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Stock Market Performance Evaluation of Listed Food and Beverage Companies in Istanbul Stock Exchange with MCDM Methods

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ABSTRACT

The analysis of the stock market performance ratios is crucial for investors and fund managers. The food and beverage industry in Turkey is the largest sector in the Istanbul Stock Exchange (ISE). It contributes over half of the country's GDP and is a highly attractive sector. This study aims to rank the top food and beverage companies based on their stock market performance ratios. The criteria weights were determined by using DEMATEL and CRITIC methods, with the help of three experts for DEMATEL. The stock market performances of the companies were evaluated by using three MCDM methods; EDAS, WASPAS, and TOPSIS, with the weights obtained from both DEMATEL and CRITIC. The robustness of the results was tested by applying various combinations of weighting and evaluation methods. According to the DEMATEL, earnings per share had the highest weight while CRITIC found the market value to book value ratio as the most important criterion. The study concluded that the best-ranked companies are CCOLA and TBORG. Also, there is no significant stability in other companies' rankings. To reveal which methods produced similar rankings, Spearman's Rank Correlation analysis was conducted: while WASPAS combinations produced similar rankings, all EDAS and TOPSIS combinations gave similar findings.

1. Introduction

The food and beverage sector is a crucial part of the Turkish economy since it contributes over 20% of the country's Gross Domestic Product (GDP) [1]. Thus, investors and fund managers need to evaluate the stock market performance of food and beverage companies when making investment decisions [2]. This study aims to help these individuals select the best companies for their investment portfolios by conducting a financial ratio analysis of Turkish food and beverage companies listed on the Istanbul Stock Exchange (ISE).

The background motivation of this study is that the ratios we have selected as our evaluation criteria are not sufficient for making an investment decision without involving any judgment. These

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ratios should be considered, with each one holding varying levels of importance in the process of measuring the stock performance of companies. In this process, we assess companies' performance for each evaluation criterion using MCDM methods to ensure that each criterion contributes to the overall evaluation results.

The comprehensive methodology used in this study effectively justifies the use of many approaches, each adapted to specific goals and contributing to a thorough evaluation of stock market performance in the food and beverage industry. The strategic use of Multi-Criteria Decision Making (MCDM) approaches demonstrates an awareness of the sector's complexities, allowing for the simultaneous evaluation of several stock performance indicators [3]. EDAS technique quantifies the stock market performance of firms by accounting for both positive and negative deviations from the average solution [4]. This technique ensures a thorough picture of performance variations, which aligns with the purpose of gaining a full view of corporate standings. WASPAS approach improves the analysis even further by tolerating different levels of relevance among financial ratios, assuring appropriate criterion weighting that accurately reflects their actual value. Simultaneously, TOPSIS technique simplifies company comparison and ranking based on stock performance metrics, providing significant insights into their relative positions [5].

Recognizing the critical importance of precise criteria weighing, the study applies the DEMATEL and CRITIC approaches. The inclusion of DEMATEL is due to its capacity to solve criterion weighting complexities while accounting for linked stock performance indicators. The DEMATEL technique, which involves academic experts, adds a subjective layer to criterion evaluation by capturing subtle links between features. Furthermore, DEMATEL reveals not only the subjective weights of criteria but also the influences between qualities, resulting in a holistic evaluation [6]. CRITIC's objective method incorporated internal standard deviations and correlation coefficients for a robust weighting process. The selection of these methodologies collectively enables a thorough evaluation of stock market performance, tailored to the complexities and specificities of the food and beverage sector [7].

To the best of our knowledge, this paper is the first portfolio selection study that uses both objective and subjective MCDM techniques for the criteria weighting in combination with other suitable MCDM methods for evaluating the performance of each alternative. The study considers 27 food and beverage companies listed on ISE. The financial ratio analysis is based on their annual financial reports for the fiscal year 2021, obtained from Yahoo Finance. The ultimate goals are to rank the companies based on their stock market performance indicator ratios and provide investors and fund managers with the information they need to make informed investment decisions for their financial portfolios. The robustness analysis was performed by comparing the final rankings of alternatives found by 6 combinations: DEMATEL-EDAS, CRITIC-EDAS, DEMATEL-WASPAS, CRITIC-WASPAS, DEMATEL-TOPSIS, CRITIC-TOPSIS.

The main purpose of this study is to recommend high-performing stocks in the Turkish food and beverage sector for individual investors and fund managers to consider including in their investment portfolios. Our secondary goal is to identify underperforming stocks for exclusion. The robustness tests that are conducted by using various MCDM techniques for alternative evaluations suggest that the results of this study are only valid for the top-ranked company and the second-ranked company.

The paper is structured as follows. Chapter 2 provides a literature review of the study. Methods are studied with mathematical details. Recent articles including financial MCDM analysis are discussed. Chapter 3 gives all the analysis results with explanatory tables and figures. The companies and criteria considered are explained first. Then, each of the method applications is explained. Chapter 4 presents a discussion of the findings. First, the difference between the criteria rankings produced by DEMATEL and CRITIC was studied. Then, Spearman's Rank Correlation analysis is detailed in order to show the differences and similarities between alternative rankings obtained by different MCDM combinations. Chapter 5 concludes the study with a general overview of the paper and future research suggestions.

2. Literature Review

MCDM presents a crucial and practical technique perspective in the Operations Research (OR) field that is used to improve managerial decision-making activities in a wide range of disciplines such as business, government, and many fields of engineering. While making a choice, decision-makers can use MCDM to examine multiple strategies, options, and alternatives with respect to multiple criteria. This is especially beneficial when decision-makers must assess trade-offs between competing objectives and criteria [8].

Hwang and Yoon (1981) pictured the field of managerial decision-making and classified MCDM techniques into two categories which are based on the nature of the decision space and the available alternatives:

- MODM (Multiple Objective Decision Making) focuses on decision issues with a continuous decision space. This means that decision-makers can select any value within a specific range to meet their conflicting objectives.
- MADM (Multiple Attribute Decision Making) is used when there is a discrete decision space presenting a set of prespecified options. In other words, decision-makers are restricted to selecting from a predefined range of alternatives [9].

To summarize, MCDM is a strong tool that allows decision-makers to take into account many alternatives and criteria while making decisions. MODM and MADM, the two primary categories of MCDM methods, offer distinct perspectives on different decision issues. There are various MADM strategies, each with its own set of strengths and flaws, that may be utilized to assist in making educated judgments.

With this study, our contribution to the field is the application of MADM methodologies to help managers create a more informed and sophisticated investment portfolio. The focus of this study is on the food and beverage industry, and the goal is to rank the companies based on their stock market performance. To do this, we used EDAS, TOPSIS, and WASPAS which evaluate the companies' overall stock performance by combining the importance weights determined through DEMATEL and CRITIC. One advantage of the MCDM methodologies applied in this study is the option of negative (exclusionary) portfolio screening, which refers to the exclusion of the worst-performing stocks from the investment portfolio. This approach can provide managers with a more accurate and nuanced understanding of the food and beverage industry's performance and help them make more improved and informed decisions about their investment portfolios. The results of this study can contribute to the advancement of financial decision-making science and inform future research in this field.

2.1 DEMATEL

The Decision-Making Trial and Evaluation Laboratory (DEMATEL) approach which was developed by the Science and Human Affairs Program of the Battelle Memorial Institute of Geneva, is a powerful tool for addressing complex and interconnected problems [10]. The goal of the approach is to examine the interdependent relationships between different components and identify the key factors that influence the decision-making process. To achieve this, DEMATEL creates a visual structural model that represents the interrelationships between the components and allows for a better understanding of the problem. This method is particularly useful for situations where multiple factors are interdependent and affect the outcome of the decision-making process. The DEMATEL approach has proven to be an effective tool for analyzing and solving complex and interrelated problems in various fields. Battal [11] analyzed the financial problems of the Turkish airline industry with DEMATEL. Yalnız and Candan [12] assessed the factors influencing the investment decision analysis under uncertainty by using DEMATEL on a dataset collected from 10 financial experts in Turkey. Ersin *et al*. [13] used DEMATEL to evaluate the investment criteria considered by municipalities in Turkey. [14] aimed to reveal the relationship between risk factors (variables) that make up the financial markets and included sixteen risk factors identified for this purpose.

DEMATEL is employed to examine and solve complex and entangled problems by confirming interdependence among components and assisting in the building of a map to depict relative relationships among them. The algorithm of DEMATEL is as follows [15]:

Step 1: Generate the group direct influence matrix Z:

Before creating the matrix, assume that *l* experts in a decision group are asked to assess the direct effect of factor F_i on factor F_j on an integer scale of "no influence (0)", "low influence (1)", "medium influence (2)", "high influence (3)", and "very high influence (4)". Then, the individual direct influence matrix $Z_k = \left[\, z_{ij}^k \right]_{n*n}$ is provided by the k^{th} expert where all principal diagonal elements are equal to zero and z_{ij}^k represents the judgment of decision-maker E_k on the degree to which factor F_i affects factor F_j. The $Z = \left[\, z_{ij} \right]_{n*n}$ matrix is created by averaging the same factors in each of those matrices.

$$z_{ij} = \frac{1}{l}\sum_{k=1}^{l} z_{ij}^k \qquad i,j = 1,2,\dots,n. \tag{1}$$

Step 2: Establish the normalized direct influence matrix *X*:

After obtaining the group direct influence matrix $Z = \left[\, z_{ij} \right]_{n*n}$ and by using Eq. (2.2), the normalization process is achieved.

$$X = \frac{Z}{s} \quad \text{where} \quad s = \max\left(\max_{1 \le i \le n} \sum_{i=1}^{n} z_{ij} \ , \max_{1 \le j \le n} \sum_{i=1}^{n} z_{ij} \right) \tag{2}$$

Step 3: Construct the total influence matrix T:

The total influence matrix $T = \left[\, t_{ij} \right]_{n*n}$ is produced by adding the direct and all the indirect effects of *X*.

$$T = X + X^2 + X^3 + \cdots + X^h = X(I - X)^{-1} \quad \text{when} \quad h \to \infty \tag{3}$$

and *I* represent the identity matrix.

