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An Integrated MCDM Framework for Sensitivity of Weighting Methods and Ranking Aggregation: Evidence From Financial Performance Evaluation

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ABSTRACT

This study proposes an integrated framework for evaluating alternatives in Multi-Criteria Decision Making (MCDM) by addressing weight sensitivity and ranking integration. The aim is to examine the effects of different criteria-weighting methods on ranking results and to develop a more consistent decision-making structure by integrating the resulting rankings. Financial performance indicators of Derimod Konfeksiyon A.Ş., listed on Borsa Istanbul (BIST), were evaluated using the Entropy, WENSLO, and MPSI weighting methods, while the MACAD method was employed to rank the alternatives. The analysis was initially conducted for the 2018–2024 period; however, identical rankings obtained across all weighting methods limited the assessment of weight sensitivity. Therefore, the analysis period was extended to 2015–2024, resulting in ranking variations that enabled a more meaningful comparison of the weighting methods. In the final stage, the resulting rankings were integrated into a single consensus ranking using the CURLIA method. The findings indicate that the proposed framework reduces inconsistencies arising from the use of different weighting methods and produces more stable and reliable performance evaluations. Consequently, the study contributes to the MCDM literature by presenting an integrated methodological framework and demonstrating its applicability to financial performance evaluation.

1. Introduction

Decision-making is a mentally complex process that plays a role in solving different problems. This process can be rational or irrational and is based on explicit or implicit assumptions influenced by physiological, biological, cultural, and social factors. Elements such as authority structure and risk level also increase the complexity of the decision-making process. Today, complex decision problems can be solved more systematically using mathematical and statistical methods and computer-aided tools. In this context, Multi-Criteria Decision Making (MCDM) or Multi-Criteria Decision Analysis (MCDA) is recognised as one of the commonly used approaches in structuring the decision-making process [1].

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The MCDM is a decision support approach that enables decision-makers (DM) to prioritise alternatives based on their preferences regarding a specific set of criteria. This approach ensures that alternatives are evaluated in a clear and transparent manner, typically taking into account numerous criteria that may conflict with each other. Decision-makers assign a relative importance level to each criterion and express these importance levels through criterion weights. Criterion weights constitute one of the fundamental components of MCDM problems, as they directly influence the ranking of alternatives and, consequently, the outcome of the decision-making process. The objective or subjective nature of criteria and, in some cases, their incomparable or conflicting characteristics necessitate the selection of an appropriate weighting method. Therefore, the selection of a weighting method that quantitatively determines the relative importance of criteria has a significant impact on the reliability and accuracy of decision outcomes [2].

The MCDM framework consists of multiple criteria, a set of alternatives, and a systematic comparison between these alternatives. This framework improves the decision-making process by enabling differentiation between options and establishing a preference hierarchy. MCDM techniques provide analytical methods for ranking alternatives evaluated according to different criteria and determining the preferred option [3].

A comprehensive understanding of the characteristics, advantages and limitations of the MCDM methods is important for selecting the most appropriate method for the problem. These methods are widely used to support the decision-making process in many fields, such as economics, engineering, medicine, and education. Two key elements play a decisive role in the MCDM process: the methods used to determine criterion weights and the MCDM technique applied to evaluate alternatives. These elements directly influence the interpretation of decision outcomes by creating differences in the ranking of alternatives. Criterion weighting methods are classified as subjective, objective, and mixed approaches. Objective methods are more commonly preferred in the literature because they produce results independent of the subjective judgements of decision-makers [4, 5].

Various criteria weighting and alternative ranking methods have been developed in the literature for solving MCDM problems. Criteria weighting methods are generally classified into two groups: direct (scaling, ranking, and score assignment) and indirect (based on theoretical and mathematical models). Although many studies assume that decision-makers are aware of the criterion weights, it is important to consider the validity of weights calculated using different weighting methods in order to obtain reliable results. In this context, one of the oldest and most common approaches is the Weighted Sum Method (WSM), and the Weighted Product Method (WPM) was developed over time to address its shortcomings. Furthermore, alternative ranking methods such as the Analytic Hierarchy Process (AHP), VIšekriterijumsko KOmpromisno Rangiranje (VIKOR), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) are widely used in many MCDM studies today [6].

Determining criterion weights is an important area of research in the MCDM literature, and depending on the weighting method used, significant differences may arise in the ranking of alternatives. Subjective, objective, and integrative approaches are based on different assumptions and lead to variations in decision outcomes. This necessitates the evaluation of rankings obtained from different weighting methods using a holistic approach in order to increase the reliability of decision outcomes [3].

1.1 Motivation for Conducting Research

Different criteria weighting methods can determine the levels of importance of criteria according to different approaches, and this may lead to differences in the ranking results of the alternatives. Although the impact of criterion weighting methods on decision outcomes has been extensively examined in the literature, the systematic and computationally efficient integration of rankings obtained from different weighting methods is important for the joint evaluation of the decision outcomes produced by these different methods. This situation necessitates that the ranking differences arising from weighting methods be addressed under a single, consistent ranking, rather than being evaluated in isolation. Consequently, the evaluation of alternative approaches to integrating the ranking results obtained from different weighting methods constitutes the primary research motivation of this study.

1.2 Practical and Methodological Aims of the Study

The primary methodological aim of this study is to examine the effect of criterion weights, obtained using different criterion weighting methods, on the Measurement Alternatives by a Combination of Angle and Distance (MACAD) ranking results, and to integrate the alternative rankings derived from different weighting MACAD combinations using the CURLI-AGGREGATOR (CURLIA) method. Accordingly, criterion weights were determined using three different objective criterion weighting methods ENTROPY, Weights by ENvelope and SLOpe (WENSLO) and Modified Preference Selection Index (MPSI) and these weights were used to rank the alternatives using the MACAD method. The resulting different rankings were then integrated into a single final ranking using the CURLIA method.

Another methodological objective of the study is to assess the consistency of the ranking results produced by different weighting approaches and the sensitivity of the rankings to changes in the weights assigned to the criteria. In this context, the ranking results obtained were evaluated through sensitivity analysis and comparative analyses carried out using different ranking methods.

As preliminary analyses initially carried out for the 2018–2024 period showed that different weighting approaches produced the same ranking results, the analysis period was extended to cover the years 2015–2024 in order to assess the contribution of the CURLIA method to the integration process more meaningfully. This has thus enabled the integration of rankings obtained from different weighting MACAD combinations under a more diverse temporal data structure, and the assessment of the proposed approach's applicability.

The practical aim of this study is to apply the proposed methodological approach to the assessment of the financial performance of Derimod Konfeksiyon A.Ş., a company listed on the BIST and operating in the textile, ready-to-wear and leather goods sectors of the manufacturing industry. Within this framework, the company's financial performance was examined in light of the results obtained from various criterion weighting methods, and the resulting rankings were evaluated using the MACAD and CURLIA methods.

The ENTROPY method objectively determines criterion weights by considering uncertainty and information content in the data [7], while the WENSLO method aims to reduce subjectivity by considering the non-linear effects of criteria [8]. The MPSI method offers an objective weighting approach based on preference variation [9, 10]. The MACAD method enables a more precise distinction between alternatives in high-dimensional problems [11], while the CURLIA method allows for the reliable and statistically consistent integration of different rankings [12].

1.3 The contributions of the study

The main contributions of this study can be summarised as follows:

i. To investigate the effect of the Entropy, WENSLO and MPSI objective weighting methods on the MACAD ranking method,
ii. By integrating the MACAD rankings obtained using different weighting methods with the CURLIA method to produce a more consistent and reliable final ranking,

iii. The fact that the proposed integrated approach provides a decision-making framework that supports the making of more reliable and comprehensive decisions in financial performance evaluation problems,
iv. Assessment of the model's robustness and usability in response to changes in the criteria weights and different ranking methods, through sensitivity and comparative analyses.

1.4. Organization of the Paper

The remainder of the study is structured as follows. The second section details the determination of criterion weights in multi-criteria decision-making processes and the applications of subjective and objective weighting approaches, as well as integrated methods, in the literature. It also covers alternative ranking integration techniques and provides a literature review of the methods used in the study. The third chapter outlines the study's methods and the theoretical framework of the CURLIA approach. The fourth chapter presents the application results and discusses the findings obtained from the sensitivity analysis and comparative analyses. The final chapter discusses the study's results, highlights its contributions to the literature and suggests areas for future research.

2. Literature Review

In multi-criteria decision-making problems, the determination of criterion preferences is achieved by establishing criterion weights, which constitutes one of the critical steps in MCDM methods due to its decisive impact on the final results [13]. The methods for determining weights can generally be classified as subjective and objective approaches. In subjective weighting methods, expert knowledge is utilised through various techniques such as pairwise comparisons of criteria, evaluation relative to alternatives, or scoring. With this approach, decision-makers or experts determine the relative importance of each criterion based on their experience and knowledge. In contrast, objective weighting methods rely on data and statistical analysis. With this approach, criterion weights are calculated based on quantitative data in the decision matrix, minimising the impact of subjective judgements. Therefore, objective methods provide more consistent results, particularly in situations where data-driven and measurable criteria are available [14].

Numerous MCDM methods establish performance indicators for alternatives by considering the weights of the criteria. Criterion weights quantitatively express the relative importance of criteria and can significantly influence the outcomes of the decision-making process. Numerous studies in the literature highlight that the solution exhibits high sensitivity to changes in criterion weights and demonstrate that different weighting approaches can lead to meaningful differences in the final ranking of alternatives. In this context, Van Dua *et al.* [5] investigated the effect of different method combinations on ranking consistency and decision outcomes by integrating objective weighting methods such as Entropy, MEthod based on the Removal Effects of Criteria (MEREC), LOgarithmic Percentage Change-driven Objective Weighting (LOPCOW), CRiteria Importance Through Inter-criteria Correlation (CRITIC) and MEAN with the Magnitude of the Area for the Ranking of Alternatives (MARA), Root Assessment Method (RAM) and Proximity Indexed Value (PIV) ranking methods. Similarly, Li *et al.* [15] integrated the Analytic Hierarchy Process (AHP) and the Entropy Weight Method (EWM) with Grey Relational Analysis (GRA), demonstrating that the combined use of subjective and objective weighting approaches more comprehensively reflects the influence of criterion weights on the decision-making process and yields more reliable and realistic assessment results.

Mukhametzyanov [16], by comparing objective weighting methods such as Entropy, CRiteria Importance Through Inter-criteria Correlation (CRITIC), and Standard Deviation (SD), revealed that criterion weights have a significant impact on MCDM outcomes and that different weighting methods may generate different criterion weights. Therefore, the study emphasized that comparing and analysing the weights obtained from different methods is essential for achieving more reliable decision-making processes. Baydaş and Elma [17] examined the impact of different weighting approaches and multi-criteria decision-making (MCDM) methods on the results of financial performance evaluation. The study compared equal weighting, entropy and hybrid weighting methods with the TOPSIS, Weighted Sum Approach (WSA) and PROMETHEE methods; it was demonstrated that different weighting approaches and multi-criteria decision-making (MCDM) methods can lead to significant differences in the alternative rankings.

In this context, one of the fundamental steps in the MCDM is the accurate and reliable determination of the weights of the relevant criteria. Criterion weights can be calculated using subjective-based methods (e.g., AHP [18], Best Worst Method (BWM) [19], Defining Interrelationships Between Ranked criteria (DIBR) [20]), objective-based methods (e.g., Entropy [16], CRITIC [21], MEREC [22], Criterion Impact Loss (CILOS) [23]), or a combination of these two approaches (Fuzzy AHP-Entropy [24]) [25]. The accuracy of weights significantly influences the results obtained from MCDM analyses. Therefore, integrated weighting methods have been developed in the literature, aiming to combine the advantages of subjective and objective weighting approaches. The Deviation Maximisation Method [26] and the Modified Integrated Weighting (MIW) method [27] are among the integration techniques in this context. These integrated approaches aim to increase the accuracy of assessments and the reliability of decision outcomes by combining the characteristics of both subjective and objective weights [28].

