.36
TOASO	0.66	0.23	0.34	2.26	4.52	0.21	0.12
TRCAS	4.50	2.18	0.73	6.33	5.48	0.85	0.26
TTKOM	2.38	1.01	0.73	0.45	0.71	0.64	0.08
TTRAK	2.51	2.02	0.73	0.90	4.05	0.49	0.24
TUPRS	1.19	0.39	0.39	16.29	9.05	0.06	0.20
VKGYO	4.63	2.26	1.31	10.41	4.76	1.00	0.53

Appendix 4: FUCA final score rankings for the second quarter of 2019

Alternative	Rank	Alternative	Rank	Alternative	Rank
AEFES	13	ENJSA	8	PINSU	19
AGHOL	38	ENKAI	9	PNSUT	16
AKSA	12	GARFA	33	PRKAB	30
AKSGY	20	GLYHO	39	SEKFK	7
ALARK	2	HLGYO	17	SISE	24
ARCLK	10	HURGZ	35	TATGD	34
ASELS	40	IHEVA	5	TAVHL	11
AYGAZ	28	IHLAS	27	TOASO	3
BTCIM	37	ISFIN	41	TRCAS	21
CCOLA	14	LIDFA	36	TTKOM	1
CRDFA	26	LOGO	18	TTRAK	6
DGGYO	23	MGROS	29	TUPRS	31
DOAS	4	OTKAR	32	VKGYO	25
DOHOL	15	PETUN	22		

Abbreviations

MCDA	Multiple-criteria decision-making analysis
SD	Standard deviation
RR	Rank reversal
Rho	Spearman's rank correlation coefficient
SR	Return on share
CODAS	Combinative distance-based assessment
MOORA	Multi-objective optimization on the basis of ratio analysis
TOPSIS	Technique for order preference by similarity to ideal solution
PROMETHEE II	Preference ranking organization method for enrichment of evaluations II
VIKOR	Viekriterijumsko compromisno rangiranje
ELECTRE III	Elimination Et Choix Traduisant la reality III
FUCA	Faire Un Choix Adéquat
SWARA	Step-wise weight assessment ratio analysis

Acknowledgements
Not applicable.

Author contributions
MB's tasks on the article: Conceptualization, Investigation, Methodology, Validation, Writing-Reviewing and Editing. OEE's tasks on the article: Conceptualization, Investigation, Validation, Writing-Original draft and Editing. Both authors read and approved the final manuscript. ŽS's tasks on the article Investigation, Validation and Editing.

Funding
This particular study did not receive any grant from funding agencies.

Availability of data and materials
The data used for this financial performance research can be obtained from the authors on reasonable request.

Declarations

Competing interests
Authors don't have any competing financial, professional, or personal interests from other parties.

Received: 8 November 2022 Accepted: 20 June 2023
Published online: 01 January 2024

References

Altman EI (1968) Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. J Financ 23(4):589–609. https://doi.org/10.2307/2978933

Altman EI, Hotchkiss E (2006) Corporate financial distress: predict and avoid bankruptcy, analyze and invest in distressed debt (3rd ed). Wiley (Chapter 11)