Step 4: Produce the influential relation map (IRM):

First, *R* and *C* parameters indicating the total sum of the rows and columns of T are determined through the Eqs. (4-5):

$$R = \left[r_i\right]_{n\times 1} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} \tag{4}$$

$$C = \left[c_j\right]_{1\times n} = \left[\sum_{i=1}^{n} t_{ij}\right]^{T}_{1\times n} \tag{5}$$

We calculate Prominence value (*R*+*C*) denoting the degree to which the factor is essential to the system, and Relation value (*R*-*C*) showing the net influence that the factor has on the system.

- If (r_j-c_j) > 0, the factor F_j has a net influence on the other factors and is classified into the "cause" group.
- If (r_j-c_j) < 0, the factor F_j is influenced by the other factors and is classified into the "effect" group.

In the IRM, while Prominence values are shown on the *x*-axis, Relation values are presented on the *y*-axis. Then, all attributes are placed according to their Prominence and Relation values on IRM. Additionally, significant influences can be drawn as directed arrows. In order to obtain which influences are significant, a threshold (θ) should be applied to *T*. The influences having this condition are classified as a significant one: $t_{ij} > \theta$. In the literature, there are some methods proposed for determining θ. The average of all elements in *T* is selected in this study.

Step 5: Calculate the weights of each criterion:

One of the objectives of this study is to compute the subjective weights of criteria:

$$w_i = \frac{r_{i+}c_i}{\sum_{i=1}^{n} r_{i+}c_i} \tag{6}$$

2.2 CRITIC

Criteria Importance Through Intercriteria Correlation (CRITIC) method was developed by Diakoulaki *et al* [16]. and it aims to determine the objective weights of criteria in an MCDM problem. This method focuses on computing the correlation between the various criteria involved in a decision-making process, taking into consideration both direct and indirect relationships between the criteria, and determining their relative importance in the process. The CRITIC is useful for situations where the criteria considered are complex and interrelated, and it helps to achieve a more comprehensive and objective evaluation of a decision's elements. Bayram [17] evaluated the criteria importance of financial performance indicators of Turkish participation banks for 2016-2019. [18] assessed the importance weights of the factors of the Global Talent Competitiveness Index 2021 for G20 countries. Doğan [19] analyzed the macroeconomic performance of Türkiye for the years 2010-2020. Pala [20] built a CRITIC-based financial MCDM method for the ISE insurance index.

CRITIC approach for allocating objective weights to criteria is explained below [16]:

Step 1: Generate the decision matrix:

To begin, a decision matrix is built utilizing information about the available alternatives: $R = [r_{ij}]_{m*n}$ where $i = 1, \dots, m\,; j = 1, \dots, n$ and r_{ij} is the element of the decision matrix for i^{th} alternative with respect to j^{th} attribute.

Step 2: Compute normalized decision matrix:

For benefit attributes:

$$x_{ij} = \frac{r_{ij} - r_j^-}{r_j^+ - r_j^-} \qquad i = 1,2, \dots, m\,;\; j = 1,2, \dots, n \tag{7}$$

and for the cost ones:

$$x_{ij} = \frac{r_{ij} - r_j^+}{r_j^- - r_j^+} \qquad i = 1,2, \dots, m\,;\; j = 1,2, \dots, n \tag{8}$$

where x_{ij} represents the normalized values, $r_j^+ = \max_j(r_{1j}, r_{2j}, \dots, r_{mj})$, $r_i^- = \min_j(r_{1j}, r_{2j}, \dots, r_{mj})$.

Step 3: Calculate the correlation coefficients between attribute pairs:

$$\rho_{ij} = \frac{\sum_{i=1}^{m}(x_{ij} - \underline{x_j})(x_{ik} - \underline{x_k})}{\sqrt{\sum_{i=1}^{m}\left(x_{ij} - \underline{x_j}\right)^2 \sum_{i=1}^{m}\left(x_{ik} - \underline{x_k}\right)^2}} \tag{9}$$

where $\underline{x_j}$ and $\underline{x_k}$ are the means of j^{th} and k^{th} attributes:

Step 4: Compute the standard deviations:

$$\sigma_j = \sqrt{\frac{1}{n-1} \sum_{j=1}^{n}\left(x_{ij} - \underline{x_j}\right)^2} \quad ; \ i = 1,2, \dots, m \tag{10}$$

Step 5: Obtain the index C_j:

$$C_j = \sigma_j \sum_{k=1}^{n}(1 - \rho_{ik}) \quad ; \quad j = 1,2, \dots, n \tag{11}$$

Step 6: Reveal the weights of attributes:

$$W_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{12}$$

2.3 EDAS

Ghorabaee *et al*. [21] introduced the Evaluation Based on Difference from Average Solution (EDAS) approach. This method is particularly effective in scenarios where there are conflicting features, and it determines the best option by measuring the distance of each alternative from an average value. EDAS bases its alternative ranking on a distance measure from the average. Unlike other commonly used distance based MCDM methods such as VIKOR and TOPSIS, it does not require any complex calculation of positive and negative ideal solutions. This feature makes it a more streamlined option for decision-making in complex scenarios [8].

EDAS approach is grounded in the philosophy of measuring the difference between the average solution and each alternative through geometric calculation. To determine this distance, two measures, namely PDA (positive distance from average) and NDA (negative distance from average), are employed to evaluate the alternative's desirability. The benefit or cost nature of the criteria is used to quantify these distances, with higher PDA and/or lower NDA values for an alternative signifying its superiority over the average solution.

The EDAS approach has been utilized in various areas. Koşaroğlu [22] utilized EDAS to evaluate the performances of the banks that are listed in ISE. Öndeş and Özkan [23] evaluated the effects of the Covid-19 outbreak on the financial performance of IT companies via a CRITIC-EDAS hybrid method. Özdemir and Parmaksız [24] used EDAS to analyze the performances of the energy companies listed in ISE. Çakalı [25] assessed the performance of deposit banks with financial ratios by conducting an EDAS application.

The following steps outline the procedural phases of EDAS [21].

Step 1: Choose the most relevant criteria, which describe decision alternatives for specific decision problems.

Step 2: Construct the decision matrix of $X = [x_{ij}]_{n*m}$ where x_{ij} signifies the *i^th^* alternative's performance value on the *j^th^* criteria.

Step 3: Calculate the average solution based on all the criteria:

$$AV_j = \frac{\sum_{i=1}^{n} x_{ij}}{n} \tag{13}$$

Step 4: Calculate the PDA and NDA values based on the criteria (benefit and cost) stated below.

- Benefit criteria:

$$PDA_{ij} = \frac{max(\,0,(x_{ij} - AV_j))}{AV_j} \tag{14}$$

$$NDA_{ij} = \frac{max(\,0,(AV_j - x_{ij}))}{AV_j} \tag{15}$$

- Cost criteria:

$$PDA_{ij} = \frac{max(\,0,(AV_j - x_{ij}))}{AV_j} \tag{16}$$

$$NDA_{ij} = \frac{max(\,0,(x_{ij} - AV_j))}{AV_j} \tag{17}$$

Step 5: Determine the weighted sum of PDA and NDA for all alternatives:

$$SP_i = \sum_{j=1}^{m} w_j \, PDA_{ij} \tag{18}$$

$$SN_i = \sum_{j=1}^{m} w_j \, NDA_{ij} \tag{19}$$

where w_j is the weight of the j^{th} criterion.

Step 6: Normalize the SP and SN values for all alternatives:

$$NSP_i = \frac{SP_i}{Max_i(SP_i)} \tag{20}$$

$$NSN_i = 1 - \frac{SN_i}{Max_i(SN_i)} \tag{21}$$

Step 7: Calculate the appraisal score (AS) for each alternative:

$$AS_i = \frac{1}{2}\,(NSP_i + NSN_i) \tag{22}$$

Step 8: Rank the alternatives in decreasing order of ASs. The alternative with the greatest AS is the best decision.

2.4 TOPSIS

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach is a widely used method in decision-making problems. It was first introduced by Hwang and Yoon (1981). The objective of this approach is to rank alternatives based on their similarity to ideal solutions representing the best and worst solutions from all perspectives. The ideal solution is a theoretical concept that does not exist in reality, but it can be approached [26]. In TOPSIS, the best alternative is determined by measuring the Euclidean distance between each alternative and the positive ideal solution as well as the negative ideal solution. The alternative with the shortest distance from the positive ideal and the farthest distance from the negative ideal solution is considered the best alternative [27]. The literature on TOPSIS is very fruitful. Yamaltdinova [28] evaluated the Kyrgyzstan banks' financial performances by TOPSIS. Alsu *et al.* [29] analyzed the financial performances of international participation banks via TOPSIS. Bilice [30] integrated TOPSIS with ratio analysis and analyzed the financial performance of Tourism companies. Gül [31] enriched TOPSIS with an entropy-weighting method for analyzing the performance evaluations of Turkish banks. Paksoy and Dawai [32] used classical and fuzzy versions of TOPSIS to assess Sudan's macroeconomic performance.

TOPSIS process is summarized in a stepwise manner as follows (Hwang and Yoon, 1981):

Step 1: Construct the decision matrix of $X = \left[x_{ij}\right]_{n*m}$ where x_{ij} signifies the *i^th^* alternative's performance value on the *j^th^* criteria.