However, in the MCDM process, the determination of criterion weights is not the only critical issue; the consistency and reliability of the ranking results obtained based on these weights also represent important challenges. As highlighted in the literature, even when the same dataset and set of criteria are employed, different MCDM methods and weighting approaches may yield different, or even contradictory, rankings of alternatives. This variability makes it difficult for decision-makers to obtain a reliable and generalisable outcome based solely on a single method, thereby necessitating the integration of multiple ranking results to derive a comprehensive final ranking [29]. Accordingly, various ranking aggregation methods have been developed in the literature to combine ranking results generated by different weighting and MCDM approaches within a unified consensus framework. These approaches aim to provide more robust and reliable ranking outcomes by integrating preference information obtained from diverse methods [29–31].

Borda Count and Copeland approaches are among the commonly used methods in the literature for integrating alternative rankings derived from different multi-criteria decision-making (MCDM) methods [32, 33]. Among these approaches, the Borda Count method has been widely employed to aggregate multiple alternative rankings into a single comprehensive ranking. For example, Khorasani Nejad *et al.* [32] developed an integrated MCDM framework for structural feasibility assessment in infrastructure projects by employing TOPSIS, VIKOR, COPRAS, CODAS, SAW, and PROMETHEE methods, and combined the rankings obtained from these methods using the Borda Count approach to achieve a more balanced and reliable final ranking. Similarly, Filiz [34] separately evaluated the offensive and defensive performances of NBA teams using the TOPSIS method and integrated the resulting rankings through the Borda Count method to obtain a single final ranking. Aleksić *et al.* [35] determined the most suitable shooting conditions for preparatory shooting with a long-range rifle by integrating the alternative rankings obtained from the AHP and VIKOR methods through the Borda Count method. In another study, Uluskan *et al.* [36] evaluated the performance of foundation universities by combining the rankings obtained from the AHP, COPRAS, SAW, and TOPSIS methods using the Borda Count method and generated an integrated university performance ranking. Matejová and Paralič [37], on the other hand, evaluated suitable Explainable Artificial Intelligence

(XAI) methods using the AHP and CRITIC methods to determine criterion weights, and integrated the resulting rankings with the Borda Count, VIKOR, WASPAS and WSM methods, and integrated the resulting rankings using the Borda Count. Zavadskas *et al.* [33], on the other hand, assessed the sustainability performance of 21 neighbourhoods in Vilnius using the COPRAS, SAW, TOPSIS and Evaluation Based on Distance from Average Solution (EDAS) methods in conjunction with the Entropy, CILOS and Integrated Determination of Objective Criteria Weights (IDOCRIW) weighting methods, and integrated the resulting rankings using the Borda count, Copeland and ranking average methods. Similarly, Rouhani Rad *et al.* [38] determined the criterion weights using the Bayesian Best-Worst method, ranked 14 food and beverage companies listed on the Tehran Stock Exchange using the Combined Compromise Solution (CoCoSo) and Measurement Alternatives and Ranking according to Compromise Solution (MARCOS) methods, and integrated the resulting rankings using the Borda Count and Copeland methods. In a related study, Erarslan *et al.* [39] determined the criterion weights using the AHP and Stepwise Weight Assessment RAtio (SWARA) methods, evaluated suppliers in the turbocharger industry using the MOORA and WASPAS methods, integrated the resulting rankings using the Borda Count and Copeland methods, and carried out sensitivity analyses under different scenarios. In this context, Chen *et al.* [40] developed a hybrid collaborative text generation model that integrates the Entropy, CRITIC, MEREC, CILOS and Standard Deviation methods with MARCOS to evaluate generative AI-supported collaborative text generation tools, and examined the ranking results using the Borda count, Copeland, correlation and sensitivity analyses.

In the study by Sen and Neogi [41], the efficiency of 28 cement companies in India was assessed using DEA and super-radial DEA; the rankings obtained using the LOPCOW and Axial-Distance-based Aggregated Measurement (ADAM) methods were examined using sensitivity analysis and the Friedman test, and integrated using the Copeland method. Kumar and Pratihar [42] integrated the CRITIC, Entropy, MEREC, Standard Deviation and Gini weighting methods for material selection in ankle-foot prostheses with the CoCoSo, MABAC and Multi Attributive Ideal-Real Comparative Analysis (MAIRCA) methods, COPRAS, TOPSIS and WASPAS methods, and by combining the resulting rankings using the Copeland method, they validated the results using Finite Element Analysis (FEA). Ma *et al.* [43], drawing on the SOR theoretical framework, combined the rankings obtained using the TOPSIS- Characteristic Object MEthod (COMET), CoCoSo, EDAS, MAIRCA and MABAC methods using the Copeland method, and evaluated the factors determining purchase intention on community-based e-commerce platforms through a sensitivity analysis. Çakrak and Altuntaş [44] examined the sustainability performance of 10 airlines against 22 criteria, determined the criterion weights using the Entropy method, and integrated the rankings obtained from the Range Of Value (ROV), CoCoSo, Multi-Objective Optimization on the basis of Simple Ratio Analysis (MOOSRA), MARCOS, Additive Ratio Assessment System (ARAS) and Weighted Sum methods using the Copeland method. Shamsi *et al.* [45], with the aim of evaluating the sustainability performance of green concrete mixes containing recycled tyres, determined the criterion weights using the SImple WEight Calculation (SIWEC) method and compared different concrete mixes by combining the rankings obtained from the Deviation-Based Pairwise Assessment Ratio Technique (DEPART), Approximate Reasoning based Logical Ordering Number (ARLON), Ranking of Alternatives with Weights of Criterion (RAWEC), Alternative Ranking Order Method Accounting for Two-Step Normalization (AROMAN) and MARCOS methods using the Copeland method.

The Borda Count method aggregates stakeholders' preference rankings by converting them into points and uses only ordinal information based on ranking positions [46]. This approach relies solely on ordinal information and does not directly consider the levels of consistency between rankings or the magnitude of performance differences between alternatives. Furthermore, the simplicity of the method brings with it certain methodological limitations. In particular, its inability to adequately reflect the interactions between different criteria can lead to the incorrect or inadequate classification of some alternatives in multi-dimensional decision problems [47]. The Copeland method evaluates alternatives based on pairwise comparisons, thus relying on majority preference and producing rankings based on clear 'win–lose' scores. However, the likelihood of tied rankings increases, particularly as the number of alternatives grows. The Borda and Copeland methods focus on producing group rankings and do not include a mechanism for directly measuring the level of similarity or agreement between rankings [48]. In this context, there is a need for more comprehensive collective ranking approaches that not only determine the relative positions of alternatives but also assess the level of harmony and consistency between different rankings. Therefore, while these methods retain their importance in the literature, they may not be sufficient on their own, particularly in studies where consensus and consistency measurement are critical.

The CURLIA method, developed to address these limitations, aims to combine rankings obtained from different MCDM methods into a single, consistent global ranking. CURLIA enables the generation of more reliable aggregate ranking outputs by systematically addressing the integration of different MCDM results [12]. In this context, studies in the literature have been reviewed with the aim of highlighting the applications of the criteria weighting, ranking and ranking aggregation methods used in this research. The findings of the review indicate that, within the MCDM literature, objective weighting methods in particular, and the integration of these methods with various ranking techniques, are widely used.

In this context, it is observed that the entropy weighting method is frequently used in conjunction with various MCDM approaches. Chodha *et al.,* [7] demonstrated the effectiveness of the method by applying the Entropy–TOPSIS approach to the selection of an industrial arc welding robot. Mukhametzyanov [16] conducted a comparative analysis of the Entropy, CRITIC and standard deviation (SD) methods, examining the effect of different decision matrices on the weights. Wang *et al.,* [49] combined the Entropy and CoCoSo methods to assess the sustainability of road transport. El-Araby *et al.,* [50] applied the Entropy method, integrated with TOPSIS, GRA, EDAS and CoCoSo, to the logistics centre location selection problem and demonstrated that the CoCoSo method, in particular, produced consistent results. Zafar *et al.,* [51] evaluated blockchain platforms by using the Entropy, CRITIC and Entropy-CRITIC weight method (ECWM) methods in conjunction with WSM, TOPSIS and VIKOR. Gezen Ucar [52], meanwhile, utilised the GE-GRA approach, based on Entropy and GRA, to evaluate Turkey's energy policies.

Similarly, it is observed that entropy-based approaches are being extended to different fields. Wang *et al.,* [53] evaluated the sustainability performance of third-party logistics service providers using the Entropy–MARCOS model. Singh and Mohanty [54] contributed to climate-resilient water management by applying the Entropy–TOPSIS approach to the evaluation of rainfall data. Settu and Jayalakshmi [55] applied the Entropy and VIKOR methods to the selection of advanced resource robots and validated the model through sensitivity analysis. Dasgupta *et al.,* [56] meanwhile, applied the Entropy–TOPSIS approach to the problem of selecting sustainable polymer composite materials. Mastilo [57] assessed the innovation performance of EU countries and the United Kingdom using the Entropy-CORASO approach and found that Sweden, Denmark and the Netherlands were the frontrunners.

In recent years, the WENSLO weighting method has been featured increasingly frequently in the literature. Popović *et al.,* [58] applied the WENSLO–Weighted Euclidean Distance-Based Approach (WEDBA) to the problem of green supplier selection and demonstrated that suppliers with high social and environmental performance may be relatively weaker in terms of economic performance. Keleş and Kahveci [59] applied the WENSLO–Adaptive Standardized Intervals (ARTASI) method to the evaluation of countries' logistics performance. Gürler and Özçalıcı [60] analysed countries'

Sustainable Development Goals performance by integrating the WENSLO and CoCoSo methods. Bayazit Bedirhanoğlu [61] and Aryanti *et al.,* [62] used the WENSLO–AROMAN approach in the problems of university sustainability performance and restaurant staff selection, respectively. Wang *et al.,* [8] applied the WENSLO–RAWEC approach to a warehouse location selection problem and demonstrated the method's consistency. Kaya *et al.,* [63] used the WENSLO–Multiple Criteria Ranking by Alternative Trace (MCRAT) model to evaluate carbon and energy taxation performance in BRICS-T countries. Ozcalici *et al.* [64] significantly improved the predictive performance of the Transformer neural network model in forecasting share prices of large US corporations by weighting input features using the Entropy Weighting (EW), SD, MEREC, Simultaneous Evaluation of Criteria and Alternatives (SECA), CRITIC, CILOS and WENSLO methods.

However, MPSI-based approaches have also gained significant prominence in the literature. Ersoy *et al.,* [65] used the MPSI–Ranking Alternatives by Perimeter Similarity (RAPS) model to assess the performance of European Union countries against the Sustainable Development Goals and analysed the sensitivity of their methodology. Demir [66] applied the MPSI–RAWEC approach to assess the sustainability performance of commercial banks in Turkey. Gligorić *et al.,* [10] applied the MPSI–MARA model to the problem of selecting a support system in underground mining. Akbulut and Aydın [67] conducted a sustainability analysis of deposit-taking banks by integrating the MSD and MPSI methods with RAWEC. Yalçın and Edinsel [68] used the MPSI–MABAC approach to assess countries' climate change performance. Şeyranlıoğlu *et al.* [69] meanwhile, applied the MPSI–RAPS model to the financial performance analysis of textile firms listed on the BIST. Kaya *et al.* [70] using the MPSI-CoCoSo approach assessed the life insurance performance of EU and EEA countries and found that ROE was the most important criterion.

