

Research Article (Special Issue) | Araştırma Makalesi (Özel Sayı)

Nonlinear Multi-Criteria Decision Making for Financial Performance Evaluation: Evidence from Borsa Istanbul

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Abstract

In this study, we evaluate the financial performance of 157 non-financial firms listed on Borsa Istanbul for the period 2022–2024 by a novel nonlinear multi-criteria decision-making framework. The criteria used to assess financial performance are from profitability, liquidity, solvency, operational efficiency, market valuation, audit quality and growth perspectives. In order to overcome the limitations of the linear aggregation, the weights of the objective criteria are obtained through an ensemble of three complementary methods that are LOPCOW, MEREC and SITDE. The results show that the qualified audit opinion, market-to-book ratio and leverage ratio are the main discriminators of financial performance, with remarkable temporal stability over the three years. Three recently developed nonlinear ranking algorithms based on triangular norms, DOBI, ALWAS and SWEM, are used to rank the companies for each year, and the results are combined across years via an extended Borda count to obtain a consensus ranking. The consensus ranking identifies ARSAN, ESCOM, and MGROS as the top-performing firms, reflecting strong profitability, moderate leverage, and clean audit opinions, while MARTI, TEKUTU, and LYDHO consistently rank at the bottom due to high leverage, weak profitability, and qualified audit opinions. The findings reveal a high degree of inter-method concordance, strong year-to-year consistency, and exceptional robustness to weight perturbations, outlier treatment, and rank reversal tests.

Keywords: Financial Performance, Multi-Criteria Decision Making, Nonlinear Aggregation, Borsa Istanbul**JEL Codes:** C44, C60, G30, M40666

Finansal Performans Değerlendirmesi için Doğrusal Olmayan Çok Kriterli Karar Verme : Borsa İstanbul Örneği

Öz

Bu çalışmada Borsa İstanbul'da işlem gören 157 finansal olmayan firmanın 2022, 2023 ve 2024 mali yıllarındaki finansal performansı, yeni bir doğrusal olmayan çok kriterli karar verme çerçevesiyle değerlendirilmektedir. Finansal performansı değerlendirmek için kullanılan kriterler karlılık, likidite, ödeme gücü, operasyonel verimlilik, piyasa değeri, denetim kalitesi ve büyüme perspektiflerinden oluşmaktadır. Doğrusal toplamaların sınırlamalarının üstesinden gelmek için, objektif kriterlerin ağırlıkları, LOPCOW, MEREC ve SITDE olmak üzere üç tamamlayıcı yöntemin birleşimiyle elde edilmiştir. Sonuçlar, nitelikli denetim görüşü, piyasa değeri/defter değeri oranı ve kaldıraç oranının finansal performansın ana ayırt edicileri olduğunu ve bu bulguların üç yıl boyunca istikrarlı kaldığını göstermektedir. Şirketleri sıralamak için yakın zamanda geliştirilen, üçgen normlara dayalı üç doğrusal olmayan sıralama algoritması (DOBI, ALWAS ve SWEM) her yıl için ayrı ayrı kullanılmış ve sonuçlar, genişletilmiş Borda sayımı yoluyla yıllar arasında birleştirilerek bir konsensüs sıralaması elde edilmiştir. Konsensüs sıralaması, güçlü kârlılık, ılımlı kaldıraç ve temiz denetim görüşlerini yansıtacak şekilde ARSAN, ESCOM ve MGROS'u en iyi performans gösteren firmalar olarak belirlerken; MARTI, TEKUTU ve LYDHO yüksek kaldıraç, zayıf kârlılık ve nitelikli denetim görüşleri nedeniyle sürekli olarak en alt sıralarda yer almaktadır. Bulgular, yöntemler arası yüksek derecede uyumluluk, güçlü yıllar arası tutarlılık ve ağırlık değişimlerine, aykırı değer işleme ve sıralama tersine çevirme testlerine karşı olağanüstü sağlamlık ortaya koymaktadır.