Step 2: The normalized decision matrix $R = \left[r_{ij}\right]_{n*m}$ is obtained by using Euclidean-type normalization:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{23}$$

Step 3: The weighted normalized decision matrix is obtained by multiplying the weights of the attributes and normalized performance values: $V = \left[v_{ij}\right]_{n*m}$ where

$$v_{ij} = w_j r_{ij} \tag{24}$$

Step 4: Determine the positive and negative ideal solutions where A^* shows the positive ideal solution and A^- represent the negative ideal solution.

$$A^* = \left\{(\max_{i} v_{ij} \mid j \in J), (\min_{i} v_{ij} \mid j \in J') \ \mid i = 1,2, \dots, m\right\} \tag{25}$$

$$A^- = \left\{(\min_{i} v_{ij} \mid j \in J), (\max_{i} v_{ij} \mid j \in J') \ \mid i = 1,2, \dots, m\right\} \tag{26}$$

where J is the set of benefit-type attributes and J' is the set of cost-type attributes.

Step 5: Calculate the separation measures: The separation of each alternative from the positive and negative ideal solutions is calculated by the dimensional Euclidean distance.

$$S_i^* = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_i^*\right)^2} \ , \ i = 1,2, \dots, m \tag{27}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_i^-\right)^2} \ , \ i = 1,2, \dots, m \tag{28}$$

Step 6: Calculate the relative closeness to the ideal solution:

$$C_i^* = \frac{S_i^-}{(S_i^* + S_i^-)} \ , \ 0 < C_i^* < 1 \ , \ i = 1,2, \dots, m \tag{29}$$

Step 7: Rank the alternatives in preference order:
The larger the C_i^* value, the better the performance of the alternatives.

2.5 WASPAS

The Weighted Aggregated Sum Product Assessment (WASPAS) method proposed by [33], is an MCDM method aimed at solving different decision-making problems [34]. It is a combination of two well-known MCDM methods, namely the Weighted Sum Model (WSM) and the Weighted Product Model (WPM). The literature on WASPAS involves many financial applications. Eş and Kök [35] analyzed the financial performances of Turkish banks via WASPAS for the period 2015-2019. Terzioğlu *et al*. [36] utilized SWARA-weighted WASPAS for financial performance analysis of BIST100 – Energy Sector. Ural *et al*. [37] compared the financial performances of Turkish state banks for the period 2012-2016. Rençber and Avcı [38] compared the ISE-listed companies according to their capital adequacy values.

WASPAS starts with normalizing the elements of the decision matrix linearly, which involves transforming the criteria values into a common scale for comparison purposes. This is achieved through the use of the following mathematical equations and ensures that the relative importance (weight) of each criterion is taken into consideration [33].

For beneficial criteria:

$$\bar{x}_{ij} = \frac{x_{ij}}{max_j\, x_{ij}} \tag{30}$$

For cost criteria:

$$\bar{x}_{ij} = \frac{min_j\, x_{ij}}{x_{ij}} \tag{31}$$

where $\bar{x}_{ij}$ is the normalized value of x_{ij}.

Once the normalization is complete, the next step is to perform two approaches, WSM and WPM.

For WSM, the total relative importance of *i^th^* alternative is calculated as follows:

$$Q_i^{(1)} = \sum_{j=1}^{n} \bar{x}_{ij}\, w_j \tag{32}$$

where w_j is the weight j^{th} criterion.

On the other hand, according to WPM, the total relative importance of i^{th} alternative is calculated using the following expression:

$$Q_i^{(2)} = \prod_{j=1}^{n} (\bar{x}_{ij})^{w_j} \tag{33}$$

The alternatives can be ranked based on the weighted scores of WSM and WPM separately, and the one with the highest score is selected as the best alternative. WASPAS integrated $Q_i^{(1)}$ and $Q_i^{(2)}$ values with a parameter. This integration process results in a weighted score for each alternative that provides a comprehensive assessment of its strengths and weaknesses compared to the other alternatives.

To rank the alternatives, the overall importance of each alternative Q_i is calculated as follows:

$$Q_i = \lambda Q_i^{(1)} + (1-\lambda) Q_i^{(2)} \tag{34}$$

where $\lambda \in [0,1]$.

2.6 MCDM Applications

The use of MCDM techniques has received considerable attention from academic and professional groups in various commercial and financial contexts due to the diversity and complexity of judgments involved. Within the field of operations research, value-based and outranking relation methodologies have been recognized as effective tools for decision analysts to make accurate predictions and consistent evaluations of financial decision-making challenges. These methodologies are applied to analyze a wide range of financial indicators, such as stock market performance, portfolio optimization, and credit risk management [39].

The articles selected are presented in detail below. For a more comprehensive literature review, please refer to Table 1. The general findings derived from this extensive literature review are summarized after Table 1.

- Bağcı and Yerdelen Kaygın [40] evaluated the financial performance of all types of enterprises, ranging from small startups to large corporations listed in ISE. The evaluation of performance was conducted using ARAS and WASPAS.
- Evaluating the financial performance of companies, especially for those that have just gone public through an initial public offering (IPO), can be a challenging task due to the presence of uncertain information, incomplete data, and conflicting criteria. To tackle this issue, Kumaran [41] employs MCDM techniques, specifically the CRITIC for objective weights and the VIKOR for ranking the alternatives. The study focuses on IPO firms listed in the Saudi Stock Market, with the aim of helping investors identify top-performing firms and facilitating the decision-making process by allowing for comparisons among firms.
- Cerneviciene and Kabasinskas [42] discussed the utilization of MCDM methods in addressing different financial challenges such as credit score and failure prediction, portfolio management, company performance evaluation, investment appraisal, and fund selection for asset investment. MCDM methods have significant benefits in the financial decision-making process, including the capability to structure complex evaluation tasks, the consideration of both quantitative and qualitative criteria in analysis, the promotion of transparency in evaluations, and the provision of improved, practical, and universal academic methods for financial decision-making.
- Baydaş and Elma [43] examined the use of different MCDM techniques over a 5-year period, using share price data from 131 manufacturing companies listed on the ISE (2014-2018). One of the challenges in this sector is to identify the most effective MCDM and weighting technique to measure financial success. To address this challenge, the study employs the WSA, TOPSIS, and PROMETHEE methodologies.
- Shen and Tzeng [44] proposed a new method for exploring the intricate connections between crucial financial indicators and enhancing business prospects. The technique merges the VC-DRSA method with DEMATEL and employs a fuzzy inference system to assess the results. The efficiency of this method was demonstrated through a real-world case study with IT companies listed on the Taiwan stock market. The results generated a collection of decision-making rules that can be used to forecast future performance and comprehend the influence of vital variables on business prospects.
- Saini and Khanduja [45] assessed the performance of banks during the 2017-2018 fiscal year through the use of an MCDM model. The Reserve Bank of India selected 14 banks for evaluation based on a financial benchmarking set. The study utilized AHP and TOPSIS methodologies. The results help identify any weak areas and aid in the planning of more effective actions to improve performance.
- In the study of Özçalıcı *et al*. [46], the long-term financial performance of ten publicly traded deposit banks in Turkey was evaluated using an MCDM framework. The researchers considered various stock market indicators while assessing the banks' performance. They created performance metrics by calculating the average of chosen financial ratios for the period of

2014-2018. The weights of the criteria were determined through BWM, and five MCDM methods were employed for the evaluation, including ARAS, EDAS, MOORA, OCRA, and TOPSIS.

- Yıldırım and Meydan [47] aimed to evaluate the financial performance of seven publicly traded companies in the retail sector listed in ISE for 2017-2019 using the intuitionistic fuzzy EDAS (IF-EDAS) method and ten commonly used financial ratios.
- Unvan [48] conducted a study examining the financial performance of the seven largest banks in Turkey with regard to total assets from 2014 to 2018. The performance was evaluated using the TOPSIS and Fuzzy TOPSIS methodologies. Several financial ratios, reflecting various aspects of a bank's financial health, such as assets, liquidity, profitability, and income/expense, were selected as criteria for the evaluation.
- In the study of No *et al*. [49], the performance of 51 branches of the Iranian bank Keshavarzi was analyzed and ranked. The CAMEL methodology, a commonly used method for evaluating banking institutions, was used to select the criteria for performance evaluation. The criteria weights were assigned through a combination of expert opinions and Shannon's entropy. The authors proposed a modification to the traditional EDAS approach because the data used in the study was of interval type. The proposed method was compared with the interval TOPSIS method, which produced similar results.

Table 1 gives a thorough review of the approaches employed in various research publications to assess financial performance and stock selection. While there are commonalities in the approaches utilized, such as AHP, TOPSIS, and PROMETHEE, there are also differences in the combination and use of these methodologies. Some studies compare various MCDM methodologies, such as ARAS, WASPAS, and PROMETHEE, to analyze financial performance in the manufacturing sector over time. Others use specialized approaches such as VC-DRSA and DEMATEL to examine the relationships between financial indicators and company prospects in certain industries, such as Taiwan-listed IT businesses. Several studies integrated fuzzy logic with methodologies such as fuzzy AHP, fuzzy VIKOR, fuzzy ARAS, and fuzzy COPRAS to assess the financial performance of automobile businesses, banks, and food and beverage index companies. When comparing different MCDM strategies, it is common to evaluate the methods' performance and stability in terms of rankings and outcomes. The validity and consistency of the procedures are assessed using Spearman's correlation coefficient, mean ranks, and sensitivity analysis.