Finally, the RANking Comparison Method (RANCOM)–MACAD model was proposed by Keshtpour and Chakrabortty [11] for the problem of selecting a site for a desalination plant and has contributed to the literature with its capacity to produce more consistent and robust results in complex decision-making problems. In addition, the CURLIA method developed by Trung *et al.,* [12] has emerged as an innovative aggregation approach that combines rankings obtained from different multi-criteria decision-making (MCDM) methods into a single, consistent global ranking.

Whilst it is evident that various weighting, ranking and aggregation methods are widely used in the literature on multi-criteria decision-making (MCDM), a review of existing studies reveals some significant gaps. Firstly, it is noteworthy that studies in which objective weighting methods such as Entropy, WENSLO and MPSI are used simultaneously and comparatively within the same decision-making framework are quite limited. Secondly, there is insufficient research in the literature systematically analysing the sensitivity of the MACAD approach a relatively new and powerful ranking method to different weighting scenarios. Thirdly, although classical aggregation methods such as Borda and Copeland are extensively employed in the literature, there remains a notable lack of studies that integrate MACAD-based ranking outcomes derived from different weighting scenarios into a unified consensus ranking using advanced aggregation approaches such as CURLIA.

In response to these gaps, this study proposes a comprehensive and integrated MCDM framework that integrates multi-objective weighting methods (Entropy, WENSLO and MPSI) with the MACAD ranking method. The resulting different ranking outcomes are then consolidated into a single, consistent and consensus-based final ranking using the CURLIA method.

From a methodological perspective, the study presents a novel hybrid structure that comparatively examines the impact of different weighting approaches on MACAD-based ranking results under a single framework and integrates these results using an advanced aggregation mechanism. From an application perspective, the proposed approach enhances the reliability of the decision-making process by reducing inconsistencies that may arise from different weighting

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assumptions, and provides decision-makers with a more stable and interpretable final ranking. In this respect, the study makes an original contribution to the MCDM literature, both methodologically and in terms of practical application.

3. Methodology

The methodological framework used in this study consists of the following stages: creating the decision matrix, standardizing the data, determining the criterion weights, ranking the alternatives using multi-criteria decision-making methods, and integrating the obtained rankings using the CURLIA method. The methodological framework followed in the study is presented in Figure 1.

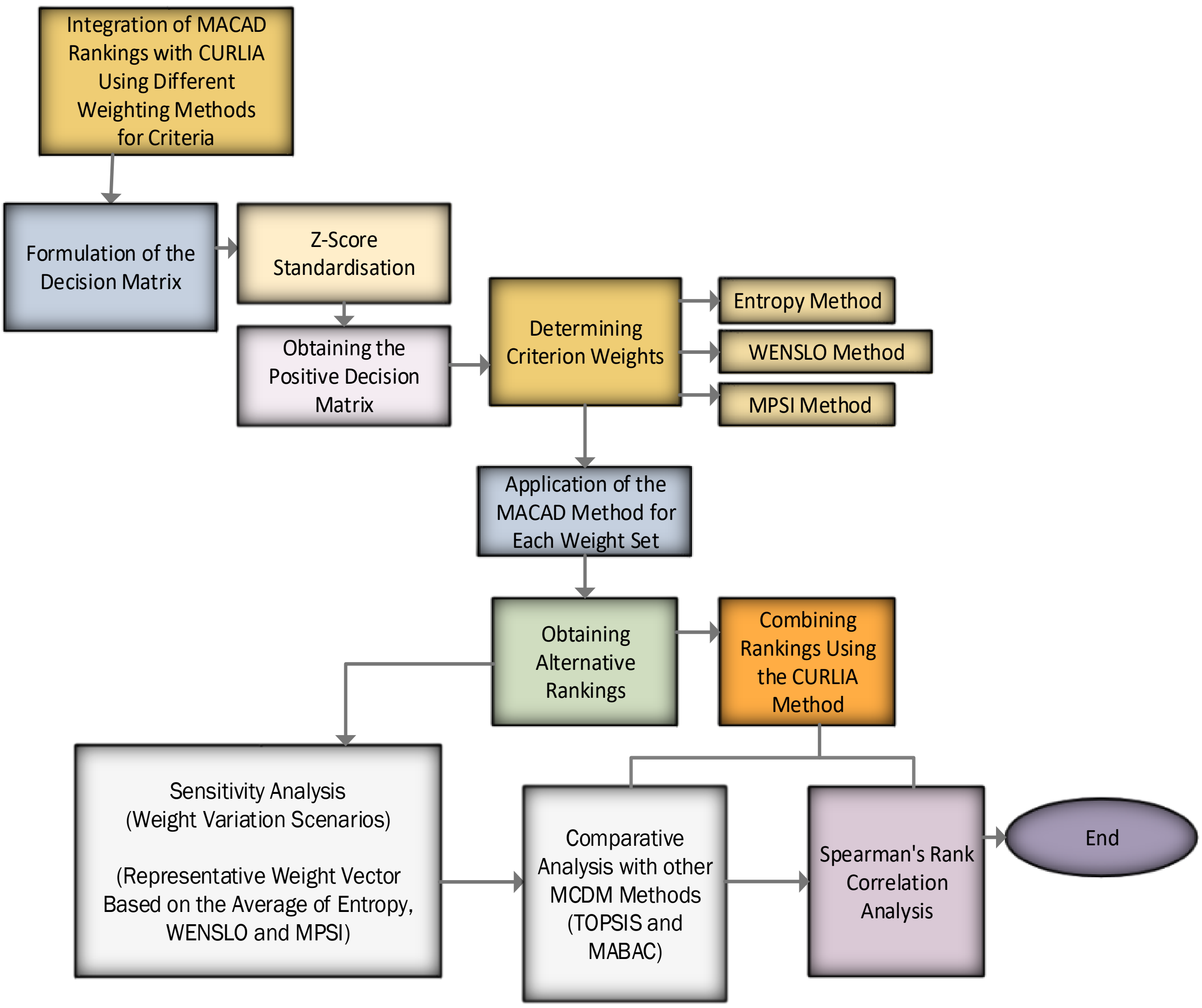

Fig. 1. Methodological framework diagram

3.1 Creating The Decision Matrix

In order to systematically evaluate the alternatives and criteria included in the study, an initial decision matrix consisting of m alternatives and n criteria was created. The decision matrix is defined as shown in Equation (1):

$$H = [h_{ij}] = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_m \end{array} \begin{array}{c} \overbrace{\begin{array}{ccccc} C_1 & C_2 & C_3 & \dots & C_n \end{array}} \\ \begin{bmatrix} h_{11} & h_{12} & h_{13} & \dots & h_{1n} \\ h_{21} & h_{22} & h_{23} & \cdots & h_{2n} \\ h_{31} & h_{32} & h_{33} & \cdots & h_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ h_{m1} & h_{m2} & h_{m3} & \dots & h_{mn} \end{bmatrix} \end{array} \tag{1}$$

Here, h_{ij} represents the performance value of the i(th) alternative A_i for the j(th) criterion C_j. This decision matrix was used in the Z-score standardization process in the study.

3.2. Z-Score Standardization

Since the criteria in the decision matrix have different scales and units, the data were standardized using Z-scores to ensure comparability between criteria. The Z-score method allows data to be evaluated on a common scale by expressing the deviation of each observation value from the mean of the relevant criterion in terms of standard deviation [71, 72].

The Z-score standardization and subsequent coordinate transformation are performed using Equations (2) and (3), respectively:

$$z_{ij} = \frac{(h_{ij} - \mu_j)}{\sigma_j} \tag{2}$$

Here

h_{ij}: The original value of the i(th) alternative in the j(th) criterion

μ_j: The average of the j(th) criterion for all alternatives

σ_j: The standard deviation of the j(th) criterion

z_{ij}: The standardized (Z-score) value of the i(th) alternative for the j(th) criterion

To prevent miscalculations that may arise from the mixing of positive and negative values between indices, all indices have been converted to positive values using a coordinate transformation method.

$$z'_{ij} = z_{ij} + A \tag{3}$$

Here, z'_{ij} represents the positive value obtained as a result of the coordinate transformation ($z'_{ij} > 0$). A, on the other hand, represents the shift constant applied to eliminate the negative values generated after Z-score standardization and to transform all elements of the decision matrix into a positive scale. The value of A is determined such that it satisfies the condition $A > |min(z_{ij})|$, and is chosen to be as close as possible to $|min(z_{ij})|$, whilst ensuring that the post-transformation values are positive.

The positive decision matrix ($Z' = [z'_{ij}]$) is defined as the values obtained as a result of Z-score standardization and positive transformation operations. In all subsequent stages of the study, calculations related to the Entropy, WENSLO, MPSI, and MACAD methods were performed on this positively transformed decision matrix.

3.3. Determining Criterion Weights

3.3.1. Entropy method

The Entropy weighting method is a weighting method that measures the distribution of values in decision-making [7]. Since the weight of any criterion reflects its importance, this method is used to determine the objective weights of each criterion [7]. This approach enables the level of uncertainty associated with each criterion to be determined during the decision-making process by expressing the degree of unpredictability or disorder within a system [73]. By analysing the distribution and level of variability of criterion values, it ensures that the relative importance of different criteria is objectively determined during the evaluation process [73]. The weighting method determines the objective weights of the criteria by utilising probability theory in the calculation of uncertain information [7]. As the method determines the levels of importance of the criteria without taking the decision-maker's preferences into account, it reduces subjective influences in the weighting process [74]. This method was preferred in the present study because it enables an impartial and data-driven determination of criterion weights without requiring decision-makers' subjective judgments. The method works as follows [7, 72]:

Step 1. Creating the Normalized Decision Matrix.

The positive decision matrix is normalized using Equation (4).

$$n_{ij} = \frac{z'_{ij}}{\sum_{i=1}^{m} z'_{ij}} \tag{4}$$

Here, n_{ij} represents the value corresponding to the jth criterion for the ith alternative.

Step 2. Calculation of Entropy Values.

The entropy value is calculated using Equation (5).

$$e_j = \frac{-1}{\ln(m)} \sum_{i=1}^{m} n_{ij} . ln\left(n_{ij}\right) \tag{5}$$

Step 3. Calculating the Weight Values for the Criteria.

The weight value for each criterion is obtained using Equation (6).

$$w_j^{ENTROPY} = \frac{\left(1-e_j\right)}{\sum_{j=1}^{n}\left(1-e_j\right)} \tag{6}$$

3.3.2. WENSLO method

The WENSLO method is an objective weighting approach introduced by Pamucar *et al.* [75]. It derives criterion weights in a data-driven manner by examining the trend and variation patterns of the criteria. Its relatively straightforward computational procedure and envelope–slope-based framework distinguish it from conventional objective weighting approaches. Although its independence from decision-maker judgments represents a significant advantage, the necessity of processing large volumes of raw data can be considered a practical limitation [61]. In this study, the WENSLO method was preferred due to its ability to determine criterion weights by incorporating changes in criterion values through envelope value analysis and the rate-of-change approach. This framework provides more informative weighting results by considering not only the distribution of the data but also the variation patterns among alternatives. Moreover, its data-oriented structure helps reduce the impact of subjective assessments during the weighting process [76]. The computational steps of the method are presented as follows [62, 75, 76]:

Step 4. Creating the Normalized Decision Matrix.

Each element in the positive decision matrix specified in Equation (3) is normalized using Equation (7).

$$n_{ij} = \frac{z'_{ij}}{\sum_{i=1}^{m} z'_{ij}} \tag{7}$$

Here, $0 < n_{ij} < 1$.

Step 5. Calculating the Criterion Class Interval, Slope, Envelope, and Envelope Slope Ratio.