Athawale VM, Chakraborty S (2011) A comparative study on the ranking performance of some multi-criteria decision-making methods for industrial robot selection. Int J Ind Eng Comput 2(4):831–850. https://doi.org/10.5267/j.ijiec.2011.05.002
Bairagi B, Dey B, Sarkar B, Sanyal SK (2015) A De Novo multi-approaches multicriteria decision making technique with an application in performance evaluation of material handling device. Comput Ind Eng 87:267–282. https://doi.org/10.1016/j.cie.2015.05.015
Banaitienė N, Banaitis A, Kaklauskas A, Zavadskas EK (2008) Evaluating the life cycle of a building: a multivariant and multiple criteria approach. Omega: Int J Manage Sci 36(3):429–441. https://doi.org/10.1016/j.omega.2005.10.010
Baourakis G, Doumpos M, Kalogeras N, Zopounidis C (2002) Multicriteria analysis and assessment of financial viability of agribusinesses: the case of marketing co-operatives and juice-producing companies. Agribusiness: Int J 18(4):543–558. https://doi.org/10.1002/agr.10031
Barzilai J, Golany B (2017) AHP rank reversal, normalization and aggregation rules. Inf Syst Oper Res 32(2):57–64. https://doi.org/10.1080/03155986.1994.11732238
Baydaş M, Elma OE (2021) An objective criteria proposal for the comparison of MCDM and weighting methods in financial performance measurement: an application in Borsa Istanbul. Decis Mak Appl Manage Eng 4(2):257–279. https://doi.org/10.31181/dmame210402257b
Baydaş M, Pamučar D (2022) Determining objective characteristics of MCDM methods under uncertainty: an exploration study with financial data. Mathematics 10(7):1115. https://doi.org/10.3390/math10071115
Baydaş M, Elma OE, Pamučar D (2022) Exploring the specific capacity of different multi criteria decision making approaches under uncertainty using data from financial markets. Expert Syst Appl 197:116755. https://doi.org/10.1016/j.eswa.2022.116755
Baydaş M, Eren T, Stević Ž, Starčević V, Parlakkaya R (2023) Proposal for an objective binary benchmarking framework that validates each other for comparing MCDM methods through data analytics. PeerJ Comput Sci 9:e1350. https://doi.org/10.7717/peerj-cs.1350
Behzadian M, Kazemzadeh RB, Albadvi A, Aghdasi M (2010) PROMETHEE: a comprehensive literature review on methodologies and applications. Eur J Oper Res 200:198–215. https://doi.org/10.1016/j.ejor.2009.01.021
Behzadian M, Otaghsara SK, Yazdani M, Ignatius J (2012) A state-of the-art survey of TOPSIS applications. Expert Syst Appl 39(17):13051–13069. https://doi.org/10.1016/j.eswa.2012.05.056
Benitez JM, Martín JC, Román C (2007) Using fuzzy number for measuring quality of service in the hotel industry. Tour Manage 28(2):544–555. https://doi.org/10.1016/j.tourman.2006.04.018
BIST (2023) Accessed at 22/2/2023. https://borsaistanbul.com/tr/sayfa/163/kurumsal-yonetim-endeksi.
Brans JP, Vincke SH (1985) A preference ranking organization method (the PROMETHEE method for multiple criteria decision-making). Manage Sci 31(6):647–656. https://doi.org/10.1287/mnsc.31.6.647
Brans JP, Vincke P, Mareschal B (1986) How to select and how to rank projects: the PROMETHEE method. Eur J Oper Res 24(2):228–238. https://doi.org/10.1016/0377-2217(86)90044-5