Table 1
MCDM applications for stock selection problem

Reference	Method	Application
Bağcı & Yerdelen Kaygın, 2020	ARAS and WASPAS	The evaluation of the financial performance of various types of enterprises listed on the Istanbul Stock Exchange (ISE).
Kumaran, 2022	CRITIC and VIKOR	The evaluation of the financial performance of IPO firms in the Saudi Stock Market
Baydaş & Elma, 2021	WSA, TOPSIS, and PROMETHEE.	The evaluation of financial performance in the manufacturing sector using various MCDM techniques over a 5-year period.
Shen & Tzeng, 2015	VC-DRSA and DEMATEL	Analyze the complex relationships between financial indicators and business prospects specifically with IT companies listed on the Taiwan stock market.
Saini, 2019	AHP and TOPSIS	

Reference	Method	Application
		The performance of banks in India during the 2017-2018 fiscal year
Özçalıcı *et al.,* 2021	ARAS, EDAS, MOORA, OCRA, and TOPSIS.	The study assessed the performance of banks in Turkey and calculated performance metrics based on selected financial ratios for the period of 2014-2018.
Yıldırım & Meydan, 2021	The fuzzy EDAS	The evaluation of the financial performance of seven publicly traded companies in the retail sector listed in ISE for 2017-2019
Unvan, 2020	TOPSIS and Fuzzy TOPSIS	The financial performance of the seven largest banks in Turkey with regard to total assets from 2014 to 2018.
No *et al.,* 2021	CAMEL, EDAS, and TOPSIS	The performance of 51 branches of the Iranian bank Keshavarzi was analyzed and ranked.
Lee *et al.,* 2009	The Gordon model, multiple criteria decision-making (MCDM), and ANP.	Establish an investment decision model for selecting stocks that offer the greatest returns.
Poklepović & Babić, 2014	COPRAS, linear assignment, PROMETHEE, SAW, and TOPSIS	The study aims to provide a more consistent and reliable ranking of stocks to invest in by considering various criteria and industry-specific factors.
Ghadikolaei *et al.,* 2014	Fuzzy AHP, fuzzy VIKOR, fuzzy ARAS, and fuzzy COPRAS	The goal of this study is to propose a hybrid approach for the financial performance evaluation of automotive companies listed on the Tehran Stock Exchange.
Aldalou & Perçin, 2019	Fuzzy EDAS, CRITIC, FTOPSIS, FVIKOR, FCOPRAS, FMOORA and FSAW	The evaluation of the financial performance of companies listed in the food and drink index of Istanbul Stock Exchange.
Wu *et al.,* 2022	TODIM	The portfolio selection based on the financial performance of firms.
Marjanović & Popović, 2020	CRITIC and TOPSIS	The evaluation of Serbian banks' financial performance.
Baydaş & Pamučar, 2022	SD, PROMETHEE, TOPSIS, MOORA, COPRAS, CODAS, SAW and FUCA	The evaluation of companies' financial performance.
Hamzaçebi & Pekkaya, 2011	AHP, and GRA	Rank the stocks of financial firms in the Financial Sector Index of the Istanbul Stock Exchange (ISE).
Varma & SunilKumar, 2012	DEMATEL	Identify and assess relevant criteria for NSE-listed companies to establish an Indian-specific portfolio analysis framework.
Hota *et al.,* 2018	AHP, TOPSIS, and SAW	Selection of stock index ranking.
Bisht & Kumar, 2022	Fuzzy TOPSIS	Generate a credible stock preference using data from the National Stock Exchange of India

3. Application

The study aims to help investors and fund managers make informed investment decisions by ranking the companies based on their financial performance. We focus on evaluating the financial performance of 27 companies in the food and beverage industry, which are listed on the ISE Food and Beverage Index. These companies are the alternatives that investors and fund managers consider while making investment decisions. The analysis uses 5 stock market performance ratios, which are the decision criteria including the price-to-earnings ratio, market value-to-book value ratio, earnings per share, dividend yield ratio, and dividend payout ratio. The data for the ratios were obtained from the annual financial reports of the companies for the year 2021 and the closing stock prices of June 6th, 2022. Table 2 contains and presents all the data collected with respect to the criteria explained below.

Price/Earnings Ratio (P/E) is a measure of the stock market price per share divided by the earnings per share (EPS) of a company. The stock market price refers to the last closing price per share and the EPS is calculated by dividing the company's net profit by the number of outstanding shares. This ratio represents investors' expectations for the future growth of the company and reflects the amount they are willing to pay for each unit of earnings. A high P/E ratio may indicate that stocks are overvalued, which is not favorable for investors, while a low P/E ratio suggests that stocks are undervalued and may be a better investment option [50]. P/E is often used as a cost-type criterion.

Table 2
The results of the ratio analysis

Alternatives	P/E	M/B	EPS	DIV. YIELD	DIV. PAYOUT
AEFES	15.597	0.426	1.804	0.064	0.912
AVOD	15.108	1.902	0.125	0.065	0.000
BANVT	109.431	8.434	0.951	0.009	0.000
CCOLA	14.437	2.226	8.929	0.068	0.267
DARDL	12.916	9.940	0.274	0.077	0.000
EKIZ	3.800	1.760	1.650	0.263	0.000
ELITE	26.929	4.425	0.697	0.036	1.077
ERSU	75.537	3.509	0.054	0.013	0.000
FADE	16.286	2.511	0.387	0.060	0.000
KRVGD	14.499	1.900	0.677	0.069	0.167
KNFRT	18.819	5.005	0.384	0.048	0.000
KRSTL	122.835	5.787	0.055	0.007	0.000
KTSKR	47.331	2.664	0.680	0.021	0.000
MERKO	211.823	1.851	0.017	0.005	0.000
ORCAY	143.263	3.162	0.124	0.007	0.000
OYLUM	35.549	3.167	0.070	0.029	0.000
PENGD	23.046	1.362	0.198	0.042	0.000
PETUN	210.163	0.807	0.113	0.005	11.457
PINSU	-18.506	2.225	-0.281	-0.053	0.000
PNSUT	7.760	0.659	3.680	0.129	0.107
SELGD	8.742	1.638	0.482	0.114	0.000
SELVA	-55.494	2.684	-0.139	-0.018	0.000
TATGD	9.134	2.481	1.641	0.105	0.129
TBORG	5.035	2.106	3.734	0.195	0.086
ULUUN	23.311	4.915	0.731	0.039	0.000
ULKER	-11.748	1.272	-1.358	-0.085	-0.596
VANGD	6.251	1.852	0.610	0.161	0.000

Market Value/Book Value Ratio (M/B): The Market Value is calculated by multiplying the stock price per share by the total number of outstanding shares. The Book Value represents the total equity in the balance sheet and is equal to the accounting value of the company's net assets [51]. M/B compares the market value of the company's stocks to its book value, representing how much more valuable the stocks are in monetary terms compared to its equities. A high ratio indicates that the stocks are overvalued, and it is not preferred by investors as it may result in a correction of the market value to align with the real value of the company's assets. Conversely, investors prefer undervalued stocks as it is expected to increase in value in accordance with the real net asset value. This ratio is considered a cost criterion.

Earnings Per Share Ratio (EPS) is calculated by dividing a company's net profit by the number of outstanding shares. A higher EPS is typically preferred as it indicates a higher degree of profitability for the company's stock on a per-share basis [52]. This ratio is considered a benefit-type criterion for investors.

Dividend Yield Ratio is determined by dividing a company's earnings per share by its stock price per share. This ratio represents the potential dividend per share [53], which the company is not required to pay to its shareholders. Instead, it could use the earnings for capital appreciation. This ratio is considered a benefit criterion.

Dividend Payout Ratio is calculated by dividing the total dividend distributed to shareholders by the company's net profit [54]. It reveals the portion of the company's earnings that are paid out to shareholders as dividends, rather than being kept by the company for potential growth. A high dividend payout ratio suggests a limited potential for company growth and is therefore considered a cost criterion in investment decision-making.

3.1 Criteria Weighting by DEMATEL

Before utilizing EDAS, WASPAS, and TOPSIS methods, we applied DEMATEL to establish the criteria weight. This choice was made because it can handle the influences among attributes. DEMATEL also organizes criteria in cause-and-effect groups and establishes causal links between them [55]. The following steps were taken to implement this method:

First, the direct influence matrices of three experts were generated via a survey that was designed specifically for this study. These three experts were two finance professors from Bahcesehir University and one professor from Istanbul Technical University. They assessed the direct influences that factor Fi has on factor Fj. The strength of this impact was indicated by Zij. The DEMATEL scale of 0 to 4, where 0 represents no influence and 4 represents a very strong influence, was provided to experts. The data collected from the experts are shown in Table 3. By taking the simple average of the cells, a group direct influence matrix was generated as seen in Table 4.

Table 3
The direct influence matrix of experts

	P/E			M/B			EPS			DIV. YIELD			DIV.PAYOUT		
	E1	E2	E3	E1	E2	E3	E1	E2	E3	E1	E2	E3	E1	E2	E3
P/E	0	0	0	3	4	2	2	4	1	4	2	3	3	2	3
M/B	1	4	2	0	0	0	2	2	1	1	1	1	2	1	1
EPS	4	4	4	3	2	2	0	0	0	4	4	4	3	2	3
DIV. YIELD	0	2	1	1	1	0	1	4	1	0	0	0	2	4	2
DIV. PAYOUT	0	2	0	0	1	0	0	2	0	0	4	0	0	0	0

Table 4
The group direct influence matrix Z

	P/E	M/B	EPS	DIV. YIELD	DIV. PAYOUT
P/E	0.000	3.000	2.333	3.000	2.667
M/B	2.333	0.000	1.667	1.000	1.333
EPS	4.000	2.333	0.000	4.000	2.667
DIV. YIELD	1.000	0.667	2.000	0.000	2.667
DIV. PAYOUT	0.667	0.333	0.667	1.333	0.000

Then, the normalized direct influence matrix was obtained (Table 5) by performing Eq. (2). The normalization parameter is found as S = 13. The total influence matrix (Table 6) was produced by adding the direct and indirect effects to the normalized direct influence matrix as Eq. (3) indicates.