The class interval, slope, envelope, and envelope slope ratio for each criterion are calculated using Equations (8), (9), (10), and (11), respectively.

$$\Delta Z_j = \frac{\underbrace{max}_{i=1,2,\dots,m} n_{ij} - \underbrace{min}_{i=1,2,\dots,m} n_{ij}}{1+3.322*\log(m)} \tag{8}$$

$$tan\vartheta_j = \frac{\sum_{i=1}^{m} n_{ij}}{(m-1)\Delta Z_j} \tag{9}$$

$$E_j = \sum_{i=1}^{m-1} \sqrt{\left(n_{i+1,j} - n_{ij}\right)^2 + \Delta Z_j^{\,2}} \tag{10}$$

$$q_j = \frac{E_j}{tan\vartheta_j} \tag{11}$$

Step 6. Calculating the Weight Values of the Criteria.

The weight value for each criterion is obtained using Equation (12).

$$w_j^{WENSLO} = \frac{q_j}{\sum_{j=1}^{n} q_j} \tag{12}$$

3.3.3. MPSI method

The MPSI method is an objective weighting approach based on the degree of change in preference values for each criterion. This change is determined by measuring the Euclidean distance between the normalized value and the average value of the criterion in question. It is assumed that as the deviation based on the criterion increases, the discriminating power of the criterion in question also increases. In this study, the MPSI method was chosen because it has a simple and straightforward computational structure, can determine weighting coefficients quickly, and offers a flexible approach that can be applied to various multi-criteria decision-making problems. The analysis process is carried out in the following stages [10].

Step 7. Creating the Normalized Decision Matrix.

Each element in the positive decision matrix is normalized in the direction of the criteria using Equation (13).

$$n_{ij} = \begin{cases} \dfrac{z'_{ij}}{\underbrace{max z'_{ij}}_{i=1,2,\dots,m}}, & j \in B \\ \dfrac{\underbrace{min z'_{ij}}_{i=1,2,\dots,m}}{z'_{ij}}, & j \in C \end{cases} \tag{13}$$

Here, B is the set of benefit criteria, and C is the set of cost criteria.

Step 8. Calculation of Normalized Average Values and Preference Variation Values for Criteria.

The normalized average values and preference variation value for each criterion are calculated using Equation (14) and Equation (15), respectively.

$$\upsilon_j = \frac{1}{m} \sum_{i=1}^{m} n_{ij} \tag{14}$$

$$\rho_j = \sum_{i=1}^{m} \left(n_{ij} - \upsilon_j\right)^2 \tag{15}$$

Step 9. Calculating the Weight Values of the Criteria.

The weight values for each criterion are obtained using Equation (16).

$$w_j^{MPSI} = \frac{\rho_j}{\sum_{j=1}^{n} \rho_j} \tag{16}$$

3.4. Ranking Alternatives Using The MACAD Method

The MACAD method is a geometry-based MCDM approach that evaluates both the proximity of alternatives to the ideal solution and their directional compatibility by combining the angular similarity between the alternative vector and the ideal vector with the distance criterion to the anti-ideal point. This framework enables more detailed comparisons, particularly in multi-criteria environments where linear assumptions fall short; it offers enhanced spatial resolution, decision accuracy and robustness. Furthermore, thanks to its robust geometric foundation, it offers graphical interpretability and ease of computation, and, thanks to its flexible design, it can be applied to a wide range of multi-criteria decision-making problems. However, as the MACAD method is based on numerical weights, its fundamental limitation is that it does not directly incorporate qualitative expert preferences. The steps of this method are outlined below [11].

Step 10. Creating the Normalized Matrix.

To balance the effect of criteria with different scales and units within the positive decision matrix $Z' = \left[z'_{ij}\right]$, each z'_{ij} element is normalized using Equation (17), and the normalized decision matrix $\aleph = \left[n_{ij}\right]$ is created.

$$n_{ij} = \frac{z'_{ij}}{\sqrt{\sum_{i=1}^{m} {z'_{ij}}^2}} \tag{17}$$

Step 11. Creating the Weighted Normalized Decision Matrix.

After the values of the initial decision matrix are normalized and the criterion weights w_j are determined, the weight of each criterion is multiplied by its normalized values as in Equation (18) to obtain the weighted normal matrix $\varepsilon = \left[e_{ij}\right]$, which reflects the relative performance of the alternatives.

$$e_{ij} = n_{ij} * w_j \tag{18}$$

Step 12. Calculation of the Ideal and Anti-Ideal Solution.

Ideal (A^*) and anti-ideal $(\boldsymbol{A}^-)$ points are calculated according to the direction of the criteria using Equations (19)-(20).

$$A^* = [x_1^*, x_2^*, \dots, x_n^*], \qquad x_j^* = \begin{cases} \underbrace{max}_{i}\, e_{ij} & j\in B \\ \underbrace{min}_{i}\, e_{ij} & j\in C \end{cases} \tag{19}$$

$$A^- = [x_1^-, x_2^-, \dots, x_n^-]\,, \;\; x_j^- = \begin{cases} \underbrace{min}_{i}\, e_{ij} & j\in B \\ \underbrace{max}_{i}\, e_{ij} & j\in C \end{cases} \tag{20}$$

Here, B is the set of benefit criteria, and C is the set of cost criteria.

Step 13. Calculating the Alternative and Ideal Vectors.

After determining the ideal A^* and anti-ideal A^- points with the weighted normalized matrix ε, the corresponding vector $\vec{U_i}$ for each alternative and the vector $\vec{U}^*$ for the ideal alternative are created using Equation (21) and Equation (22), respectively.

$$\vec{U}_i = [u_{ij}] \ , u_{ij} = (z'_{ij} - x_j^-) \tag{21}$$

$$\vec{U}^* = [u_j^*] \quad u_j^* = (x_j^* - x_j^-) \tag{22}$$

Here, z'_{ij} is an element of the positive decision matrix, x_j^* is the jth element of the ideal point, and x_j^- is the jth element of the anti-ideal point.

Step 14. Calculating the Lengths of Alternative and Ideal Vectors.

The lengths of alternative and ideal vectors are determined using (23) and (24) so that the angle between them (β_i) can be calculated.

$$\|\vec{U}_i\| = \sqrt{\sum_{j=1}^{n} u_{ij}^2} \tag{23}$$

$$\|\vec{U}^*\| = \sqrt{\sum_{j=1}^{n} (u_j^*)^2} \tag{24}$$

Step 15. Calculating the dot product of the alternative vector and the ideal vector.

The dot product between the alternative vector and the ideal vector is calculated using equation (25).

$$\vec{U}_i . \ \vec{U}^* = \sum_{j=1}^{n} u_{ij} \times u_j^* \tag{25}$$

Step 16. Calculating the angle between the alternative vector and the ideal vector.

The angle β_i between the alternative vector and the ideal vector is calculated using the inverse cosine function with equation (26).

$$\beta_i = cos^{-1}\left(\frac{\vec{U}_i . \ \vec{U}^*}{\|\vec{U}_i\|\|\vec{U}^*\|}\right) \tag{26}$$

Step 17. Calculating the distance from the negative ideal point.

In this step, the Euclidean distance D_i^-, of each alternative to the anti-ideal point is found using Equation (27).

$$D_i^- = \sqrt{\sum_{j=1}^{n} (e_{ij} - x_j^-)^2} \tag{27}$$

Step 18. Selection of the most suitable alternative.

The MACAD scores for each alternative are obtained using Equation (28), and the alternative with the smallest φ_i value is selected as the best alternative.

$$\varphi_i = \frac{D_i^- . \beta_i + (\sum_{i=1}^{m} D_i^-)(\sum_{i=1}^{m} \beta_i)}{D_i^- . (\sum_{i=1}^{m} \beta_i)} \tag{28}$$

3.5. Integration of Ranking Results Using The CURLIA Method

In this study, the CURLIA method was used to combine alternative rankings obtained using different weighting methods. CURLIA is an enhanced version of the CURLI method, which was proposed in 2016 to address the problem of creating collaborative ranked preference lists in medical education selection processes. Whilst CURLI is a multi-criteria decision-making (MCDM) approach focused on the direct ranking of alternatives, CURLIA is a ranking aggregation method developed to combine ranking results obtained from different methods into a single consolidated ranking. Although traditional ranking aggregation methods such as the Borda Count and Copeland are simple and practical, they have certain limitations, including an increase in computational load as the number of alternatives rises, difficulties in resolving ties, and the processing of ranking results in large-scale problems. For this reason, the CURLIA method a new approach designed to combine ranking results obtained from different methods in a more comprehensive and reliable manner has been adopted. The four-step systematic structure of the CURLIA method is as follows [12]:

Step 19. Creation of the Initial Ranking Matrix

The ranking data obtained from different MCDM methods are collected in a common structure using the initial ranking matrix specified in Equation (29).

$$O = [o_{ij}] = \begin{array}{c c} & \begin{array}{ccccc} R_1 & R_2 & R_3 & \dots & R_l \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} o_{11} & o_{12} & o_{13} & \dots & o_{1l} \\ o_{21} & o_{22} & o_{23} & \cdots & o_{2l} \\ o_{31} & o_{32} & o_{33} & \cdots & o_{3l} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ o_{m1} & o_{m2} & o_{m3} & \dots & o_{ml} \end{bmatrix} \end{array} \tag{29}$$

Here, m denotes the number of alternatives, l denotes the number of MCDM methods used, and o_{ij} denotes the ranking of alternative i determined by method j.

In this matrix, the rows $A_1, A_2, \dots, A_m$ correspond to the alternatives, and the columns $R_1, R_2, \dots, R_l$ correspond to the MCDM methods.

Step 20. Creating the Pairwise Comparison Matrices

For each MCDM method, mxl square matrices, known as pairwise comparison matrices, are created. According to the rule expressed in Equation (30), each cell of these matrices is assigned a value of -1, 0, or 1.

$$\mathfrak{B}_{il} = \begin{cases} 1, & o_i < o_k \quad i \neq k \\ 0, & o_i = o_k \quad i \neq k \\ -1, & o_i > o_k \quad i \neq k \end{cases} \tag{30}$$

Step 21. Obtaining the Total Scores of the Alternatives

The total score for the alternatives is obtained with Equation (31).

$$\mathfrak{F}_i = \sum_{j=1}^{l} \mathfrak{B}_{il} \tag{31}$$

The ranking of alternatives is determined according to the decreasing order of their overall scores. The alternative with the highest overall score is considered the best alternative.

4. Application

This study aims to bring together the alternative rankings produced using different criterion weighting approaches within an integrated assessment framework. In this regard, the financial performance indicators of Derimod Konfeksiyon A.Ş. (DERIM), a company listed on BIST and operating in the textile, clothing and leather products sector of the manufacturing industry, were selected as the application area for the years 2015–2024.

In the first stage of the analysis process, the ENTROPY, WENSLO, MPSI, and MACAD methods were applied to the 2018–2024 period. The results showed that all weighting methods produced identical ranking results. Under these circumstances, integrating the rankings using the CURLIA method would provide limited methodological insight, as the aggregation process would inevitably reproduce the same ranking. Consequently, the analysis period was extended to cover the years 2015–2024 in order to evaluate the performance of the proposed integration framework under a data structure exhibiting greater temporal variability. The inclusion of additional years increased the number of alternatives and enabled the CURLIA method to be evaluated under conditions where minor ranking differences among the weighting methods could be observed. The purpose of extending the analysis period was not to obtain different ranking results, but to examine the robustness and applicability of the proposed integrated decision-making framework under more comprehensive conditions.

The indicators were selected from among the criteria frequently used in studies examining financial performance in the manufacturing sector, such as those by Akbulut and Rençber [77], Çelik and Ayan [78], Yanık and Eren [79], Şahin and Bilgin Sarı [80], and Bardi [81]. These indicators are summarised in Table 1. The company's annual indicators were obtained from the Public Disclosure Platform (KAP), and a decision matrix was constructed as presented in Table 2. In this framework, the weights of the indicators were determined using the Entropy, WENSLO, and MPSI objective weighting methods. Subsequently, the alternatives were ranked by applying the MACAD method based on the calculated weight values. In the final stage, the CURLIA aggregation method was applied to combine the ranking results obtained from different weighting methods into a single final ranking.