Brans JP, De Smet Y (2016) PROMETHEE methods. In: Greco S, Ehrgott M, Figueira JR (eds) Multiple criteria decision analysis: state of the art surveys. Springer, Berlin
Brauers WK, Zavadskas EK (2006) The MOORA method and its application to privatization in a transition economy. Control Cybern 35(2):445–469
Brockett PL, Golden LL, Jang J, Yang C (2006) A comparison of neural network, statistical methods, and variable choice for life insurers' financial distress prediction. J Risk Insur 73(3):397–419. https://doi.org/10.1111/j.1539-6975.2006.00181.x
Buede DM, Maxwell DT (1995) Rank disagreement: a comparison of multi-criteria methodologies. J Multi-Criteria Decis Anal 4(1):1–21. https://doi.org/10.1002/mcda.4020040102
Buyukozkan G, Ruan D (2008) Evaluation of software development projects using a fuzzy multi-criteria decision approach. Math Comput Simul 77:464–475. https://doi.org/10.1016/j.matcom.2007.11.015
Camelia B, Vasile B (2009) A company performance analysis based on value creation. Metalurgia Int 14(7):180–185
Canbas S, Cabuk A, Kilic SB (2005) Prediction of commercial bank failure via multivariate statistical analysis of financial structures: the Turkish case. Eur J Oper Res 166(2):528–546. https://doi.org/10.1016/j.ejor.2004.03.023
Carton RB, Hofer CW (2006) Measuring organizational performance: Metrics for entrepreneurship and strategic management research. Edward Elgar Publishing.
Chakraborty S (2011) Applications of the MOORA method for decision making in manufacturing environment. Int J Adv Manuf Technol 54(9):1155–1166. https://doi.org/10.1007/s00170-010-2972-0
Chao X, Dong Y, Kou G, Peng Y (2021) How to determine the consensus threshold in group decision making: a method based on efficiency benchmark using benefit and cost insight. Ann Oper Res. https://doi.org/10.1007/s10479-020-03927-8
Chatterjee P, Athawale VM, Chakraborty S (2011) Materials selection using complex proportional assessment and evaluation of mixed data methods. Mater Des 32:851–860. https://doi.org/10.1016/j.matdes.2010.07.010
Chen TY (2014) A PROMETHEE-based outranking method for multiple criteria decision analysis with interval type-2 fuzzy sets. Soft Comput 18(5):923–940. https://doi.org/10.1007/s00500-013-1109-4
Chen MH, Kim WG, Chen CY (2007) An investigation of the mean reversion of hospitality stock prices towards their fundamental values: the case of Taiwan. Int J Hosp Manag 26(2):453–467. https://doi.org/10.1016/j.ijhm.2006.04.003
Dagdeviren M (2008) Decision making in equipment selection: an integrated approach with AHP and PROMETHEE. J Intell Manuf 19(4):397–406. https://doi.org/10.1007/s10845-008-0091-7
De Almeida AT, Cavalcante CAV, Alencar MH, Ferreira RJP, De Almeida-Filho AT, Garcez TV (2015) Multicriteria and multiobjective models for risk, reliability and maintenance decision analysis. Springer, New York
Diakoulaki D, Mavrotas G, Papayannakis L (1995) Determining objective weights in multiple criteria problems: the critic method. Comput Oper Res 22(7):763–770. https://doi.org/10.1016/0305-0548(94)00059-H
Dincer H, Hacioglu U, Yuksel S (2016) Managerial and market-based appraisal of agriculture banking using ANP and ELECTRE method. Manage Organ Stud 3(3):29–40. https://doi.org/10.5430/mos.v3n3p29