Anahtar Kelimeler: Finansal Performans, Çok Kriterli Karar Verme, Doğrusal Olmayan Birleştirme, Borsa İstanbul**JEL Kodları:** C44, C60, G30, M40

Introduction

The efficiency of financial markets in the allocation of capital resources and performance evaluation of publicly traded firms are the basic issues for investors, creditors and policy makers (Zopounidis and Douplos, 2002). Stock exchanges play a vital role in any economy. They act as vital intermediaries, mobilizing savings to productive investment, and reflect the health of the macroeconomy and the quality of corporate governance of listed companies. Ranking companies on the basis of a number of financial indicators, each reflecting a different aspect of corporate health, has created a large literature at the interface of financial analysis, operations research and decision science (Zavadskas and Turskis, 2011).

How to cite this article / Bu makaleye atıf vermek için:Özarslan, A., (2026). Nonlinear Multi Criteria Decision Making for Financial Performance Evaluation: Evidence from Borsa Istanbul. *KOCATEPEİİBFD*, 28(Special Issue), 22-42. <https://doi.org/10.33707/akuiibfd.1948460>

Firms have traditionally been evaluated using single criterion frameworks such as market capitalization or earnings per share. The problem here is that such indicators are intentionally blind to the multidimensionality of corporate performance: a firm's true position depends on its profitability, liquidity, solvency, operational efficiency, growth prospects and market valuation simultaneously (Keeney and Raiffa, 1993). In this sense, Multi-Criteria Decision Making (MCDM) has gained popularity as a powerful methodological alternative that offers transparent and traceable procedures for combining heterogeneous performance dimensions into composite scores (Zavadskas et al., 2014).

In the last two decades, classical MCDM methods have been widely applied to several business problems such as bank ranking, stock selection, credit assessment and portfolio optimization. However, what is often neglected is the major limitation of most of this literature which is the almost exclusive use of linear aggregation operators, especially the weighted arithmetic mean, for combining individual criterion scores (Beliakov et al., 2007). The assumption of linearity is problematic in the presence of extreme outliers, heaviness of tails or non-linear interdependences between criteria which are typical characteristics of the real-world financial environments (Grabisch et al., 2008).

In order to address these shortcomings, a new generation of MCDM methods has emerged recently, in contrast to the traditional linear logic. The advanced techniques are based on non-linear normalization strategies, data driven weighting schemes and flexible aggregation operators based on Aczél-Alsina, Dombi and Schweizer-Sklar triangular norms. Also, the use of Bonferroni mean operators related to ordered weighted averaging functions allows decision makers to express different levels of risk aversion and to model complicated interdependencies between criteria (Bonferroni, 1950; Yager, 1988). They have shown promise in engineering, supply chain management, and sustainability assessment, but have not been well studied with respect to comparative financial performance rankings. In the context of the primary stock exchange of Türkiye, Borsa İstanbul (BIST), such an investigation is of practical relevance. BIST is one of the largest exchanges in emerging markets. Companies traded on the BIST are from various industrial sectors and operate in different macroeconomic environments, such as the persistent high inflation, volatility in the exchange rate and the rapidly changing capital market regulations (Yalcin et al., 2012). The application of nonlinear MCDM frameworks to rank BIST companies fills a specific gap in the Turkish financial literature, and also offers methodological insights that can be readily transferred to other emerging market contexts (Ecer, 2021).

These considerations motivate the present study with two main aims. A systematic comparative study is first conducted on the recent nonlinear MCDM approaches namely LOGarithmic Percentage Change-driven Objective Weighting (LOPCOW), METHod based on the Removal Effects of Criteria (MEREC), and Skewness Impact Through Distributional Evaluation (SITDE) for objective criteria weighting and Dombi–Bonferroni (DOBI), Aczél–Alsina Weighted Assessment (ALWAS), and Schweizer–Sklar Weighted Evaluation Model (SWEM) for ranking in the context of financial performance evaluation. Secondly, this framework is applied to a dataset of 157 non-financial companies listed on BIST for the fiscal years 2022, 2023, and 2024, using 13 financial criteria, thereby providing a practical benchmark for investment decision-making and a longitudinal perspective on performance stability. The analysis is extended beyond a single fiscal year in order to investigate the temporal consistency of the firms' rankings and the stability of the importance of the criteria. This is a response to the frequent criticism that cross-sectional MCDM evaluations may reflect transitory differences rather than structural differences in performance. In this respect, a systematic comparison of performances of these non-linear aggregation strategies through years is performed and the stability of the resulting rankings is validated by a set of robustness checks.