Table 1
Criteria considered within the scope of the study

Dimension	Code	Financial Ratio	Formula	Direction
Liquidity	CO	Current Ratio	Current Assets / Current Liabilities	Max
Liquidity	ATO	Quick Ratio	(Current Assets − Inventories) / Current Liabilities	Max
Activity	ADH	Accounts Receivable Turnover	Net Sales / Accounts Receivable	Max
Activity	AKDH	Total Asset Turnover	Net Sales / Total Assets	Max
Profitability	AKO	Return on Assets (ROA)	Net Income / Total Assets	Max
Profitability	ÖKO	Return on Equity (ROE)	Net Income / Shareholders' Equity	Max
Profitability	NKM	Net Profit Margin	Net Income / Net Sales	Max
Financial Structure	FK	Debt Ratio	Total Debt / Total Assets	Min

Table 2
Decision matrix [82]

Criteria	CO	ATO	ADH	AKDH	AKO	ÖKO	NKM	FK
Years/Criterion Direction	max	max	max	max	max	max	max	min
2018	1.4893	1.4311	0.9421	0.8154	-0.0025	-0.0177	-0.0031	0.8587
2019	1.5479	1.4902	1.0221	0.8593	-0.0191	-0.0818	-0.0222	0.7668
2020	1.4271	1.3705	0.9036	0.7791	-0.0167	-0.0744	-0.0214	0.7757
2021	1.2490	1.1384	1.5970	0.9590	0.0069	0.0370	0.0072	0.8123
2022	1.3541	1.2199	3.4217	1.9825	0.0725	0.2857	0.0366	0.7463
2023	1.3572	1.2268	4.7523	2.9000	0.0136	0.0532	0.0047	0.7436
2024	1.4709	1.3556	3.8911	2.6556	0.0550	0.1841	0.0207	0.7014

Upon examining the decision matrix in Table 2, it is observed that the data for some indicators are negative. In order to ensure that the normalisation processes for the methods can be carried out correctly, these values have been converted to positive values using z-score standardisation and coordinate transformation methods. All analyses conducted during the research were performed using the resulting positive decision matrix.

4.1. Application of Z-Score Standardisation And Coordinate Transformation

Equation (2) with the decision matrix in Table 2 has been standardised, and the standardised decision matrix has been created as shown in Table 3.

Table 3
Standardised decision matrix

	CO	ATO	ADH	AKDH	AKO	ÖKO	NKM	FK
	max	max	max	max	max	max	max	min
2018	0.7502	0.8831	-0.8774	-0.8053	-0.5166	-0.5360	-0.2951	1.6959
2019	1.3309	1.3484	-0.8280	-0.7581	-0.9874	-1.0073	-1.1923	-0.1041
2020	0.1328	0.4060	-0.9013	-0.8443	-0.9192	-0.9523	-1.1548	0.0704
2021	-1.6324	-1.4211	-0.4726	-0.6509	-0.2481	-0.1334	0.1889	0.7875
2022	-0.5900	-0.7796	0.6555	0.4495	1.6133	1.6954	1.5636	-0.5051
2023	-0.5594	-0.7254	1.4781	1.4359	-0.0581	-0.0145	0.0696	-0.5586
2024	0.5680	0.2887	0.9457	1.1732	1.1161	0.9481	0.8200	-1.3860

Coordinate transformation was performed using Equation (3), and a positive decision matrix was obtained (Table 4).

Table 4
Positive decision matrix

	CO	ATO	ADH	AKDH	AKO	ÖKO	NKM	FK
	max	max	max	max	max	max	max	min
2018	2.3826	2.5156	0.7550	0.8271	1.1158	1.0964	1.3374	3.3283
2019	2.9633	2.9808	0.8044	0.8743	0.6450	0.6252	0.4401	1.5284
2020	1.7652	2.0384	0.7311	0.7881	0.7133	0.6801	0.4776	1.7028
2021	0.0000	0.2113	1.1598	0.9816	1.3843	1.4990	1.8213	2.4199
2022	1.0424	0.8528	2.2879	2.0819	3.2457	3.3278	3.1961	1.1274
2023	1.0730	0.9070	3.1105	3.0683	1.5743	1.6179	1.7021	1.0738
2024	2.2004	1.9211	2.5781	2.8056	2.7485	2.5805	2.4524	0.2464

Note: The values presented in Table 4 have been rounded to four decimal places to ensure a consistent presentation and a uniform level of numerical precision across all data. Consequently, the value displayed as 0.0000 does not represent an actual zero but rather a very small positive value greater than zero. Since all calculations were performed using the original unrounded values, no mathematically undefined operations resulting from zero values occurred during the analyses.

4.2. Calculation of Criterion Weights Using The Entropy Method

Table 4, Equation (4), Equation (5) and Equation (6) were used to calculate the normalised decision matrix, entropy values and weight values for each criterion, which are shown in Table 5.

Table 5
Normalized decision matrix, Entropy values, and criterion weights

	CO	ATO	ADH	AKDH	AKO	ÖKO	NKM	FK
	max	max	max	max	max	max	max	min
2018	0.2085	0.2201	0.0661	0.0724	0.0976	0.0960	0.1170	0.2913
2019	0.2593	0.2609	0.0704	0.0765	0.0564	0.0547	0.0385	0.1338
2020	0.1545	0.1784	0.0640	0.0690	0.0624	0.0595	0.0418	0.1490
2021	0.0000	0.0185	0.1015	0.0859	0.1211	0.1312	0.1594	0.2118
2022	0.0912	0.0746	0.2002	0.1822	0.2840	0.2912	0.2797	0.0987
2023	0.0939	0.0794	0.2722	0.2685	0.1378	0.1416	0.1490	0.0940
2024	0.1926	0.1681	0.2256	0.2455	0.2405	0.2258	0.2146	0.0216
e_j	0.8855	0.9042	0.9181	0.9199	0.9207	0.9200	0.9107	0.9118
$w_j^{ENTROPY}$	0.1614	0.1351	0.1155	0.1130	0.1119	0.1128	0.1259	0.1244

4.3. Calculation of Criterion Weights Using The WENSLO Method

The normalised decision matrix was obtained by applying Equation (7) to the positive decision matrix. Subsequently, the class interval, slope, envelope, and envelope slope ratio of the criteria were calculated using Equations (8)–(11), and the criterion weights were determined according to Equation (12) based on these values. The results obtained are presented in Table 6.

Table 6
Calculation results of class interval, slope, envelope, envelope slope ratio, and corresponding criterion weights

	CO	ATO	ADH	AKDH	AKO	ÖKO	NKM	FK
	max	max	max	max	max	max	max	min
2018	0.2085	0.2201	0.0661	0.0724	0.0976	0.0960	0.1170	0.2913
2019	0.2593	0.2609	0.0704	0.0765	0.0564	0.0547	0.0385	0.1338
2020	0.1545	0.1784	0.0640	0.0690	0.0624	0.0595	0.0418	0.1490
2021	0.0000	0.0185	0.1015	0.0859	0.1211	0.1312	0.1594	0.2118
2022	0.0912	0.0746	0.2002	0.1822	0.2840	0.2912	0.2797	0.0987
2023	0.0939	0.0794	0.2722	0.2685	0.1378	0.1416	0.1490	0.0940
2024	0.1926	0.1681	0.2256	0.2455	0.2405	0.2258	0.2146	0.0216
ΔZ_j	0.0681	0.0637	0.0547	0.0524	0.0598	0.0621	0.0633	0.0708
$\tan\vartheta_j$	2.4470	2.6182	3.0475	3.1800	2.7882	2.6830	2.6311	2.3528
E_j	0.6807	0.6098	0.4514	0.4285	0.6669	0.6701	0.6704	0.6456
q_j	0.2782	0.2329	0.1481	0.1347	0.2392	0.2497	0.2548	0.2744
w_j^{WENSLO}	0.1535	0.1285	0.0817	0.0744	0.1320	0.1378	0.1406	0.1514

4.4. Calculation of Criterion Weights Using the MPSI Method

In this study, within the scope of the MPSI method, the positive decision matrix was first normalised according to the direction of the criteria using Equation (13). Subsequently, the normalised average values and preference variation values for the criteria were calculated using Equations (14) and (15), respectively. Finally, the criterion weights were determined based on the obtained preference variations using Equation (16). The results obtained are presented in Table 7.

Table 7
Normalized average values, preference variations, and final criterion weights calculated under the MPSI method

	CO	ATO	ADH	AKDH	AKO	ÖKO	NKM	FK
	max	max	max	max	max	max	max	min
2018	0.8040	0.8439	0.2427	0.2696	0.3438	0.3295	0.4184	0.0740
2019	1.0000	1.0000	0.2586	0.2850	0.1987	0.1879	0.1377	0.1612
2020	0.5957	0.6838	0.2350	0.2569	0.2198	0.2044	0.1494	0.1447
2021	0.0000	0.0709	0.3729	0.3199	0.4265	0.4505	0.5699	0.1018
2022	0.3518	0.2861	0.7355	0.6785	1.0000	1.0000	1.0000	0.2186
2023	0.3621	0.3043	1.0000	1.0000	0.4851	0.4862	0.5325	0.2295
2024	0.7426	0.6445	0.8288	0.9144	0.8468	0.7754	0.7673	1.0000
υ_j	0.5509	0.5476	0.5248	0.5320	0.5030	0.4905	0.5108	0.2757
ρ_j	0.6833	0.6753	0.6201	0.6373	0.5696	0.5418	0.5874	0.6312
w_j^{MPSI}	0.1382	0.1365	0.1254	0.1289	0.1152	0.1095	0.1188	0.1276

4.5. Ranking Alternatives Using the MACAD Method

Criterion weighting methods only affect the criterion weight values; the algorithmic structure and application steps of the MACAD method remain unchanged. Therefore, instead of presenting the operation of the MACAD method separately according to three different weighting methods, the method steps are explained through the representative Entropy weighting approach; the results of the other weighting methods are presented comparatively in Table 13.

First, the positive decision matrix in Table 4 was normalised using Equation (17), and the resulting normalised decision matrix is given in Table 8.

Table 8
Normalised decision matrix

	CO	ATO	ADH	AKDH	AKO	ÖKO	NKM	FK
	max	max	max	max	max	max	max	min
2018	0.4799	0.5066	0.1521	0.1666	0.2247	0.2208	0.2693	0.6703
2019	0.5968	0.6003	0.1620	0.1761	0.1299	0.1259	0.0886	0.3078
2020	0.3555	0.4105	0.1473	0.1587	0.1437	0.1370	0.0962	0.3429
2021	0.0000	0.0426	0.2336	0.1977	0.2788	0.3019	0.3668	0.4874
2022	0.2099	0.1718	0.4608	0.4193	0.6537	0.6702	0.6437	0.2271
2023	0.2161	0.1827	0.6265	0.6180	0.3171	0.3258	0.3428	0.2163
2024	0.4432	0.3869	0.5192	0.5651	0.5536	0.5197	0.4939	0.0496

Equation (18) was applied to each element in the normalised decision matrix in Table 8, which was then multiplied by the weight values in Table 5 to create a weighted normalised decision matrix (Table 9).