Ece N, Ozdemir F (2011) Halka açık finansal kiralama ve faktöring şirketlerinin performans ölçümü ve analizinde kullanılan EVA ve TOPSIS yöntemlerinin hisse senedi değerleri ile karşılaştırmalı analizi. Finans Politik Ve Ekonomik Yorumlar Dergisi 48(561):83–95
Eldrandaly K, Ahmed AH, AbdelAziz N (2009) An expert system for choosing the suitable MCDM method for solving a spatial decision problem. In: 9th International conference on production engineering, design and control, Alexandria, Egypt, pp 10–12 February 2009
Elma OE (2023) A Comparative MCDA application on the long-term performance of IPOs during the pandemic on Borsa Istanbul. J Econ Bus Polit Res 8(20):269–293. https://doi.org/10.25204/iktisad.1242437
Emamat MSMM, Mota CMDM, Mehregan MR, Sadeghi Moghadam MR, Nemery P (2022) Using ELECTRE-TRI and FlowSort methods in a stock portfolio selection context. Financ Innovat 8(1):1–35. https://doi.org/10.1186/s40854-021-00318-1
Ertugrul I, Karakasoglu N (2008) Banka şube performanslarının VIKOR yöntemi ile değerlendirilmesi. Endüstri Mühendisliği Dergisi 20(1):19–28
Fernando MML, Escobedo JLP, Azzaro-Pantel C, Pibouleau L, Domenech S, Aguilar-Lasserre A (2011) Selecting the best portfolio alternative from a hybrid Multi-objective GA-MCDM approach for new product development. In: IEEE symposium on computational intelligence in multicriteria decision-making, Paris, France, pp 11–15 April 2011.
Gallizo JL, Salvador M (2003) Understanding the behavior of financial ratios: the adjustment process. J Econ Bus 55(3):267–283. https://doi.org/10.1016/S0148-6195(03)00022-5
García-cascales MS, Lamata MT (2012) On rank reversal and TOPSIS method. Math Comput Model 56:123–132. https://doi.org/10.1016/j.mcm.2011.12.022
Ghorabaee M, Zavadskas EK, Turskis Z, Antucheviciene J (2016) A new combinative distance-based assessment (CODAS) method for multi-criteria decision-making. Econom Comput Econom Cybernet Stud Res 50:25–44
Gomes LFAM, de Mattos Fernandes JE, de Mello JCCS (2014) A fuzzy stochastic approach to the multicriteria selection of an aircraft for regional chartering. J Adv Transp 48(3):223–237. https://doi.org/10.1002/atr.206
Greco S, Figueira J, Ehrgott M (2016) Multiple criteria decision analysis, vol 37. Springer, New York
Guarini MR, Battisti F, Chiovitti A (2018) A methodology for the selection of multi-criteria decision analysis methods in real estate and land management processes. Sustainability 10(2):507. https://doi.org/10.3390/su10020507
Guitouni A, Martel JM (1998) Tentative guidelines to help choosing an appropriate MCDA method. Eur J Oper Res 109(2):501–521. https://doi.org/10.1016/S0377-2217(98)00073-3
Haddad M, Sanders D, Tewkesbury G (2020) Selecting a discrete multiple-criteria decision making method for boeing to rank four global market regions. Trans Res Part a: Policy and Pract 134:1–15. https://doi.org/10.1016/j.tra.2020.01.026
Hallerbach WG, Spronk J (2002) The relevance of MCDM for financial decisions. J Multi-Criteria Decis Anal 11(4–5):187–195. https://doi.org/10.1002/mcda.328
Hashemi SS, Hajiagha SHR, Zavadskas EK, Mahdiraji HA (2016) Multicriteria group decision making with ELECTRE III method based on interval-valued intuitionistic fuzzy information. Appl Math Model 40(2):1554–1564. https://doi.org/10.1016/j.apm.2015.08.011
Kalogeras N, Baourakis G, Zopounidis C, van Dijk G (2005) Evaluating the financial performance of agri-food firms: a multi criteria decision-aid approach. J Food Eng 70(3):365–371. https://doi.org/10.1016/j.jfoodeng.2004.01.039
Karabašević D, Paunkovic J, Stanujkić D (2016) Ranking of companies according to the indicators of corporate social responsibility based on SWARA and ARAS methods. Serbian J Manage 11(1):43–53
Kersuliene V, Turskis Z (2011) Integrated fuzzy multiple criteria decision-making model for architect selection. Technol Econ Dev Econ 17(4):645–666. https://doi.org/10.3846/20294913.2011.635718
Kersuliene V, Zavadskas EK, Turskis Z (2010) Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA). J Bus Econ Manag 11(2):243–258
Kim JJ, Ahn JH, Yun JK (2004) Economic value added (EVA) as a proxy for market value added (MVA) and accounting earnings: empirical evidence from the business cycle. J Account Finance Res 12(1):40–48
Kong F (2011) Rank reversal and rank preservation in TOPSIS. Adv Mater Res 204–210:36–41. https://doi.org/10.4028/www.scientific.net/AMR.204-210.36
Kou G, Lu Y, Peng Y, Shi Y (2012) Evaluation of classification algorithms using MCDM and rank correlation. Int J Inf Technol Decis Mak 11(01):197–225. https://doi.org/10.1142/S0219622012500095
Kou G, Olgu Akdeniz Ö, Dinçer H, Yüksel S (2021a) Fintech investments in European banks: a hybrid IT2 fuzzy multidimensional decision-making approach. Financ Innovat 7(1):39. https://doi.org/10.1186/s40854-021-00256-y
Kou G, Xu Y, Peng Y, Shen F, Chen Y, Chang K, Kou S (2021b) Bankruptcy prediction for SMEs using transactional data and two-stage multiobjective feature selection. Decis Support Syst 140:113429. https://doi.org/10.1016/j.dss.2020.113429
Kou G, Yüksel S, Dinçer H (2022) Inventive problem-solving map of innovative carbon emission strategies for solar energy-based transportation investment projects. Appl Energy 311:118680. https://doi.org/10.1016/j.apenergy.2022.118680
Kumaraswamy M, Ramaswamy R (2016) Performance evaluation of software projects using criteria importance through inter-criteria correlation technique. Int J Soft Comput Softw Eng 6(3):28–36
Li H, Sun J (2008) Ranking-order case-based reasoning for financial distress prediction. Knowl-Based Syst 21(8):868–878. https://doi.org/10.1016/j.knosys.2008.03.047
Li Y, Kou G, Li G, Peng Y (2022) Consensus reaching process in large-scale group decision making based on bounded confidence and social network. Eur J Oper Res 303(2):790–802. https://doi.org/10.1016/j.ejor.2022.03.040
Livingstone JL, Grossman T (2001) The portable MBA in finance and accounting. Wiley, New Jersey
Lootsma FA (1993) Scale sensitivity in the multiplicative AHP and SMART. J Multi-Criteria Decis Anal 2(2):87–110. https://doi.org/10.1002/mcda.4020020205
Luce RD, Raiffa H (1957) Games and decisions: Introduction and critical survey. Wiley, New York