The remainder of this study is organized as follows. In Section 2, the literature on MCDM application in financial markets, objective weighting methods, non-linear aggregation operators and previous studies on BIST are reviewed. Section 3 presents the data, the criteria selection and preprocessing procedures and the methodological framework explaining each weighting method and ranking algorithm. The empirical results are shown in Section 4. The study ends with conclusions and implications for investors and practitioners, and outlines limitations and avenues for future research in Section 5.

1. Literature Review

The literature of MCDM can be traced back to the classical works of Koopmans (1951) on efficient frontier analysis and Charnes et al. (1978) on Data Envelopment Analysis, but the current operational MCDM framework was developed in the 1970s and the 1980s by Roy (1968) on outranking methods, Hwang and Yoon (1981) on TOPSIS and Saaty (1980) on the AHP. These methodological bases were gradually adapted to professional contexts as the researchers realized that single criterion models were not adequate to capture the complexity of the corporate performance.

Table 1 presents a chronological summary of the proposed methods for solving MCDM problems and classifies these techniques as weighting or ranking algorithms according to their basic functions. These methods encompass a development process spanning approximately 80 years, from Shannon's entropy-based weighting approach developed in 1948 to the most current ranking models. While early studies generally established basic ranking logics such as TOPSIS, COPRAS, and VIKOR, the 2010s witnessed a

significant enrichment in both weighting and ranking techniques, reflecting the need for methodological diversity.

1.1. Weighting Methods

Determining criterion weights is one of the most strategic and emphasized stages of any MCDM process. Subjective weighting methods derive the importance levels of criteria from the subjective preferences of domain experts; generally through pairwise comparisons or direct rating procedures. In this area, AHP remains the most widely used subjective weighting tool. BWM overcomes the fundamental limitations of AHP by reducing the need for intensive pairwise comparisons in high-dimensional sets of criteria. FUCOM further improves the number of comparisons and adds transitivity constraints to avoid logical contradictions. Although LBWA and DIBR offer new subjective approaches that require less processing and yield higher consistency than AHP or BWM, the OPA method contributes to the literature by simultaneously evaluating criteria, alternatives, and experts using linear programming.

Objective weighting methods avoid the need for expert elicitation by obtaining the importance of the criteria from the statistical characteristics of the decision matrix itself. The Shannon Entropy Weight Method assigns more weight to criteria with greater dispersion across alternatives. The CRITIC method improves entropy weights by considering both the contrast intensity of each criterion and conflicts among criteria. MEREC quantifies the weight of each criterion by evaluating the change in the total performance score when that criterion is eliminated from the decision matrix. The LOPCOW method removes the problem of scale bias by calculating the logarithmic ratio of the root mean square and standard deviation for each criterion and can address negative values without further transformation. Finally, the SITDE method complements these approaches by incorporating the asymmetric structure in the criterion distributions into the analysis process. Thus, it is able to integrate into the system the distinctive data that skewed distributions offer beyond central tendency and dispersion.

Table 1. Chronological Overview of MCDM Methods.