By using the data Table 6 contains, the parameters R and C representing the sum of rows and columns are calculated. Then, (R+C) denoting the degree to which the factor is essential to the system, and (R-C) illustrating the net influence that the factor has on the system is computed. Table 7 presents the findings. As a result, P/E, M/B, and EPS are put in the Cause group while DIV. YIELD and DIV. PAYOUT are assigned to the Effect group. The interpretation of this finding is that any direct improvement for the Cause group criteria may potentially create an indirect improvement for the Effect group criteria. To see the details of these influences, IRM showing significant relations is given in Figure 1. As suggested in the literature, θ threshold value is determined by averaging all elements in T: θ = 0.2944.

Table 5
The normalized direct influence matrix *X*

	P/E	M/B	EPS	DIV. YIELD	DIV. PAYOUT
P/E	0.000	0.231	0.179	0.231	0.205
M/B	0.179	0.000	0.128	0.077	0.103
EPS	0.308	0.179	0.000	0.308	0.205
DIV. YIELD	0.077	0.051	0.154	0.000	0.205
DIV. PAYOUT	0.051	0.026	0.051	0.103	0.000

Table 6
The total influence matrix *T*

	P/E	M/B	EPS	DIV. YIELD	DIV. PAYOUT
P/E	0.246	0.391	0.372	0.480	0.470
M/B	0.321	0.142	0.261	0.272	0.293
EPS	0.533	0.395	0.266	0.597	0.532
DIV. YIELD	0.219	0.167	0.261	0.180	0.358
DIV. PAYOUT	0.122	0.087	0.117	0.183	0.096

Table 7
The vectors *R* and *C* & cause-effect groupings

	R	*C*	*R+C*	*R-C*	
P/E	1.958	1.442	3.400	0.517	CAUSE
M/B	1.290	1.182	2.471	0.108	CAUSE
EPS	2.323	1.276	3.599	1.047	CAUSE
DIV. YIELD	1.185	1.714	2.899	-0.528	EFFECT
DIV. PAYOUT	0.605	1.748	2.353	-1.143	EFFECT

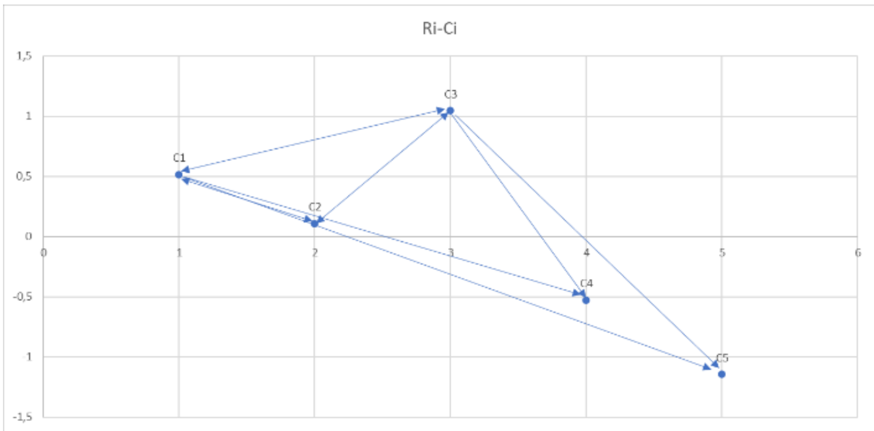


Fig. 1. The influence relation map *IRM*

To obtain the criteria weight set, (*R*+*C*) values are normalized by dividing each by the sum of the values. Table 8 presents these weights. They are accepted as subjective weights and used with EDAS, WASPAS, and TOPSIS applications. As a result, EPS is found as the most important criterion in our case.

Table 8
DEMATEL Weights of criteria

	P/E	M/B	EPS	DIV. YIELD	DIV. PAYOUT
Weights	0.231	0.168	0.244	0.197	0.160

3.2 Criteria Weighting by CRITIC

CRITIC was utilized as an objective approach that can determine the weights of each criterion. This method is considered to provide valuable insight into the decision-making process and effectively weigh the relative importance of each criterion. The first step is the normalization of the decision matrix by using Eqs. (7-8). Table 9 gives the normalized matrix.

Table 9
Normalized matrix for CRITIC

	P/E	M/B	EPS	DIV. YIELD	DIV. PAYOUT
AEFES	0.734	1.000	0.307	0.428	0.875
AVOD	0.736	0.845	0.144	0.431	0.951
BANVT	0.383	0.158	0.224	0.270	0.951
CCOLA	0.738	0.811	1.000	0.440	0.928
DARDL	0.744	0.000	0.159	0.466	0.951
EKIZ	0.778	0.860	0.292	1.000	0.951
ELITE	0.692	0.580	0.200	0.348	0.861
ERSU	0.510	0.676	0.137	0.282	0.951
FADE	0.731	0.781	0.170	0.417	0.951
KRVGD	0.738	0.845	0.198	0.443	0.937
KNFRT	0.722	0.519	0.169	0.382	0.951
KRSTL	0.333	0.437	0.137	0.264	0.951
KTSKR	0.615	0.765	0.198	0.305	0.951
MERKO	0.000	0.850	0.134	0.259	0.951
ORCAY	0.256	0.712	0.144	0.264	0.951
OYLUM	0.659	0.712	0.139	0.328	0.951
PENGD	0.706	0.902	0.151	0.365	0.951
PETUN	0.006	0.960	0.143	0.259	0.000

	P/E	M/B	EPS	DIV. YIELD	DIV. PAYOUT
PINSU	0.862	0.811	0.105	0.092	0.951
PNSUT	0.763	0.976	0.490	0.615	0.942
SELGD	0.760	0.873	0.179	0.572	0.951
SELVA	1.000	0.763	0.118	0.193	0.951
TATGD	0.758	0.784	0.292	0.546	0.940
TBORG	0.774	0.823	0.495	0.805	0.943
ULUUN	0.705	0.528	0.203	0.356	0.951
ULKER	0.836	0.911	0.000	0.000	1.000
VANGD	0.769	0.850	0.191	0.707	0.951

Then, Eq. (9) produced the correlation coefficient matrix and Eq. (10) produced the standard deviation of each criterion. Then, by using Eq. (11) index C_j was produced for each. Normalization of index values by using Eq. (12), the CRITIC objective weight set was generated. Table 10 presents all calculated values for CRITIC analysis.

As seen, M/B is the most important criterion according to CRITIC. For discussions, please see Chapter IV.

The companies are ranked by using EDAS, WASPAS, and TOPSIS methods. The findings are shared in the following chapters.

Table 10
Correlation matrix of CRITIC

	P/E	M/B	EPS	DIV. YIELD	DIV. PAYOUT
P/E	1.000	0.101	0.166	0.268	0.515
M/B	0.101	1.000	0.146	0.149	-0.199
EPS	0.166	0.146	1.000	0.434	0.048
DIV. YIELD	0.268	0.149	0.434	1.000	0.110
DIV. PAYOUT	0.515	-0.199	0.048	0.110	1.000
$\sum_{k=1}^{n}(1-\rho_{ik})$	2.949	3.803	3.206	3.038	3.525
σ_j	0.242	0.234	0.187	0.210	0.183
C_j	0.714	0.891	0.599	0.639	0.646
w_j	0.205	0.255	0.172	0.183	0.185

3.3 Alternative Ranking by EDAS

The decision matrix presented in Table 2 is based on the results of the ratio analysis. It has 27 rows showing alternatives and 5 columns depicting criteria. After normalizing the decision matrix, AV_j (Average Solution) was obtained as shown in Table 11. Then, Eqs. (14-17) were performed to build PDA and NDA matrices as given in Table 12 and Table 13.

Table 11
Normalized decision matrix for EDAS and AV

	P/E	M/B	EPS	DIV. YIELD	DIV. PAYOUT
AEFES	0.734	1.000	0.307	0.428	0.875
AVOD	0.736	0.845	0.144	0.431	0.951
BANVT	0.383	0.158	0.224	0.270	0.951
CCOLA	0.738	0.811	1.000	0.440	0.928
DARDL	0.744	0.000	0.159	0.466	0.951
EKIZ	0.778	0.860	0.292	1.000	0.951
ELITE	0.692	0.580	0.200	0.348	0.861
ERSU	0.510	0.676	0.137	0.282	0.951
FADE	0.731	0.781	0.170	0.417	0.951
KRVGD	0.738	0.845	0.198	0.443	0.937

	P/E	M/B	EPS	DIV. YIELD	DIV. PAYOUT
KNFRT	0.722	0.519	0.169	0.382	0.951
KRSTL	0.333	0.437	0.137	0.264	0.951
KTSKR	0.615	0.765	0.198	0.305	0.951
MERKO	0.000	0.850	0.134	0.259	0.951
ORCAY	0.256	0.712	0.144	0.264	0.951
OYLUM	0.659	0.712	0.139	0.328	0.951
PENGD	0.706	0.902	0.151	0.365	0.951
PETUN	0.006	0.960	0.143	0.259	0.000
PINSU	0.862	0.811	0.105	0.092	0.951
PNSUT	0.763	0.976	0.490	0.615	0.942
SELGD	0.760	0.873	0.179	0.572	0.951
SELVA	1.000	0.763	0.118	0.193	0.951
TATGD	0.758	0.784	0.292	0.546	0.940
TBORG	0.774	0.823	0.495	0.805	0.943
ULUUN	0.705	0.528	0.203	0.356	0.951
ULKER	0.836	0.911	0.000	0.000	1.000
VANGD	0.769	0.850	0.191	0.707	0.951
AV	0.641	0.731	0.227	0.401	0.909

In Eq. (18-19), we first used the weights determined by DEMATEL to determine SP and SN values. NSP and NSN values were determined by Eqs. (20-21). By Eq. (22), the AS scores were computed and used for ranking the alternatives. All these results of SP, SN, NSP, NSN, AS, and the company ranks are summarized in Table 14. As seen, the first three ranked alternatives are CCOLA, TBORG, and EKIZ.