Macharis C, Springael J, De Brucker K, Verbeke A (2004) PROMETHEE and AHP: the design of operational synergies in multicriteria analysis: Strengthening PROMETHEE with ideas of AHP. Eur J Oper Res 153:307–317. https://doi.org/10.1016/S0377-2217(03)00153-X
Madić M, Radovanović M (2015) Ranking of some most commonly used nontraditional machining processes using ROV and CRITIC methods. UPB Sci Bull Series D 77(2):193–204
Mallin C (2007) Corporate Governance, 2nd edn. Oxford University Press, Oxford
Moyer RC, McGuigan JR, Rao RP (2014) Contemporary financial management. Cengage Learning, Cincinnati
Mufazzal S, Muzakkir SM (2018) A new multi-criterion decision making (MCDM) method based on proximity indexed value for minimizing rank reversals. Comput Ind Eng 119:427–438. https://doi.org/10.1016/j.cie.2018.03.045
Omurbek N, Mercan Y (2014) İmalat alt sektörlerinin finansal performanslarının TOPSIS ve ELECTRE yöntemleri ile değerlendirilmesi. Çankırı Karatekin Üniversitesi İktisadi Ve İdari Bilimler Fakültesi Dergisi 4(1):237–266
Opricovic S (1998) Multicriteria optimization of civil engineering systems. Faculty Civ Eng Belgrade 2(1):5–21
Opricovic S, Tzeng GH (2004) Compromise solution by MCDM methods: a comparative analysis of VIKOR and TOPSIS. Eur J Oper Res 156(2):445–455. https://doi.org/10.1016/S0377-2217(03)00020-1
Opricovic S, Tzeng GH (2007) Extended VIKOR method in comparison with outranking methods. Eur J Oper Res 178(2):514–529. https://doi.org/10.1016/j.ejor.2006.01.020
Pamučar D, Stević Ž, Sremac S (2018) A new model for determining weight coefficients of criteria in MCDM models: full consistency method (FUCOM). Symmetry 10(9):393. https://doi.org/10.3390/sym10090393
Penpece D, Elma OE (2014) Predicting sales revenue by using artificial neural network in grocery retailing industry: a case study in Turkey. Int J Trade Econ Financ 5(5):435. https://doi.org/10.7763/IJTEF.2014.V5.411
Pohekar SD, Ramachandran M (2004) Application of multi criteria decision making to sustainable energy planning: a review. Renew Sustain Energy Rev 8:365–381. https://doi.org/10.1016/j.rser.2003.12.007
Rao MP (2000) A simple method to link productivity to profitability. Manag Account Q 1(4):12–17
Rashid T, Beg I, Husnine SM (2014) Robot selection by using generalized interval-valued fuzzy numbers with TOPSIS. Appl Soft Comput 21:462–468. https://doi.org/10.1016/j.asoc.2014.04.002
Roy B (1968) Classement et choix en présence de points de vue multiples (la méthode ELECTRE). La Revue D'informatique Et De Recherche Opérationelle 8:57–75
Saaty TL, Sagir M (2009) An essay on rank preservation and reversal. Math Comput Model 49:1230–1243. https://doi.org/10.1016/j.mcm.2008.08.001
Sałabun W (2015) The characteristic objects method: a new distance-based approach to multicriteria decision-making problems. J Multi-Criteria Decis Anal 22(1–2):37–50. https://doi.org/10.1002/mcda.1525
Salamai A (2021) An integrated neutrosophic SWARA and VIKOR method for ranking risks of green supply chain. Neutrosophic Sets and Systems 41:113–126
Sandoval E (2001) Financial performance measures and shareholder value creation: an empirical study for Chilean companies. J Appl Bus Res 17(3):109–122. https://doi.org/10.19030/jabr.v17i3.2239