Table 9
Weighted normalised decision matrix

	CO	ATO	ADH	AKDH	AKO	ÖKO	NKM	FK
eij	max	max	max	max	max	max	max	min
2018	0.0775	0.0684	0.0176	0.0188	0.0251	0.0249	0.0339	0.0834
2019	0.0963	0.0811	0.0187	0.0199	0.0145	0.0142	0.0112	0.0383
2020	0.0574	0.0555	0.0170	0.0179	0.0161	0.0154	0.0121	0.0427
2021	0.0000	0.0057	0.0270	0.0223	0.0312	0.0340	0.0462	0.0607
2022	0.0339	0.0232	0.0532	0.0474	0.0731	0.0756	0.0811	0.0283
2023	0.0349	0.0247	0.0724	0.0698	0.0355	0.0367	0.0432	0.0269
2024	0.0715	0.0523	0.0600	0.0638	0.0619	0.0586	0.0622	0.0062

Applying Equations (19) and (20) to the values in Table 9, taking into account the direction of the criteria, Ideal (A^{*}) and Anti-Ideal (A^{-}) points were obtained (Table 10).

Table 10
Ideal and anti-ideal points

A*	0.0963	0.0811	0.0724	0.0698	0.0731	0.0756	0.0811	0.0062
A-	0.0000	0.0057	0.0170	0.0179	0.0145	0.0142	0.0112	0.0834

Using the data presented in Tables 4 and 10, together with Equations (21) and (22), the corresponding $\vec{U_i}$ vectors for each alternative and the ideal alternative vector $\vec{U}^{*}$ were constructed. The obtained vectors are presented in Table 11.

Using Table 9, Table 10, and Table 11 along with Equations (23)–(28), the lengths of the alternative and ideal vectors, the dot products and angular values between the alternative vectors and the ideal vector, the distances from the negative ideal point, and the MACAD scores for each alternative were calculated. The findings obtained are presented in Table 12.

Table 11
The vectors $\vec{U}_i$ and $\vec{U}^*$

	CO	ATO	ADH	AKDH	AKO	ÖKO	NKM	FK
$\vec{U}_i$	max	max	max	max	max	max	max	min
2018	2.3826	2.5098	0.7380	0.8092	1.1013	1.0822	1.3262	3.2449
2019	2.9633	2.9751	0.7874	0.8564	0.6305	0.6110	0.4290	1.4449
2020	1.7652	2.0326	0.7141	0.7702	0.6987	0.6659	0.4665	1.6194
2021	0.0000	0.2055	1.1428	0.9636	1.3698	1.4848	1.8101	2.3365
2022	1.0424	0.8470	2.2709	2.0640	3.2311	3.3136	3.1849	1.0439
2023	1.0730	0.9012	3.0935	3.0504	1.5598	1.6037	1.6909	0.9904
2024	2.2004	1.9153	2.5611	2.7877	2.7340	2.5663	2.4412	0.1630
$\vec{U}^*$	0.0963	0.0753	0.0554	0.0519	0.0586	0.0614	0.0699	-0.0772

Table 12
Vector lengths, dot products, angular values, negative ideal distances and MACAD scores of alternatives

Year	$\lVert\vec{U}_i\rVert$	$\vec{U}_i.\ \vec{U}^*$	β_i	D_i^-	φ_i	Ranking
2018	5.2770	0.4745	1.0965	0.1033	7.6650	5
2019	4.6934	0.5905	0.8776	0.1304	6.0755	3
2020	3.4817	0.3920	0.9620	0.0862	9.1327	6
2021	3.8851	0.2462	1.2431	0.0504	15.5680	7
2022	6.6238	0.9317	0.7750	0.1370	5.7741	2
2023	5.4483	0.7323	0.8194	0.1118	7.0548	4
2024	6.5488	1.1185	0.5209	0.1550	5.0765	1
	$\lVert\vec{U}^*\rVert$					
	0.1969					

An examination of the findings in Table 12 reveals that DERIMOD achieved its highest financial performance in 2024. This year is followed, in order of performance, by 2022, 2019, 2023, 2018, 2020 and 2021. The lowest financial performance was recorded in 2021.

The comparative financial performance scores and ranking results obtained from the Entropy-MACAD, WENSLO-MACAD, and MPSI-MACAD approaches are presented in Table 13.

Table 13
DERIMOD's financial performance scores and ranking results by year according to Entropy-MACAD, Wenslo-MACAD and MPSI-MACAD methods

	Entropy-MACAD		Wenslo-MACAD		MPSI-MACAD	
	φ_i	Sıralama	φ_i	Sıralama	φ_i	Ranking
2018	7.6650	5	8.1567	5	8.0830	5
2019	6.0755	3	6.3368	3	6.3621	3
2020	9.1327	6	9.2476	6	9.3859	6
2021	15.5680	7	13.9963	7	15.4603	7
2022	5.7741	2	5.3316	2	5.6637	2
2023	7.0548	4	7.5679	4	6.6044	4
2024	5.0765	1	4.9772	1	4.9843	1

When examining the MACAD scores (φ_i) presented in Table 13, DERİMOD's financial performance has been consistently evaluated using the Entropy-MACAD, Wenslo-MACAD, and MPSI-MACAD methods. Across all methods, 2024 has been identified as the highest-performing year, with the lowest φ_i value. This is followed by 2022, 2019, 2023, 2018, and 2020, respectively. The lowest performance was observed in 2021 across all methods. This indicates that, despite variations in φ_i values among the different MACAD methods used, the overall performance ranking remains largely consistent.

The consistency of ranking results obtained using different weighting methods demonstrates that the decision model established possesses a highly stable structure. In line with this finding, the scope of the study was expanded to test the validity of this stability over time. Analyses were re-conducted using the same methodological framework, incorporating an alternative set of years (2015, 2016, and 2017), resulting in a total of 10 alternatives. The ranking results are presented in Table 14.

Table 14
MACAD performance rankings based on different weighting methods for the period 2015–2024

	Entropy- MACAD	Sıralama	WENSLO-MACAD	Sıralama	MPSI -MACAD	Ranking
2015	7.6303	3	7.2901	3	7.4747	3
2016	14.3928	8	13.8626	7	15.4717	9
2017	15.4940	9	14.8909	9	15.0029	8
2018	12.0084	6	11.6085	6	11.1710	6
2019	9.3820	5	9.4918	4	8.8114	4
2020	13.3820	7	14.0218	8	12.7911	7
2021	17.6861	10	17.6107	10	19.0755	10
2022	6.9052	2	6.5465	1	7.3445	2
2023	9.1906	4	10.5950	5	9.2493	5
2024	6.6397	1	6.7922	2	6.7830	1

According to the ranking results presented in Table 14, the company ranked in the same position across all weighting methods in 2015 (3rd place), 2018 (6th place) and 2021 (10th place). However, in other years, such as 2016, 2017, 2019 and 2020, some differences in ranking positions between methods are observed. This indicates that in some years, the rankings between methods are completely consistent, while in other years they contain minor variations.

4.6. Combining Ranking Results Using the CURLIA Method

The ranking data obtained from the different weighting methods presented in Table 14 were combined using Equation (29) to construct the ranking matrix. The resulting ranking matrix is presented in Table 15.

Table 15
Ranking matrix

Year	Entropy- MACAD	WENSLO-MACAD	MPSI -MACAD
2015	3	3	3
2016	8	7	9
2017	9	9	8
2018	6	6	6
2019	5	4	4
2020	7	8	7
2021	10	10	10
2022	2	1	2
2023	4	5	5
2024	1	2	1

For each method, mxm-sized pairwise comparison matrices were created, and each cell was assigned a value of −1, 0, or 1 according to the rule specified in Equation (30). As a result of this process, pairwise comparison matrices for the methods were obtained, and the relevant matrices are presented in Tables 16 and Table 17, and Table 18 respectively.

Table 16
Pairwise comparison matrix for Entropy-MACAD method

Entropy-MACAD		3	8	9	6	5	7	10	2	4	1
		2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
3	2015	0	1	1	1	1	1	1	-1	1	-1
8	2016	-1	0	1	-1	-1	-1	1	-1	-1	-1
9	2017	-1	-1	0	-1	-1	-1	1	-1	-1	-1
6	2018	-1	1	1	0	-1	1	1	-1	-1	-1
5	2019	-1	1	1	1	0	1	1	-1	-1	-1
7	2020	-1	1	1	-1	-1	0	1	-1	-1	-1
10	2021	-1	-1	-1	-1	-1	-1	0	-1	-1	-1
2	2022	1	1	1	1	1	1	1	0	1	-1
4	2023	-1	1	1	1	1	1	1	-1	0	-1
1	2024	1	1	1	1	1	1	1	1	1	0

Table 17
Pairwise comparison matrix for WENSLO-MACAD method

WENSLO-MACAD		3	7	9	6	4	8	10	1	5	2
		2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
3	2015	0	1	1	1	1	1	1	-1	1	-1
7	2016	-1	0	1	-1	-1	1	1	-1	-1	-1
9	2017	-1	-1	0	-1	-1	-1	1	-1	-1	-1
6	2018	-1	1	1	0	-1	1	1	-1	-1	-1
4	2019	-1	1	1	1	0	1	1	-1	1	-1
8	2020	-1	-1	1	-1	-1	0	1	-1	-1	-1
10	2021	-1	-1	-1	-1	-1	-1	0	-1	-1	-1
1	2022	1	1	1	1	1	1	1	0	1	1
5	2023	-1	1	1	1	-1	1	1	-1	0	-1
2	2024	1	1	1	1	1	1	1	-1	1	0

Table 18
Pairwise comparison matrix for MPSI-MACAD method

MPSI-MACAD		3	9	8	6	4	7	10	2	5	1
		2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
3	2015	0	1	1	1	1	1	1	-1	1	-1
9	2016	-1	0	-1	-1	-1	-1	1	-1	-1	-1
8	2017	-1	1	0	-1	-1	-1	1	-1	-1	-1
6	2018	-1	1	1	0	-1	1	1	-1	-1	-1
4	2019	-1	1	1	1	0	1	1	-1	1	-1
7	2020	-1	1	1	-1	-1	0	1	-1	-1	-1
10	2021	-1	-1	-1	-1	-1	-1	0	-1	-1	-1
2	2022	1	1	1	1	1	1	1	0	1	-1
5	2023	-1	1	1	1	-1	1	1	-1	0	-1
1	2024	1	1	1	1	1	1	1	1	1	0

Equation (31) was applied to calculate the total score of each alternative, and the resulting scores and rankings are presented in Table 19. Table 20 summarises the rankings obtained using different weighting methods for alternative years, combined with the rankings obtained using the CURLIA method.

Looking at Table 20, it can be seen that the rankings obtained using the Entropy-MACAD, WENSLO-MACAD, MPSI-MACAD and CURLIA methods are largely consistent with each other. In particular, the fact that all methods produced the same ranking in 2015 and 2018 indicates that the company's financial performance in those years was assessed similarly, regardless of the method used. Although there were minor ranking differences in 2016, 2017 and 2020, the methods produced similar results in terms of overall performance trends. The year 2021 was identified as the year of lowest performance by all methods, whereas the company's high ranking in 2022 and 2024 suggests a strong recovery across the methods. The combined rankings obtained using the CURLIA method provided a conciliatory and consistent assessment, reflecting the common trend of different weighting approaches. This suggests that the analysis results show a high degree of consistency across methods and that the findings regarding the company's financial performance are supported by the results. This is also supported by the Spearman rank correlation analysis presented in Table 21.