Method	Category	Original Source	Key Feature
Entropy	Weighting	Shannon (1948)	Objective method based on information entropy
AHP	Weighting	Saaty (1980)	Hierarchical pairwise comparisons
TOPSIS	Ranking	Hwang and Yoon (1981)	Distance to ideal and anti-ideal solutions
COPRAS	Ranking	Zavadskas et al. (1994)	Complex proportional assessment
CRITIC	Weighting	Diakoulaki et al. (1995)	Combines std. dev. and inter-criteria correlation
VIKOR	Ranking	Opricović (1998)	Group utility and individual regret
ARAS	Ranking	Zavadskas and Turskis (2010)	Additive ratio assessment
SWARA	Weighting	Keršulienė et al. (2010)	Stepwise ratio assessment
WASPAS	Ranking	Zavadskas et al. (2012)	Weighted aggregated sum product
BWM	Weighting	Rezaei (2015)	Best-Worst method
EDAS	Ranking	Keshavarz-Ghorabae et al. (2015)	Distance from average solution
MABAC	Ranking	Pamučar and Ćirović (2015)	Multi-attributive border approximation area
CODAS	Ranking	Keshavarz-Ghorabae et al. (2016)	Combinative distance-based assessment
IDOCRIW	Weighting	Zavadskas and Podvezko (2016)	Integrated entropy-CILOS weighting
MAIRCA	Ranking	Gigović et al. (2016)	Ideal-real comparative analysis
FUCOM	Weighting	Pamučar et al. (2018)	Full consistency; n-1 comparisons
CoCoSo	Ranking	Yazdani et al. (2019)	Combined compromise solution
LBWA	Weighting	Žižović and Pamučar (2019)	Level-based weight assessment
BCM	Weighting	Haseli and Sheikh (2022)	Base-criterion method
MACONT	Ranking	Wen et al. (2020)	Mixed aggregation by comprehensive normalization
MARCOS	Ranking	Stević et al. (2020)	Measurement alternatives and ranking

OPA	Weighting	Ataei et al. (2020)	Ordinal priority approach
RAFSI	Ranking	Žižović et al. (2020)	Functional mapping of criterion sub-intervals
SPOTIS	Ranking	Dezert et al. (2020)	Stable preference ordering; rank-reversal-free
DIBR	Weighting	Pamučar et al. (2021)	Interrelationships between ranked criteria
MEREC	Weighting	Keshavarz-Ghorabae et al. (2021)	Removal effects of criteria
DOBI	Ranking	Ecer and Pamučar (2022)	Dombi–Bonferroni nonlinear aggregation
LOPCOW	Weighting	Ecer and Pamučar (2022)	Logarithmic percentage change; handles negatives
AROMAN	Ranking	Bošković et al. (2023)	Two-step normalization ranking
ALWAS	Ranking	Pamučar et al. (2024a)	Aczél–Alsina weighted assessment
RANCOM	Weighting	Więckowski et al. (2023)	Ranking comparison method
SPC	Weighting	Gligorić et al. (2023)	Symmetry point of criterion
SRP	Ranking	Zakeri et al. (2023)	Simple ranking process; rank-reversal-free
WENSLO	Weighting	Pamučar et al. (2024a)	Weights by envelope and slope
ARLON	Ranking	Kara et al. (2024)	Two-step logarithmic normalization; Heronian mean
ARTASI	Ranking	Pamučar et al. (2024b)	Adaptive standardized intervals
COBRAC	Weighting	Pamučar et al. (2024b)	Comparisons between ranked criteria
LODECI	Weighting	Pala (2024)	Logarithmic decomposition of criteria importance
MAXC	Weighting	Gligorić et al. (2024)	Maximum of criterion
RAWEC	Ranking	Puška et al. (2024b)	Ranking with weights of criterion
SIWEC	Weighting	Puška et al. (2024a)	Simple weight calculation
SITDE	Weighting	Gopisetty and Sama (2025)	Skewness impact; distributional evaluation
TODIFFA	Ranking	Gligorić et al. (2024)	Total differential of alternative
ALPAS	Ranking	Ulutaş et al. (2025b)	Dual scoring (utility and power)
DEPART	Ranking	Keshavarz-Ghorabae et al. (2025)	Deviation-based pairwise assessment
MUNRA	Ranking	Ulutaş et al. (2025a)	Multiple normalization rating analysis
PROVAN	Ranking	Biswas et al. (2026)	Root value with five aggregated normalizations
SWEM	Ranking	Ecer et al. (2026)	Schweizer–Sklar weighted evaluation model

Recent applications of the LOPCOW method across different domains provide evidence of its effectiveness. For instance, LOPCOW has been successfully integrated with the RAFSI method under spherical fuzzy rough numbers to evaluate LLM-integrated smart product-service systems (Liu et al., 2026). In airport security management, an integrated LOPCOW-AROMAN framework with softmax Hamacher aggregation operators has been proposed to enhance screening efficiency under uncertainty (Riaz et al., 2026). LOPCOW has also been employed with machine learning algorithms in a decision-support system for electric vehicle selection, where LOPCOW scores were used as target variables for predictive models (Şimşek et al., 2025). Additionally, LOPCOW has been utilized for evaluating blockchain-based waste management investments in smart cities (Shahab et al., 2026) and for supplier selection and performance evaluation in global supply chains (Xiang & Zhang, 2025).