Shil NC (2009) Performance measures: an application of economic value added. Int J Bus Manage 4(3):169–177
Siew LW, Fai LK, Hoe LW (2017) Evaluation on the financial performance of the Malaysian banks with TOPSIS model. Am J Serv Sci Manage 4(2):11–16
SPK (2023). Accessed at 22/2/2023. https://spk.gov.tr/kurumlar/derecelendirme-kuruluslari/tanitim-rehberi.
Stanujkic D, Djordjevic B, Djordjevic M (2013) Comparative analysis of some prominent MCDM methods: a case of ranking Serbian banks. Serbian J Manage 8(2):213–241. https://doi.org/10.5937/sjm8-3774
Stević Ž, Das DK, Tešić R, Vidas M, Vojinović D (2022) Objective criticism and negative conclusions on using the fuzzy SWARA method in multi-criteria decision making. Mathematics 10(4):635
Stewart B (2013) Best-Practice EVA: The definitive guide to measuring and maximizing shareholder value, 1st edn. Wiley, New Jersey
Tan M, Ayhan E, Baydaş M (2016) Sustainability and cleaner production: case of textile and clothing sectors in Bingöl. J MacroTrends Energy Sustain 4(1):22–33
Tavana M (2021) Decision analytics in the world of big data and colorful choices. Decis Anal J 1:100002
Triantaphyllou E (2001) Two new cases of rank reversals when the AHP and some of its additive variants are used that do not occur with the multiplicative AHP. J Multi-Criteria Decis Anal 10(1):11–25. https://doi.org/10.1002/mcda.284
Triantaphyllou, E (2000) Multi-criteria decision-making methods. In: Multi-criteria decision making methods: a comparative study. Applied Optimization, vol 44. Springer, Boston. Doi:https://doi.org/10.1007/978-1-4757-3157-6_2
Uygunturk H, Korkmaz T (2012) Finansal performansın TOPSIS çok kriterli karar verme yöntemi ile belirlenmesi: ana metal sanayi işletmeleri üzerine bir uygulama. Eskişehir Osmangazi Üniversitesi İİBF Dergisi 7(2):95–115
Verly C, De Smet Y (2013) Some results about rank reversal instances in the PROMETHEE methods. Int J Multicriteria Decis Mak 3(4):325–345
Wang YM, Elhag TM (2006) Fuzzy TOPSIS method based on alpha level sets with an application to bridge risk assessment. Expert Syst Appl 31(2):309–319. https://doi.org/10.1016/j.eswa.2005.09.040
Wang Y, Luo Y (2009) On rank reversal in decision analysis. Math Comput Model 49:1221–1229. https://doi.org/10.1016/j.mcm.2008.06.019
Wang Z, Rangaiah GP (2017) Application and analysis of methods for selecting an optimal solution from the Pareto-Optimal front obtained by Multi-Objective Optimization. Ind Eng Chem Res 56:560–574. https://doi.org/10.1021/acs.iecr.6b03453
Wang X, Triantaphyllou E (2008) Ranking irregularities when evaluating alternatives by using some ELECTRE methods. Omega 36:45–63. https://doi.org/10.1016/j.omega.2005.12.003
Wang Z, Parhi SS, Rangaiah GP, Jana AK (2020) Analysis of weighting and selection methods for Pareto-Optimal solutions of multi-objective optimization in chemical engineering applications. Ind Eng Chem Res 59(33):14850–14867. https://doi.org/10.1021/acs.iecr.0c00969
Wątróbski J, Jankowski J, Ziemba P, Karczmarczyk A, Zioło M (2019) Generalized framework for multi-criteria method selection: rule set database and exemplary decision support system implementation blueprints. Data Brief 22:639–642. https://doi.org/10.1016/j.dib.2018.12.015