DEMATEL approach has a subjective perspective since it bases its results on expert judgments. So, when the decision analyst changes the experts, the judgments will change and naturally, the weight set of attributes will change. In order to avoid this drawback, the weight set of CRITIC was integrated with MCDM methods to see how the ranking results of alternatives change. Table 15 summarizes all the values and company rankings found by conducting a CRITIC-based EDAS method. When we look at the first three alternatives, we see an order of CCOLA, TBORG, and EKIZ. As seen, there is no change in the first three alternatives in both applications. For the comparison of all alternative rankings, please see Chapter 4.

Table 12
PDA matrix

	P/E	M/B	EPS	DIV. YIELD	DIV. PAYOUT
AEFES	0.000	0.000	0.356	0.067	0.037
AVOD	0.000	0.000	0.000	0.074	0.000
BANVT	0.403	0.783	0.000	0.000	0.000
CCOLA	0.000	0.000	3.412	0.096	0.000
DARDL	0.000	1.000	0.000	0.160	0.000
EKIZ	0.000	0.000	0.290	1.492	0.000
ELITE	0.000	0.207	0.000	0.000	0.052
ERSU	0.205	0.075	0.000	0.000	0.000
FADE	0.000	0.000	0.000	0.038	0.000
KRVGD	0.000	0.000	0.000	0.103	0.000
KNFRT	0.000	0.290	0.000	0.000	0.000
KRSTL	0.481	0.403	0.000	0.000	0.000
KTSKR	0.040	0.000	0.000	0.000	0.000
MERKO	1.000	0.000	0.000	0.000	0.000
ORCAY	0.600	0.025	0.000	0.000	0.000
OYLUM	0.000	0.026	0.000	0.000	0.000
PENGD	0.000	0.000	0.000	0.000	0.000

	P/E	M/B	EPS	DIV. YIELD	DIV. PAYOUT
PETUN	0.990	0.000	0.000	0.000	1.000
PINSU	0.000	0.000	0.000	0.000	0.000
PNSUT	0.000	0.000	1.161	0.533	0.000
SELGD	0.000	0.000	0.000	0.425	0.000
SELVA	0.000	0.000	0.000	0.000	0.000
TATGD	0.000	0.000	0.286	0.361	0.000
TBORG	0.000	0.000	1.184	1.005	0.000
ULUUN	0.000	0.277	0.000	0.000	0.000
ULKER	0.000	0.000	0.000	0.000	0.000
VANGD	0.000	0.000	0.000	0.762	0.000

Table 13
NDA matrix

	P/E	M/B	EPS	DIV. YIELD	DIV. PAYOUT
AEFES	0.145	0.368	0.000	0.000	0.000
AVOD	0.148	0.156	0.364	0.000	0.046
BANVT	0.000	0.000	0.010	0.327	0.046
CCOLA	0.152	0.110	0.000	0.000	0.022
DARDL	0.161	0.000	0.300	0.000	0.046
EKIZ	0.214	0.177	0.000	0.000	0.046
ELITE	0.079	0.000	0.119	0.133	0.000
ERSU	0.000	0.000	0.394	0.298	0.046
FADE	0.141	0.069	0.252	0.000	0.046
KRVGD	0.151	0.156	0.127	0.000	0.031
KNFRT	0.126	0.000	0.253	0.047	0.046
KRSTL	0.000	0.000	0.394	0.341	0.046
KTSKR	0.000	0.047	0.126	0.241	0.046
MERKO	0.000	0.164	0.410	0.355	0.046
ORCAY	0.000	0.000	0.364	0.341	0.046
OYLUM	0.029	0.000	0.388	0.184	0.046
PENGD	0.101	0.234	0.333	0.090	0.046
PETUN	0.000	0.314	0.369	0.355	0.000
PINSU	0.344	0.110	0.538	0.771	0.046
PNSUT	0.191	0.335	0.000	0.000	0.036
SELGD	0.185	0.194	0.211	0.000	0.046
SELVA	0.560	0.044	0.477	0.520	0.046
TATGD	0.183	0.073	0.000	0.000	0.034
TBORG	0.207	0.127	0.000	0.000	0.038
ULUUN	0.100	0.000	0.104	0.112	0.046
ULKER	0.305	0.247	1.000	1.000	0.100
VANGD	0.199	0.163	0.156	0.000	0.046

Table 14
Results of EDAS with DEMATEL weights

	SP	SN	NSP	NSN	AS	Ranking
AEFES	0.106	0.095	0.125	0.833	0.479	10
AVOD	0.015	0.157	0.017	0.725	0.371	23
BANVT	0.224	0.074	0.263	0.870	0.567	5
CCOLA	0.853	0.057	1.000	0.900	0.950	1
DARDL	0.199	0.118	0.234	0.793	0.513	8
EKIZ	0.365	0.086	0.428	0.848	0.638	3
ELITE	0.043	0.073	0.050	0.871	0.461	11
ERSU	0.060	0.162	0.070	0.715	0.392	21
FADE	0.008	0.113	0.009	0.802	0.405	20

	SP	SN	NSP	NSN	AS	Ranking
KRVGD	0.020	0.097	0.024	0.829	0.426	18
KNFRT	0.049	0.108	0.057	0.811	0.434	16
KRSTL	0.179	0.171	0.209	0.700	0.455	14
KTSKR	0.009	0.093	0.011	0.836	0.423	19
MERKO	0.231	0.205	0.271	0.640	0.455	13
ORCAY	0.143	0.164	0.167	0.713	0.440	15
OYLUM	0.004	0.145	0.005	0.746	0.375	22
PENGD	0.000	0.169	0.000	0.703	0.351	24
PETUN	0.389	0.213	0.456	0.626	0.541	6
PINSU	0.000	0.389	0.000	0.317	0.159	26
PNSUT	0.389	0.106	0.456	0.814	0.635	4
SELGD	0.084	0.134	0.098	0.764	0.431	17
SELVA	0.000	0.363	0.000	0.362	0.181	25
TATGD	0.141	0.060	0.165	0.895	0.530	7
TBORG	0.487	0.075	0.571	0.868	0.720	2
ULUUN	0.047	0.078	0.055	0.863	0.459	12
ULKER	0.000	0.569	0.000	0.000	0.000	27
VANGD	0.150	0.119	0.176	0.791	0.483	9

Table 15
Results of EDAS with CRITIC weights

	SP	SN	NSP	NSN	AS	Ranking
AEFES	0.080	0.124	0.133	0.752	0.443	16
AVOD	0.014	0.141	0.023	0.717	0.370	23
BANVT	0.282	0.070	0.468	0.860	0.664	4
CCOLA	0.603	0.063	1.000	0.874	0.937	1
DARDL	0.285	0.093	0.472	0.814	0.643	5
EKIZ	0.323	0.097	0.535	0.805	0.670	3
ELITE	0.062	0.061	0.104	0.878	0.491	12
ERSU	0.061	0.131	0.101	0.738	0.419	19
FADE	0.007	0.098	0.012	0.803	0.408	21
KRVGD	0.019	0.098	0.031	0.803	0.417	20
KNFRT	0.074	0.086	0.123	0.827	0.475	14
KRSTL	0.201	0.139	0.333	0.722	0.528	9
KTSKR	0.008	0.086	0.014	0.827	0.420	18
MERKO	0.205	0.186	0.339	0.627	0.483	13
ORCAY	0.129	0.134	0.214	0.732	0.473	15
OYLUM	0.007	0.115	0.011	0.770	0.391	22
PENGD	0.000	0.163	0.000	0.674	0.337	24
PETUN	0.388	0.209	0.643	0.582	0.612	7
PINSU	0.000	0.340	0.000	0.317	0.159	26
PNSUT	0.297	0.131	0.492	0.737	0.614	6
SELGD	0.078	0.132	0.129	0.735	0.432	17
SELVA	0.000	0.311	0.000	0.376	0.188	25
TATGD	0.115	0.062	0.191	0.875	0.533	8
TBORG	0.387	0.082	0.642	0.836	0.739	2
ULUUN	0.071	0.067	0.117	0.865	0.491	11
ULKER	0.000	0.499	0.000	0.000	0.000	27
VANGD	0.139	0.118	0.231	0.764	0.497	10

3.4 Alternative Ranking by TOPSIS

The second analysis tool considers TOPSIS in integration with the weight set presented by DEMATEL. The data contained by the decision matrix given in Table 1 were normalized by using Eq.

(23). This formula will ensure that all the criteria are on the same scale, allowing for a fair comparison of the alternatives. The normalized decision matrix was weighted by using Eq. (24) and the weighted normalized decision matrix was obtained as given in Table 16. Applying Eqs. (25-26) produced the positive and negative ideal solutions.

Then, the distinctive feature of TOPSIS is considered and separation measures are calculated with Eqs. (27-28) presenting the distances between each alternative and positive and negative ideal solutions, respectively. Eq. (29) provided the relative closeness measure, e.g., C^*. The alternatives were ranked in decreasing order of C^*, which means the highest value shows the best alternative. Table 17 summarizes all these measures and alternative ranking. The best three alternatives are determined as CCOLA, TBORG, and PNSUT.