The DOBI method was initially applied together with LOPCOW for the assessment of sustainability performance in the Turkish banking sector (Ecer & Pamučar, 2022). This LOPCOW-DOBI framework has then been extended to the selection of third-party logistics provider under sustainability perspectives (Nila & Roy, 2023). The MEREC approach has been the subject of much attention in the assessment of financial performance. MEREC has been applied in a comparative study of financial performance of banks with Entropy, LOPCOW and SPC weighting methods (Chinh et al., 2025). In the BIST context, MEREC-COBRA (Vatansever & Bayraktar, 2025) was used to evaluate the financial performance of manufacturing companies in the BIST Participation Sustainability Index. The same integrated framework was used to evaluate the profitability performance of BIST retail companies

(Oğuz & Satır, 2024).

1.2. Ranking Methods

The ranking stage has undergone an equally profound transformation, shifting from linear additive models to nonlinear aggregation. Classical distance-based algorithms such as TOPSIS, VIKOR, COPRAS and ARAS still remain benchmarks but the most notable breakthroughs came with the introduction of explicitly non-linear aggregation strategies. The CoCoSo and MACONT were among the first to bring together different normalization schemes into a single framework. The MARCOS introduced a ranking based on a utility function that considers the alternatives with respect to ideal and anti-ideal solutions. On these foundations, recently few truly non-linear ranking methods have emerged, characterized by the use of advanced aggregation operators. The DOBI method integrates Dombi norms with the Bonferroni mean operator to construct a flexible aggregation function capable of capturing various degrees of risk aversion. The ALWAS method is based on two strategies, weighted averaging and weighted geometric averaging, both grounded in Aczél-Alsina triangular norms, and combines them using a flexible parameter. The SWEM follows a similar logic but uses Schweizer-Sklar norms, which have been shown to be particularly stable under extreme data conditions.

There is growing interest in applying MCDM to rank equity markets in emerging economies. Yalcin et al. (2012) developed a hierarchical model for financial performance evaluation of BIST manufacturing firms in Türkiye, incorporating both accounting-based and value-based measures. They determined the criterion weights using fuzzy AHP. They ranked the companies in each sector using TOPSIS and VIKOR and found highly consistent rankings across the two methods. Kaya et al. (2024) selected companies from the BIST Sustainability Index and used nine MCDM methods, CoCoSo, GRA, MABAC, MAIRCA, MOOSRA, OCRA, TOPSIS, TODIM and VIKOR, with the criteria weights determined using the FUCOM based on the ratings of four domain experts and Borda aggregation technique to reach the consensus ranking among the nine methods. Öztanır (2025) evaluated six BIST logistics companies with TOPSIS and MOORA and found that high performance was achieved with operational efficiency and less leverage, and that companies connected to aviation were severely impacted by the pandemic. The variety of methods used in that study indicates a larger issue that the literature has yet to resolve: in the absence of a ground-truth ranking, aggregating across methods is the closest approximation to a stable result.

Yalçın et al. (2025) used CRITIC as an objective weighting mechanism and MABAC for final performance ranking to evaluate the 2023 financial performance of the top 10 companies of the BIST Sustainability Index and found Turkish Airlines (THYAO) as the best performing company. Katrancı et al. (2025) used an integrated ITARA–COBRA method to rank 73 BIST 100 firms for the period 2018–2022 and reported about 89% rank-order similarity with TOPSIS and 86% similarity with CoCoSo. This finding is reassuring regarding cross-method convergence at the extremes of the ranking, but meaningful uncertainty remains for mid-ranked firms. Demirhan et al. (2025) applied the LODECI–ARLON hybrid model to assess the financial performance of 10 commercial banks listed on BIST and they found that off-balance sheet accounts were the most influential criterion.