West RC (1985) A factor-analytic approach to bank condition. J Bank Finance 9(2):253–266. https://doi.org/10.1016/0378-4266(85)90021-4
Wu CR, Lin CT, Tsai PH (2010) Evaluating business performance of wealth management banks. Eur J Oper Res 207(2):971–979. https://doi.org/10.1016/j.ejor.2010.04.034
Xiao H, Zhang Y, Kou G, Zhang S, Branke J (2023) Ranking and selection for pairwise comparison. Naval Research Logistics (NRL). https://doi.org/10.1002/nav.22093
Xu YJ, Da QL (2008) Standard deviation method for determining the weights of group Multiple Attribute Decision Making under uncertain linguistic environment. In: World congress on intelligent control and automation, Chongqing, China, 25–27 June 2008.
Yalcin N, Unlu U (2018) A multi-criteria performance analysis of Initial Public Offering (IPO) firms using CRITIC and VIKOR methods. Technol Econ Dev Econ 24(2):534–560. https://doi.org/10.3846/20294913.2016.1213201
Yucel MG, Gorener A (2016) Decision making for company acquisition by ELECTRE method. Int J Supply Chain Manage 5(1):75–83
Yuksel S, Dincer H, Emir Ş (2017) Comparing the performance of Turkish deposit banks by using DEMATEL, grey relational analysis (GRA) and MOORA approaches. World J Appl Econ 3(2):26–47
Yurdakul M, Ic YT (2003) An illustrative study aimed to measure and rank performance of Turkish automotive companies using TOPSIS. J Faculty Eng Archit Gazi Univ 18(1):1–18
Zaidan BB, Zaidan AA, Abdul Karim H, Ahmad NN (2017) A new approach based on multi-dimensional evaluation and benchmarking for data hiding techniques. Int J Inf Technol Decis Mak. https://doi.org/10.1142/S0219622017500183
Zavadskas EK, Turskis Z (2011) Multiple criteria decision making (MCDM) methods in economics: an overview. Technol Econ Dev Econ 17(2):397–427. https://doi.org/10.3846/20294913.2011.593291
Zavadskas EK, Kaklauskas A, Sarka V (1994) The new method of multicriteria complex proportional assessment of projects. Technol Econ Dev Econ 1(3):131–139
Zavadskas EK, Kaklauskas A, Peldschus F, Turskis Z (2007) Multi-attribute assessment of road design solutions by using the COPRAS method. Baltic J Road Bridge Eng 2(4):195–203
Zimmermann HJ (2001) Fuzzy set theory—and its applications. Springer Science & Business Media: New York
Zolfani SH, Zavadskas EK, Turskis Z (2013) Design of products with both international and local perspectives based on Yin-Yang balance theory and SWARA method. Econ Res 26(2):153–166. https://doi.org/10.1080/1331677X.2013.11517613

Publisher's Note