Table 16
The weighted normalized decision matric for TOPSIS

	P/E	M/B	EPS	DIV. YIELD	DIV. PAYOUT
AEFES	0.048	0.042	0.050	0.036	0.029
AVOD	0.048	0.036	0.023	0.036	0.032
BANVT	0.025	0.007	0.036	0.023	0.032
CCOLA	0.048	0.034	0.161	0.037	0.031
DARDL	0.048	0.000	0.026	0.039	0.032
EKIZ	0.051	0.036	0.047	0.084	0.032
ELITE	0.045	0.024	0.032	0.029	0.029
ERSU	0.033	0.029	0.022	0.024	0.032
FADE	0.048	0.033	0.027	0.035	0.032
KRVGD	0.048	0.036	0.032	0.037	0.031
KNFRT	0.047	0.022	0.027	0.032	0.032
KRSTL	0.022	0.018	0.022	0.022	0.032
KTSKR	0.040	0.032	0.032	0.026	0.032
MERKO	0.000	0.036	0.022	0.022	0.032
ORCAY	0.017	0.030	0.023	0.022	0.032
OYLUM	0.043	0.030	0.022	0.028	0.032
PENGD	0.046	0.038	0.024	0.031	0.032
PETUN	0.000	0.040	0.023	0.022	0.000
PINSU	0.056	0.034	0.017	0.008	0.032
PNSUT	0.050	0.041	0.079	0.052	0.031
SELGD	0.049	0.037	0.029	0.048	0.032
SELVA	0.065	0.032	0.019	0.016	0.032
TATGD	0.049	0.033	0.047	0.046	0.031
TBORG	0.050	0.035	0.080	0.068	0.031
ULUUN	0.046	0.022	0.033	0.030	0.032
ULKER	0.054	0.038	0.000	0.000	0.033
VANGD	0.050	0.036	0.031	0.059	0.032
A^*	0.000	0.000	0.161	0.084	0.000
A^-	0.065	0.042	0.000	0.000	0.033

In order to see how the alternative rankings changed when the objective weights were considered, all analyses were repeated with the weight set revealed by CRITIC. Table 18 presents the findings. There is a slight change in the first three alternative rankings when we compare them with the DEMATEL-based TOPSIS application's results: CCOLA, TBORG, and EKIZ. This is the same with the results of EDAS applications. For the comparison of all alternative rankings, please see Chapter 4.

Table 17
Results of TOPSIS with DEMATEL weights

	S^*	S^-	C^*	Ranking
AEFES	0.140	0.140	0.140	9
AVOD	0.161	0.161	0.161	22
BANVT	0.145	0.145	0.145	7
CCOLA	0.081	0.081	0.081	1
DARDL	0.154	0.154	0.154	11
EKIZ	0.134	0.134	0.134	4
ELITE	0.152	0.152	0.152	17
ERSU	0.161	0.161	0.161	21
FADE	0.157	0.157	0.157	20
KRVGD	0.153	0.153	0.153	16
KNFRT	0.156	0.156	0.156	18
KRSTL	0.158	0.158	0.158	14
KTSKR	0.154	0.154	0.154	19
MERKO	0.160	0.160	0.160	10
ORCAY	0.158	0.158	0.158	13
OYLUM	0.162	0.162	0.162	24
PENGD	0.162	0.162	0.162	23
PETUN	0.157	0.157	0.157	5
PINSU	0.179	0.179	0.179	26
PNSUT	0.114	0.114	0.114	3
SELGD	0.154	0.154	0.154	12
SELVA	0.176	0.176	0.176	25
TATGD	0.138	0.138	0.138	6
TBORG	0.108	0.108	0.108	2
ULUUN	0.152	0.152	0.152	15
ULKER	0.197	0.197	0.197	27
VANGD	0.150	0.150	0.150	8

Table 18
Results of TOPSIS with CRITIC weights

	S^*	S^-	C^*	Ranking
AEFES	0.123	0.051	0.292	13
AVOD	0.132	0.042	0.240	22
BANVT	0.114	0.073	0.390	6
CCOLA	0.088	0.120	0.578	1
DARDL	0.118	0.077	0.395	5
EKIZ	0.113	0.086	0.432	3
ELITE	0.122	0.048	0.283	17
ERSU	0.130	0.044	0.255	19
FADE	0.129	0.043	0.252	20
KRVGD	0.127	0.045	0.261	18
KRSTL	0.124	0.059	0.322	11
KTSKR	0.127	0.042	0.250	21
MERKO	0.132	0.064	0.326	10
ORCAY	0.128	0.054	0.295	12
OYLUM	0.131	0.040	0.236	23
PENGD	0.134	0.038	0.220	24
PETUN	0.129	0.074	0.364	7
PINSU	0.148	0.020	0.120	26
PNSUT	0.107	0.075	0.412	4
SELGD	0.127	0.052	0.289	15

	S^*	S^-	C^*	Ranking
SELVA	0.145	0.025	0.149	25
TATGD	0.116	0.057	0.331	9
TBORG	0.098	0.086	0.467	2
ULUUN	0.122	0.050	0.292	14
ULKER	0.162	0.011	0.064	27
VANGD	0.123	0.062	0.333	8

3.5 Alternative Ranking by WASPAS

The third analysis is based on WASPAS application with subjective DEMATEL weights. After normalization, WSM and WPM measures were computed. WSM results were computed by Eq. (32) and represented by $Q_i^{(1)}$ while WPM results were obtained by Eq. (33) and represented by $Q_i^{(2)}$. Eq. (34) aggregated these two results with a parameter of λ=0.5 and presented the ranking of alternatives according to the value of Q_i. All calculations and ranking results are shown in Table 19. CCOLA, TBORG, and PNSUT take the first three orders again. To check the results that were generated by considering objective weights, the CRITIC weight set was considered in a new WASPAS application. The results are presented in Table 20. As seen, the first three alternatives keep their order in the new ranking. For the comparison of all alternative rankings, please see Chapter 4.

Table 19
Results of WASPAS with DEMATEL weights

	$Q_i^{(1)}$	$Q_i^{(2)}$	Q_i	Ranking
AEFES	0.637	0.578	0.607	7
AVOD	0.584	0.474	0.529	11
BANVT	0.375	0.313	0.344	23
CCOLA	0.786	0.757	0.771	1
DARDL	0.454	0.000	0.227	25
EKIZ	0.744	0.676	0.710	4
ELITE	0.512	0.448	0.480	17
ERSU	0.472	0.381	0.427	20
FADE	0.575	0.483	0.529	10
KRVGD	0.598	0.514	0.556	9
KNFRT	0.522	0.442	0.482	16
KRSTL	0.388	0.317	0.352	22
KTSKR	0.531	0.452	0.491	14
MERKO	0.378	0.000	0.189	26
ORCAY	0.418	0.328	0.373	21
OYLUM	0.522	0.422	0.472	18
PENGD	0.575	0.465	0.520	12
PETUN	0.248	0.000	0.124	27
PINSU	0.531	0.333	0.432	19
PNSUT	0.731	0.707	0.719	3
SELGD	0.630	0.535	0.583	8
SELVA	0.578	0.407	0.492	13
TATGD	0.636	0.586	0.611	6
TBORG	0.747	0.729	0.738	2
ULUUN	0.523	0.454	0.489	15
ULKER	0.506	0.000	0.253	24
VANGD	0.658	0.566	0.612	5

Table 20
Results of WASPAS with CRITIC weights

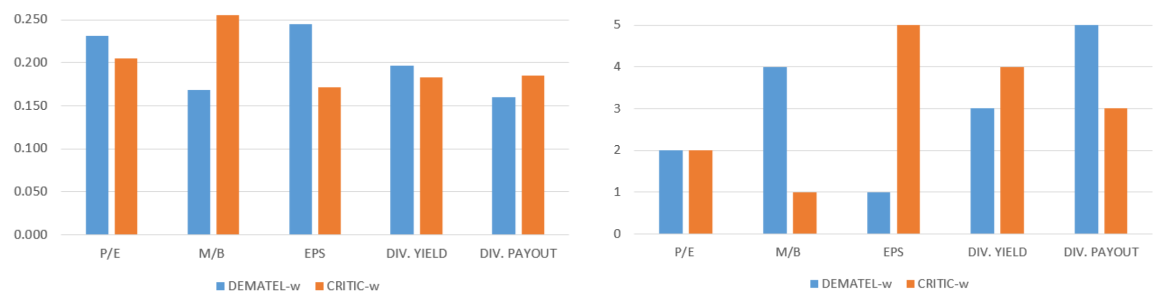
	$Q_i^{(1)}$	$Q_i^{(2)}$	Q_i	Ranking
AEFES	0.699	0.640	0.669	6
AVOD	0.646	0.548	0.597	10
BANVT	0.383	0.310	0.346	23
CCOLA	0.782	0.756	0.769	1
DARDL	0.441	0.000	0.220	26
EKIZ	0.788	0.733	0.761	4
ELITE	0.547	0.490	0.519	18
ERSU	0.528	0.440	0.484	20
FADE	0.631	0.548	0.589	12
KRVGD	0.655	0.580	0.618	9
KNFRT	0.555	0.484	0.520	17
KRSTL	0.428	0.357	0.392	22
KTSKR	0.587	0.510	0.549	14
MERKO	0.463	0.000	0.232	25
ORCAY	0.484	0.386	0.435	21
OYLUM	0.577	0.484	0.530	15
PENGD	0.644	0.540	0.592	11
PETUN	0.318	0.000	0.159	27
PINSU	0.594	0.399	0.497	19
PNSUT	0.776	0.753	0.764	3
SELGD	0.690	0.608	0.649	8
SELVA	0.631	0.474	0.553	13
TATGD	0.679	0.636	0.658	7
TBORG	0.776	0.761	0.768	2
ULUUN	0.555	0.493	0.524	16
ULKER	0.589	0.000	0.294	24
VANGD	0.713	0.636	0.675	5

4. Discussion

4.1 Comparison of Weighting Procedures

In this study, we utilized two weighting procedures. While DEMATEL is a subjective procedure, CRITIC has an objective perspective. DEMATEL is subjective because it uses expert judgments, and these results can change from one expert group to another. Thanks to its procedure of considering only performance data contained in the decision matrix, CRITIC is an objective tool, and it does not require any additional data.

Figure 2 shows the differences between weights and between importance orders of criteria obtained by DEMATEL and CRITIC. Since the methods' perspectives and algorithms are completely different, it is reasonable to see such a difference between them. According to DEMATEL, EPS is the most important criterion and Dividend Payout is the least important criterion. However, the importance degree changes in CRITIC. It results as the M/B ratio is the most important criterion while EPS is the least important one.