Among the methods used in the current study, the SITDE method has been integrated with Preference Index Value and Range of Alternatives Method for global bank performance assessment (Kamruddin et al., 2025). An extension called SITDER has been proposed to improve ranking stability across different MCDM techniques (Van Dua, 2026). The ALWAS method has been applied in a hybrid LOPCOW-CRITIC-ALWAS framework to assess urban competitiveness of European cities (Işık et al., 2024). The SWEM method, based on Schweizer-Sklar norms, has been recently proposed for industrial smart shoes design decisions in the metaverse for hazardous industries (Ecer et al., 2026). In a related development, Ullah et al. (2026) introduced novel Schweizer-Sklar aggregation operators for fuzzy bipolar soft numbers and successfully applied them to evaluate deep learning models, further demonstrating the flexibility and robustness of Schweizer-Sklar norms in multi-criteria decision-making contexts.

1.3. Research Gaps and Contributions

Most empirical studies, especially in the Turkish context, are limited to a single fiscal year, providing a static cross-sectional snapshot of performance despite this growing body of work. Longitudinal applications of MCDM, following the rankings of the firms over several periods, are very scarce, but they are crucial to distinguish the persistent structural strengths from the temporary fluctuations. However, when the existing studies on financial performance of BIST firms based on MCDM are examined, two critical and interrelated gaps are observed and the present study aims to fill these gaps. First, all previous BIST studies such as Yalcin et al. (2012) with fuzzy AHP with TOPSIS/VIKOR, Kaya et al. (2024) with FUCOM with nine linear methods (CoCoSo, GRA, MABAC, etc.), Katrancı et al. (2025) with ITARA-COBRA, Demirhan et al. (2025) with LODECI-ARLON, and Yalçın et al. (2025) with CRITIC-MABAC have been conducted based on only linear or fuzzy linear aggregation operators. None of these studies employed truly non-linear ranking algorithms based on triangular norms (Dombi, Aczél-Alsina, Schweizer-Sklar) or distribution-sensitive objective weighting methods like SITDE. The recent non-linear methods (DOBI, ALWAS, SWEM) have been tested mostly in engineering, supply chain and sustainability areas, and their performance, stability and practical usefulness for large-scale financial

performance assessment in an emerging market like Turkey have been entirely unexplored.

Second, most of the BIST-centric MCDM studies are static, offering insights for one fiscal year or combining multiple years into one cross-sectional ranking without considering the temporal dynamics. For example, Yalçın et al. (2025) evaluate only 2023, Demirhan et al. (2025) analyze only one period, and Katrancı et al. (2025) cover 2018–2022 but do not analyze year-to-year stability, rank persistence and weight evolution over time but provide a pooled ranking. Longitudinal applications that follow the rankings of firms over many different periods are extremely rare, but they are crucial to separate persistent structural strengths from temporary fluctuations, particularly in a volatile macroeconomic environment such as Türkiye's. This work fills the two specific gaps mentioned above by (i) being the first study to apply three non-linear ranking algorithms (DOBI, ALWAS, SWEM) combined with three objective weighting methods (LOPCOW, MEREC, SITDE) to BIST non-financial firms and (ii) doing so for three consecutive fiscal years (2022–2024) separately, thus providing evidence on temporal stability, year-to-year rank correlations and evolution of the importance of the criteria. This framework is tested on real financial data with negative values, extreme outliers and complex inter-criterion relationships, providing a robust benchmark for future research and investment decisions.