Table 19
Total scores and rankings of alternatives using the CURLIA method

	$\mathfrak{F}_i$	Ranking
2015	15	3
2016	-15	8
2017	-19	9
2018	-3	6
2019	7	4
2020	-11	7
2021	-27	10
2022	23	2
2023	5	5
2024	25	1

Table 20
Comparative rankings of alternative years based on different weighting methods and the CURLIA method

	Entropy- MACAD	WENSLO-MACAD	MPSI -MACAD	CURLIA
2015	3	3	3	3
2016	8	7	9	8
2017	9	9	8	9
2018	6	6	6	6
2019	5	4	4	4
2020	7	8	7	7
2021	10	10	10	10
2022	2	1	2	2
2023	4	5	5	5
2024	1	2	1	1

Table 21
Spearman rank correlation analysis

	Entropy- MACAD	WENSLO-MACAD	MPSI -MACAD	CURLIA
Entropy- MACAD	1			
WENSLO-MACAD	0.963636	1		
MPSI -MACAD	0.975758	0.951515	1	
CURLIA	0.987879	0.975758	0.987879	1

The Spearman rank correlation coefficients in Table 21 indicate a very high level of agreement between the rankings obtained using the Entropy-MACAD, WENSLO-MACAD, MPSI-MACAD and CURLIA methods. The fact that all correlation values are above 0.95 suggests that the methods evaluate the company's financial performance in a largely similar manner. In particular, the correlation between the CURLIA method and Entropy-MACAD and MPSI-MACAD, which is as high as 0.987879, shows that the combined ranking closely reflects the common trend of the other methods. Even the lowest correlation value of 0.951515 indicates a strong positive relationship and shows that there is no significant inconsistency between the methods. These findings indicate that, despite the use of different weighting approaches, the results obtained are broadly consistent and provide statistical support for the consistency of the analysis results.

4.7. Sensitivity Analysis

In this study, the criterion weights were determined using three different objective weighting methods: Entropy, WENSLO and MPSI. Alternative rankings were generated using the weights obtained and the MACAD method, and these were then integrated using the CURLIA method to produce the final ranking. Rather than relying on any single weighting method in the sensitivity analysis, a weight vector representing the common trend of the three methods was used instead. To this end, a representative weight vector was created by taking the arithmetic mean of the criterion weights obtained from the Entropy, WENSLO, and MPSI methods for the 2015–2024 period. The scenario analysis was then carried out using this weight vector. The arithmetic mean of the weight values obtained from the Entropy, WENSLO and MPSI methods was then calculated for each criterion. The calculated average weight vector is presented in Table 22.

Table 22
Criterion weights obtained using the entropy, WENSLO and MPSI methods, along with the arithmetic mean weight vector

	CO	ATO	ADH	AKDH	AKO	ÖKO	NKM	FK
$w_j^{ENTROPY}$	0.1366	0.1333	0.1048	0.1032	0.1122	0.1182	0.1433	0.1485
w_j^{WENSLO}	0.1499	0.1358	0.0801	0.0755	0.1464	0.1501	0.1401	0.1221
w_j^{MPSI}	0.1422	0.1535	0.1086	0.1113	0.1054	0.1066	0.1321	0.1402
w_j^{MEAN}	0.1429	0.1409	0.0978	0.0967	0.1214	0.1249	0.1385	0.1369

An examination of Table 22 reveals that, based on the arithmetic mean of the criterion weights obtained from the Entropy, WENSLO and MPSI methods, the criterion with the highest weight value is the CO (Current Ratio) criterion. Consequently, within the scope of the sensitivity analysis, weight variation scenarios were developed using the CO criterion as the basis. The scenarios are based on the approach of modifying the weight coefficients commonly used in the literature and redistributing the reduced weight among the other criteria whilst maintaining the total weight value [83, 84]. In this context, the weight value for the CO criterion was reduced by 5 per cent, 10 per cent, 15 per cent, 20 per cent and 25 per cent, and the resulting weight loss was distributed equally amongst the remaining seven criteria. Thus, a total of six different scenarios were created, including the base case (S0) representing the original set of weights. The criterion weight values for the generated scenarios are presented in Table 23.

Table 23
Criterion weights for the CO criterion weight change scenarios

	CO	ATO	ADH	AKDH	AKO	ÖKO	NKM	FK
S0	0.1429	0.1409	0.0978	0.0967	0.1214	0.1249	0.1385	0.1369
S1 (%5)	0.1358	0.1419	0.0989	0.0977	0.1224	0.1260	0.1395	0.1379
S2(%10)	0.1286	0.1429	0.0999	0.0987	0.1234	0.1270	0.1405	0.1390
S3(%15)	0.1215	0.1439	0.1009	0.0997	0.1244	0.1280	0.1415	0.1400
S4(%20)	0.1143	0.1450	0.1019	0.1008	0.1254	0.1290	0.1426	0.1410
S5 (%25)	0.1072	0.1460	0.1029	0.1018	0.1265	0.1300	0.1436	0.1420

For each scenario developed in Table 23, the MACAD method was reapplied and the rankings of the alternatives were recalculated. The resulting scenario-based ranking results are presented comparatively in Table 24. In this study, the final decision ranking was established by integrating the

MACAD rankings obtained using Entropy, WENSLO and MPSI weights with the CURLIA method. However, in the sensitivity analysis, as a single weight vector representing the common trend of the three objective weighting methods was used as the basis, only one MACAD ranking was obtained for each scenario and, consequently, the CURLIA method was not reapplied. In this context, the base scenario (S0) was compared with the other scenarios (S1–S5) to assess the impact of changes in the representative weight vector on the alternative rankings.

Table 24
Alternative rankings of MACAD according to weight change scenarios based on the CO criterion

S0 (ort)	2024>2022>2015>2019>2023>2018>2020>2016>2017>2021
S1 (-%5)	2024>2022>2015>2019>2023>2018>2020>2016>2017>2021
S2 (-%10)	2024>2022>2015>2019>2023>2018>2020>2016>2017>2021
S3 (-%15)	2024>2022>2015>2023>2019>2018>2020>2016>2017>2021
S4 (-%20)	2024>2022>2015>2023>2019>2018>2020>2016>2017>2021
S5 (-%25)	2024>2022>2015>2023>2019>2018>2020>2016>2017>2021

An examination of Table 24 reveals that the rankings of the alternatives in the top three and bottom five positions remain unchanged across the baseline scenario (S0) and all other scenarios. Accordingly, in all scenarios, the alternatives for the years 2024, 2022 and 2015 occupy the top three positions respectively, whilst those for the years 2018, 2020, 2016, 2017 and 2021 have retained their positions in the bottom five. In the S1 (5 per cent) and S2 (10 per cent) scenarios, the alternative rankings remained exactly the same as in the base scenario (S0). In contrast, in the S3, S4 and S5 scenarios, where the weighting of the CO criterion was reduced to 15 per cent, 20 per cent and 25 per cent respectively, only the rankings of the alternatives for 2019 and 2023 shifted by one position; no changes were observed in the rankings of any other alternatives. These changes in the alternative rankings can also be visually observed on the radar chart in Figure 2. These findings indicate that changes in the weighting of the CO criterion of up to 25 per cent have a limited effect on the alternative rankings obtained using the MACAD method, and that the ranking results remain relatively stable in the face of reasonable changes in criterion weights.

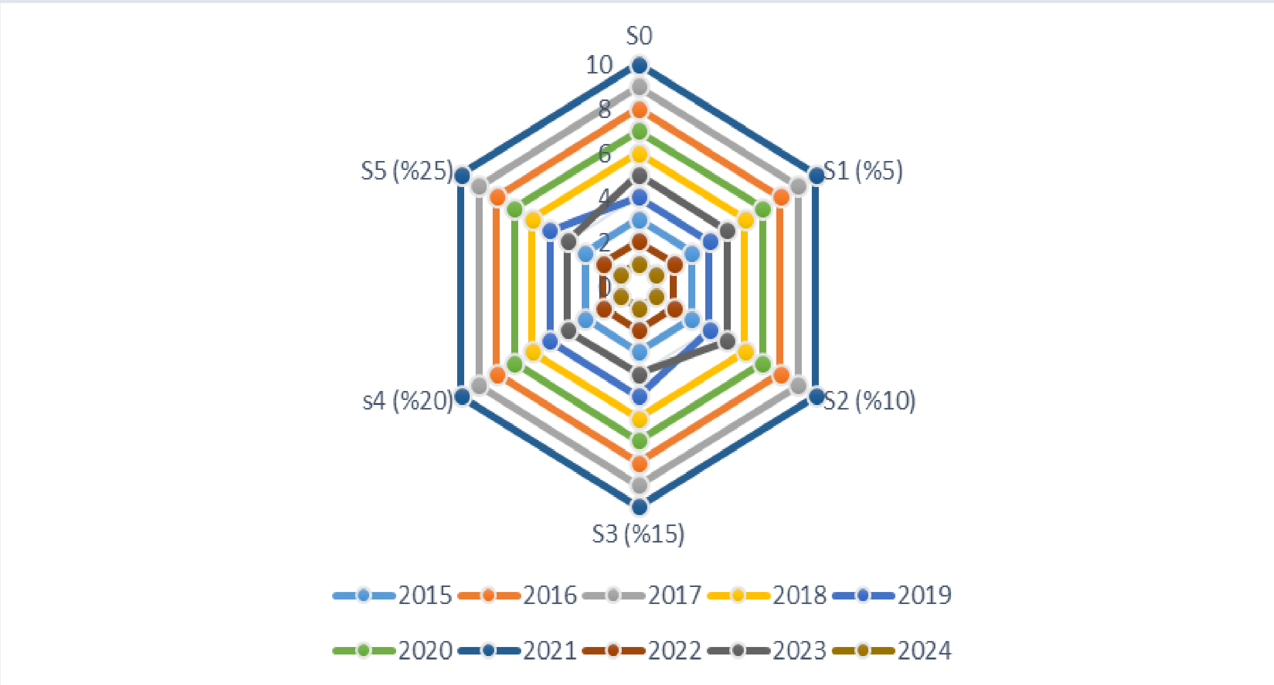

Fig. 2. Alternative MACAD rankings under different scenarios for reducing the weighting of the CO criterion

4.8. Comparative Analysis

In the development of multi-criteria decision-making (MCDM) models, comparative analysis has become a key element in validating the results obtained [83]. In this context, the aim was to compare the results obtained from the proposed integrated decision-making framework with the TOPSIS [85] and MABAC [86] methods, which are widely used in the literature. Accordingly, the TOPSIS and MABAC methods were applied using the criterion weights obtained via the Entropy, WENSLO and MPSI methods; the alternative rankings obtained from these methods were compared with the rankings obtained using the MACAD method based on the Entropy, WENSLO and MPSI weights, and with the final ranking obtained by combining these rankings using the CURLIA method. Thus, the consistency of the proposed integrated decision-making framework with respect to different multi-criteria decision-making (MCDM) methods and the reliability of its results were evaluated. The ranking results for the alternatives are presented in Table 25 and Figure 3.