(a) Criteria weights (b) Ranking of criteria

Fig. 2. Comparison of criteria weights determined by DEMATEL and CRITIC

4.2 Comparison of Alternative Ranking Procedures

In this study, we utilized six different evaluation combinations, e.g. DEMATEL-EDAS, CRITIC-EDAS, DEMATEL-WASPAS, CRITIC-WASPAS, DEMATEL-TOPSIS, and CRITIC-TOPSIS. The first two ranks are taken by the same two companies in any case: while CCOLA is the best alternative, TBORG takes the second-best position. All the other rankings change in each method application. All the rankings produced by 6 combinations are summarized in Table 21 and Figure 3. As seen, After the third rank, there is no stability in rankings. So, we conducted Spearman's rank correlation analysis to understand how these six rankings are similar or different.

Kahraman *et al*. [56] stated that Spearman's rank correlation is a statistical analysis to specify the difference between alternative rankings. A larger coefficient indicates a larger level of similarity. For a pair of the methods, Eq. (35) is performed to calculate the coefficient.

$$\rho_{AB} = 1 - \frac{6\sum_{i=1}^{m}(r_i^A - r_i^B)^2}{n(n^2-1)} \qquad \text{for} \quad A, B=1,\ldots,6 \tag{35}$$

where *A* and *B* are two different methods, r_i^A is the ranking of *i*th alternative determined by method A and r_i^B is the ranking of *i*th alternative determined by method B. In our case, we have 6 method combinations, so that (6*5)/2= 15 Spearman's rank correlation coefficients were calculated. Table 22 presents the results.

Table 22 indicates that all EDAS and TOPSIS combinations have higher correlation coefficients ($\rho > 0.90$). It means, there are no huge differences between four of the combinations: DEMATEL and CRITIC-based EDAS and TOPSIS combinations. WASPAS results are very different from those four results. However, the highest correlation was found between two WASPAS applications: $\rho = 0.993$. Thus, it can be concluded that WASPAS results are internally consistent while the results of TOPSIS and EDAS are also consistent inside. In any case, the first two alternatives keep their ranking: CCOLA and TBORG, respectively. So, the ultimate finding of the application is that investors and funders who think of investing in food and beverage companies in ISE should include CCOLA and TBORG in their portfolios.

Table 21
All rankings produced.

	DEMATEL-EDAS	DEMATEL-WASPAS	DEMATEL-TOPSIS	CRITIC-EDAS	CRITIC-WASPAS	CRITIC-TOPSIS
AEFES	10	7	9	16	6	13
AVOD	23	11	22	23	10	22
BANVT	5	23	7	4	23	6
CCOLA	*1*	*1*	*1*	*1*	*1*	*1*
DARDL	8	25	11	5	26	5
EKIZ	3	4	4	3	4	3
ELITE	11	17	17	12	18	17
ERSU	21	20	21	19	20	19
FADE	20	10	20	21	12	20
KRVGD	18	9	16	20	9	18
KNFRT	16	16	18	14	17	16
KRSTL	14	22	14	9	22	11
KTSKR	19	14	19	18	14	21
MERKO	13	26	10	13	25	10
ORCAY	15	21	13	15	21	12
OYLUM	22	18	24	22	15	23
PENGD	24	12	23	24	11	24
PETUN	6	27	5	7	27	7
PINSU	26	19	26	26	19	26
PNSUT	4	3	3	6	3	4
SELGD	17	8	12	17	8	15
SELVA	25	13	25	25	13	25
TATGD	7	6	6	8	7	9
TBORG	*2*	*2*	*2*	*2*	*2*	*2*
ULUUN	12	15	15	11	16	14
ULKER	27	24	27	27	24	27
VANGD	9	5	8	10	5	8

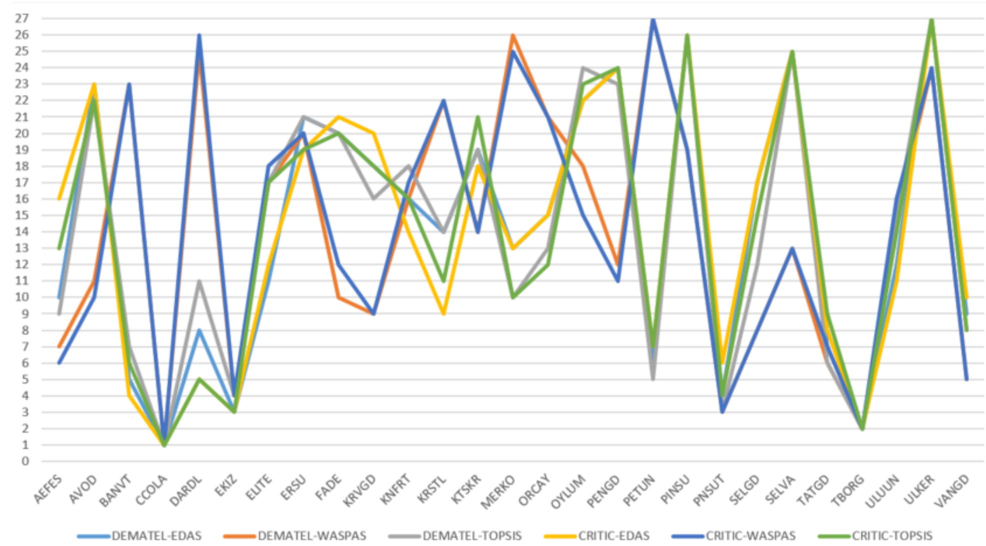


Fig. 3. Comparison of alternative rankings

Table 22
Spearman's rank correlation coefficients

	DEMATEL-EDAS	DEMATEL-WASPAS	DEMATEL-TOPSIS	CRITIC-EDAS	CRITIC-WASPAS	CRITIC-TOPSIS
DEMATEL-EDAS	-	0.332	*0.965*	*0.971*	0.306	*0.968*
DEMATEL-WASPAS		-	0.387	0.223	*0.993*	0.275
DEMATEL-TOPSIS			-	*0.919*	0.369	*0.968*
CRITIC-EDAS				-	0.192	*0.969*
CRITIC-WASPAS					-	0.252
CRITIC-TOPSIS						-

5. Conclusion

MCDM is a widely used methodology for supporting decision-makers in reaching their optimal solutions to various managerial problems. One of the financial decision-making problems is to determine the most appropriate components of an investment portfolio. The alternatives are discrete company stocks in this case. Also, their selection is based on multiple attributes, i.e., financial ratios that are computed from financial statements such as balance sheets or income statements. Thus, it is obvious that selecting the best companies for a portfolio problem is an MCDM problem.

In this study, we analyzed the food and beverage companies listed in ISE by considering five financial ratios as criteria: Price/Earnings Ratio, Market Value/Book Value Ratio, Earnings per Share Ratio, Dividend Yield Ratio, and Dividend Payout Ratio. From ratio analysis, 27 companies were evaluated with respect to each criterion. So, the decision matrix has a size of 27x5. The weights of the criteria were determined via DEMATEL and CRITIC. DEMATEL is a subjective weighting MCDM tool since it is based on the judgments of the experts. Three academic experts were consulted for this study. The ranking of criteria was found as $EPS \succ P/E \succ Div.Yield \succ M/B \succ Div.\ Payout$ by DEMATEL. CRITIC is an objective tool because it only uses the dataset in hand. The correlation coefficient between criteria values and also the standard deviations of criteria are considered as inputs of the algorithm. CRITIC reveals that the ranking of criteria is $M/B \succ P/E \succ Div.Payout \succ Div.Yield \succ EPS$. Different perspectives of weighting methods obtained completely different importance orders of criteria.

27 alternative companies were assessed in the study by EDAS which is based on the distances between alternatives and an average option, TOPSIS which considers the distances between alternatives and artificial positive/negative ideal options, and WASPAS which is a combination of two well-known MCDM tools, namely WSM and WPM. When we combined 3 alternative evaluation tools and 2 weighting results, we obtained 6 MCDM combinations: DEMATEL-EDAS, DEMATEL-TOPSIS, DEMATEL-WASPAS, CRITIC-EDAS, CRITIC-TOPSIS, and CRITIC-WASPAS. All combinations concluded that the first two alternatives are stable: CCOLA and TBORG. Independent of the method, these two alternatives can be included in a portfolio. The same cannot be said for other alternatives because there is no stability in them. The other 25 alternatives have different rankings as summarized in Fig. 3. To understand which of the methods produced similar results, a Spearman's Rank Correlation analysis was conducted. In short, we found that all EDAS and TOPSIS combinations produced similar company rankings because there are higher correlations between them, i.e., all correlation coefficients are greater than 91%. Also, DEMATEL-WASPAS and CRITIC-WASPAS produced very similar ranking results because the correlation coefficient between them is 99.3%.

For future research, there are some suggestions. Similar and more sophisticated MCDM applications can be utilized for different sectors including companies listed in ISE. Fuzzy-based techniques can handle the ambiguity and uncertainty that are hidden in decision processes, especially human judgments. The analysis can be conducted for different periods to see the changes in company performance. Intelligent techniques such as text mining, web mining, and machine learning, can empower the decision process of investors, portfolio managers, and funders.

Author Contributions

Conceptualization, C.I., M.T., and S.M.; methodology, M.T. and S.G.; software, C.I.; validation, S.G.; formal analysis, S.G.; investigation, S.M., and C.I.; resources, C.I., M.T., and S.M.; data curation, C.I., M.T., and S.M.; writing—original draft preparation, C.I., M.T., S.M., and S.G.; writing—review and editing, S.G.; visualization, M.T., and S.G.; supervision, S.G. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no competing financial interests and personal relationships that could have appeared to influence the research in this paper.

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