Table 25
Alternative rankings according to different MCDM methods

	ENTROPY -TOPSIS	WENSLO -TOPSIS	MPSI-TOPSIS	ENTROPY -MABAC	WENSLO -MABAC	MPSI-MABAC	ENTROPY -MACAD	WENSLO -MACAD	MPSI-MACAD	CURLIA
2015	3	3	3	3	3	3	3	3	3	3
2016	8	7	9	7	7	9	8	7	9	8
2017	9	8	8	8	8	8	9	9	8	9
2018	6	6	6	6	6	6	6	6	6	6
2019	5	5	5	5	5	5	5	4	4	4
2020	7	9	7	9	9	7	7	8	7	7
2021	10	10	10	10	10	10	10	10	10	10
2022	2	2	2	2	2	2	2	1	2	2
2023	4	4	4	4	4	4	4	5	5	5
2024	1	1	1	1	1	1	1	2	1	1

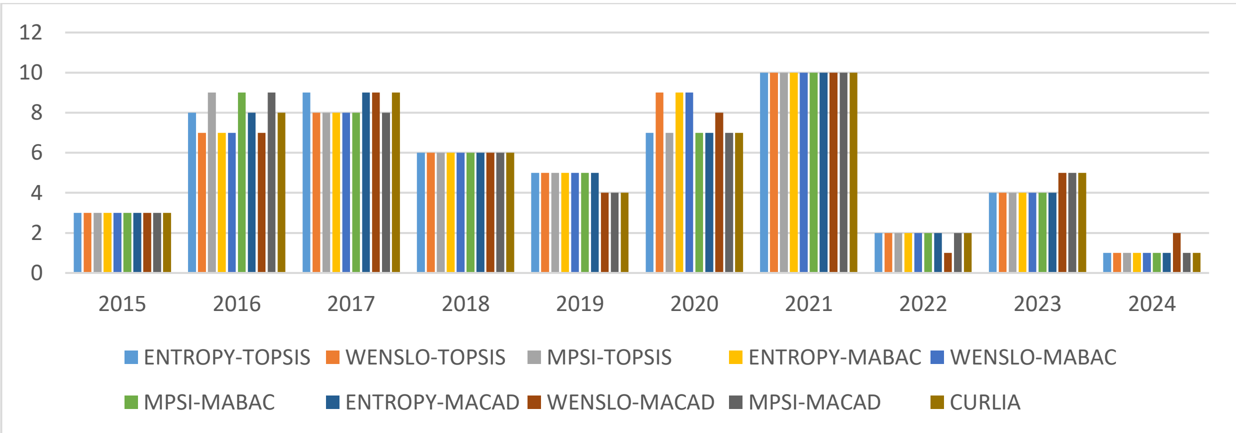

Fig. 3. Alternative rankings according to different CCA methods

An examination of Table 25 and Figure 3 reveals that the rankings for the alternative years, obtained using different MCDM methods, are generally consistent. In particular, the fact that the years 2015, 2018 and 2021 occupy the same position in all methods indicates that the financial performance assessments for these years yielded the same rankings regardless of the method used. However, the ranking results for the alternatives relating to the years 2022 and 2024 were identical across all methods except the WENSLO–MACAD method. In the WENSLO–MACAD approach, there was a change in the ranking positions of these two alternatives; the 2022 alternative was ranked first, whilst the 2024 alternative was ranked second. In contrast, in all other methods, the 2024 alternative was ranked first, indicating the highest financial performance, whilst the 2022 alternative was ranked second. Upon examining the results of the ENTROPY–MACAD method, it is observed that the alternative for 2023 was ranked fourth, and this ranking aligns with the results obtained from the ENTROPY, WENSLO and MPSI-weighted TOPSIS, as well as the MABAC methods. Similarly, the 2019 alternative was ranked fifth in the ENTROPY–MACAD method, and it was determined that this ranking was consistent with the results obtained using the ENTROPY, WENSLO and MPSI-weighted TOPSIS, and MABAC methods. In the final ranking obtained using the WENSLO–MACAD and MPSI–MACAD methods alongside the CURLIA method, however, it was ranked fourth in 2019 and fifth in 2023, yielding a ranking result that differed from that of the other methods. Whilst limited differences were observed in the rankings for 2016, 2017 and 2020, it was found that the final ranking obtained using the CURLIA method was broadly consistent with the results obtained from the other methods. A Spearman rank correlation analysis was applied to statistically evaluate the relationship between the rankings obtained from the MCDM methods and the final ranking derived using the CURLIA method; the results of this analysis are presented in Table 26.

Table 26
Results of spearman's rank correlation analysis

	ENTROPY-TOPSIS	WENSLO-TOPSIS	MPSI-TOPSIS	ENTROPY-MABAC	WENSLO-MABAC	MPSI-MABAC	ENTROPY-MACAD	WENSLO-MACAD	MPSI-MACAD	CURLIA
ENTROPY-TOPSIS	1.000000									
WENSLO-TOPSIS	0.963636	1.000000								
MPSI-TOPSIS	0.987879	0.951515	1.000000							
ENTROPY-MABAC	0.963636	1.000000	0.951515	1.000000						
WENSLO-MABAC	0.963636	1.000000	0.951515	1.000000	1.000000					
MPSI-MABAC	0.987879	0.951515	1.000000	0.951515	0.951515	1.000000				
ENTROPY-MACAD	1.000000	0.963636	0.987879	0.963636	0.963636	0.987879	1.000000			
WENSLO-MACAD	0.963636	0.963636	0.939394	0.963636	0.963636	0.939394	0.963636	1.000000		
MPSI-MACAD	0.975758	0.939394	0.987879	0.939394	0.939394	0.987879	0.975758	0.951515	1.000000	
CURLIA	0.987879	0.951515	0.975758	0.951515	0.951515	0.975758	0.987879	0.975758	0.987879	1.000000

Examining Table 26 shows a strong positive correlation between the final rankings obtained using various MCDM methods and those obtained using the CURLIA method. The Spearman rank correlation coefficients ranging from 0.939394 to 1.000000 indicate strong agreement between the rankings produced by the methods. Furthermore, the high level of correlation between the MACAD rankings obtained using the ENTROPY, WENSLO and MPSI weighting methods and those obtained using other MCDM methods indicates that the MACAD rankings are largely consistent with those obtained using other methods. Similarly, the correlation coefficients between the final ranking obtained using the CURLIA method and those obtained using other methods range from 0.951515 to 0.987879, indicating that the final CURLIA ranking is broadly consistent with the rankings obtained using the other MCDM methods.

5. Limitations and Future Research

The approach proposed in this study, which is based on the integration of the MACAD ranking method with the Entropy, WENSLO and MPSI weighting methods via the CURLIA method, has certain limitations. Firstly, the application is limited to financial data for the period 2015–2024 and to Derimod Konfeksiyon A.Ş., a company listed on the BIST. Consequently, the ability of the results to reflect longer-term economic fluctuations and their generalisability to different companies or sectors may be limited. Furthermore, the model takes into account only liquidity, operational performance, profitability and financial structure criteria; social and environmental performance indicators have not been included in the assessment. It is recommended that future studies utilise longer and more up-to-date data sets, conduct applications across different sectors and companies, and incorporate social and environmental criteria into the model.

From a methodological perspective, the weighting stage employed in this study was limited to three objective weighting methods: Entropy, WENSLO and MPSI. Consequently, the impact of subjective or hybrid weighting approaches on the results has not been assessed. In future research, examining the effect of different subjective and hybrid weighting methods on MACAD rankings could contribute to the evaluation of the approach from different weighting perspectives.

Furthermore, as the CURLIA method integrates MACAD rankings derived from different weighting methods, the complexity and computational load of the process may increase if the number of weighting and ranking methods used, as well as the number of alternatives and criteria, rises. This may lead to longer processing times, particularly when calculations are carried out in manual calculation environments such as Excel. In this study, as conducting separate scenario analyses for each weight derived from the three different weighting methods would increase the computational load, a representative weight vector created by taking the arithmetic mean of these weights was used in the sensitivity analysis. This approach reduced the computational load whilst enabling an assessment of the overall effect of the weighting methods. In future studies, it is recommended that the calculation process be automated and that more advanced software infrastructures be utilised when evaluating a greater number of weighting and ranking methods in combination.

Finally, the performance of the CURLIA method was not directly compared with the Borda, Copeland and other ranking aggregation methods in this study. Comparing CURLIA's performance in aggregating MACAD rankings derived from different weighting methods with alternative ranking aggregation approaches could enable a more comprehensive assessment of the method's relative performance. In future research, comparing CURLIA with different ranking aggregation methods and examining its scalability and computational performance across various decision problems involving more alternatives and criteria will contribute to a more comprehensive demonstration of the approach's methodological contribution.

6. Conclusions

In this study, the effects of the Entropy, WENSLO, and MPSI weighting methods on the MACAD ranking method were examined, and the resulting rankings were combined using the CURLIA method to produce a composite ranking. Derimod Konfeksiyon A.Ş., a company listed on BIST, was selected as the case study, and financial data for the 2018–2024 period were analysed in the initial stage. The rankings obtained from the Entropy-, WENSLO-, and MPSI-based MACAD applications were found to be fully consistent. This finding indicates that integrating the rankings using the CURLIA method would simply reproduce the same ranking and, therefore, would provide little additional methodological insight into the performance of the proposed integration framework. Consequently, the analysis period was extended to cover the years 2015–2024 in order to evaluate the robustness and applicability of the proposed integrated decision-making framework under a data structure with greater temporal diversity. The analyses were repeated using the expanded data set, and the resulting rankings were integrated using the CURLIA method to obtain the final composite ranking.

The analysis results show that different criterion weighting methods generally reveal a consistent trend in MACAD ranking results. Specifically, in some years (2015, 2018, and 2021), all methods produced the same ranking, while minor differences were observed in other years. This indicates that the decision model has a stable structure and that different weighting approaches have a limited impact on the ranking results.

The combination of rankings obtained using the CURLIA method with those from other methods reconciled the minor differences observed between the methods and provided the opportunity to assess the company's financial performance in a reliable and comprehensive manner over time. While 2024 and 2022 were identified as the years of highest performance, 2021 was consistently identified by all methods as the year of lowest performance.

The results of the sensitivity analysis showed that the MACAD rankings were highly stable despite changes to the criterion weights. Scenario analyses were carried out using a representative weight vector derived from the average of the weights obtained from the Entropy, WENSLO and MPSI methods. The weight of the CO criterion, which was deemed the most important, was reduced by 5%, 10%, 15%, 20% and 25%. The results showed that, in scenarios where the CO criterion weight was reduced by 5 or 10 per cent, the rankings remained exactly the same as in the base scenario. However, in the scenarios where the weight was reduced by 15%, 20% or 25%, only the rankings of the alternatives for the years 2019 and 2023 changed by one position. The positions of the alternatives in the top three and bottom five remained unchanged across all scenarios. These findings demonstrate that MACAD ranking results remain highly stable even when criterion weights change by up to 25%.

Furthermore, comparative analyses using the TOPSIS and MABAC methods have shown that the final ranking, obtained by integrating alternative MACAD rankings derived from different weighting methods using the CURLIA method, is generally consistent with those produced by other multi-criteria decision-making methods. These similarities support the view that the MACAD-based ranking approach and the aggregated ranking obtained using CURLIA produce largely similar ranking results.

The results demonstrated a high degree of consistency between the rankings obtained using the Spearman rank correlation coefficients, Entropy-TOPSIS, WENSLO-TOPSIS, MPSI-TOPSIS, Entropy-MABAC, WENSLO-MABAC, MPSI-MABAC, Entropy-MACAD, WENSLO-MACAD, MPSI-MACAD and CURLIA methods. The fact that the correlation coefficients between all method pairs range from 0.939394 to 1.000000 indicates that the alternative rankings obtained from different MCDM approaches are largely similar and show strong agreement. In particular, the high correlation coefficients between MACAD-based rankings and those from other MCDM methods indicate that the MACAD rankings remain broadly consistent across different weighting approaches. Furthermore, the correlation coefficients between the final aggregated ranking obtained through the CURLIA method and the rankings generated by the other approaches range from 0.951515 to 0.987879, indicating that the final ranking, constructed by aggregating MACAD rankings derived from different weighting methods, is broadly consistent with the rankings obtained using alternative MCDM approaches. These findings demonstrate that, despite differences in criterion weighting methods and ranking approaches, the results obtained are reliable, consistent and exhibit statistically supported agreement.

In conclusion, the study explains the effects of different weighting methods (Entropy, WENSLO, and MPSI) on MACAD ranking results and demonstrates that the collective ranking obtained using the CURLIA method provides decision-makers with a more reliable, consistent, and consensus-based evaluation of financial performance. Moreover, the sensitivity and comparative analyses further support the validity of the proposed integrated MCDM framework.

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Conflicts of Interest
The authors declare no conflicts of interest.

Use of Artificial Intelligence
This article incorporates AI-assisted revisions (ChatGPT) to improve academic language. The introduction and literature review sections were prepared by the author and revised for language and formatting using AI. The materials and methods section was entirely created by the author, with only limited language support. All analyses and calculations in the article were performed by the author. Table descriptions, findings, and conclusions sections were edited for language using AI; these sections were carefully reviewed and approved by the author.

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