2. Methodology

The section starts with methodology of criteria selection and data sources. The study employs a three-stage analytical framework applied separately to each fiscal year (2022, 2023, 2024). The first stage consists of shift transformations of raw financial data to make it compatible with logarithmic and ratio-based normalization methods. In the second stage, objective weights of 13 financial criteria are calculated for each year using three complementary methods, LOPCOW, MEREC and SITDE. Then these weights are averaged to produce a single robust weight vector per year. In the third stage, three recently developed non-linear ranking algorithms, DOBI, ALWAS and SWEM are used independently for each year to obtain three rankings of 157 non-financial firms listed on BIST. Finally, the annual rankings are aggregated across the three years using an extended Borda count to produce a multi-year consensus ranking and the stability of the results is investigated using rank reversal tests, sensitivity analyses with perturbed weights and correlation coefficients as well as winsorized data.

2.1. Criteria Selection and Data Sources

A set of 13 criteria is selected to collectively represent profitability, liquidity, solvency, operational efficiency, market valuation, audit quality and growth to holistically capture the corporate financial performance. Table 2 presents a summary of each criterion, the formula used to calculate it, the direction of optimization (benefit or cost), and the source. This selection is based on the finance literature and is specifically designed for the data environment of Turkish non-financial firms. The data of the financial statements for the fiscal years 2022, 2023, and 2024 used in the calculation of the 13 performance ratios were obtained from the Public Disclosure Platform (KAP) of Türkiye and the market-based indicators (share prices and the number of outstanding shares) were obtained from the financial data platform "Investing".

Table 2. Financial performance criteria, their formulas, and descriptions

Criterion	Formula	Type	Source
Current ratio	$\frac{\text{Current assets}}{\text{Current liabilities}}$	Benefit	Fridson and Alvarez (2022)
Operating cash flow ratio	$\frac{\text{Operating cash flow}}{\text{Current liabilities}}$	Benefit	Brealey et al. (2017)
Leverage ratio	$\frac{\text{Total liabilities}}{\text{Total assets}}$	Cost	Titman and Wessels (1988)
Receivables turnover ratio	$\frac{\text{Net sales}}{\text{Average accounts receivables}}$	Benefit	Ross et al. (2019)
Asset turnover ratio	$\frac{\text{Net sales}}{\text{Average assets}}$	Benefit	Ross et al. (2019)
Net profit margin	$\frac{\text{Net income}}{\text{Net sales}}$	Benefit	Ross et al. (2019)
ROE	$\frac{\text{Net income}}{\text{Total equity}}$	Benefit	Brealey et al. (2017)
Sales growth rate	$\frac{\text{Net sales}_t - \text{Net sales}_{t-1}}{\text{Net sales}_{t-1}}$	Benefit	Ross et al. (2019)
Qualified audit opinion	0= unqualified, 1 = qualified	Cost	Francis (2004)

Altman Z'' score	Equation (1)	Benefit	Altman (1993)
M/B	$\frac{\text{Market value of Equity}}{\text{Book value of equity}}$	Cost	Fama and French (1992)
Share price growth	$\frac{P_t - P_{t-1}}{P_{t-1}}$	Benefit	Brealey et al. (2017)
P/E	$\frac{\text{Market price per share}}{\text{Earnings per share}}$	Cost	Damodaran (2012)

Liquidity is measured by the current ratio and the operating cash flow ratio; solvency is measured by the leverage ratio; operational efficiency is measured by the receivables turnover ratio and the asset turnover ratio; profitability is measured by the net profit margin and return on equity (ROE); growth is measured by the sales growth rate. Market valuation is incorporated via the market-to-book ratio (M/B), the share price growth, and the price-to-earnings ratio (P/E). Audit quality is reflected by the qualified audit opinion indicator, while the composite likelihood of financial distress is captured by the Altman (1993) Z'' score defined in Equation (1). Smaller values of this score indicate greater vulnerability, so its coefficient in subsequent models is expected to be negative.

$$Z'' = 6.56 \times \frac{\text{Working Capital}}{\text{Total Assets}} + 3.26 \times \frac{\text{Retained Earnings}}{\text{Total Assets}} + 6.72 \times \frac{\text{EBIT}}{\text{Total Assets}} + 1.05 \times \frac{\text{Book Value of Equity}}{\text{Total Liabilities}} \quad (1)$$

In this study, the cost criteria are M/B and P/E ratios and lower values are preferred. This treatment is based on their economic interpretation. A high M/B ratio is often a sign of overvaluation of the company by the market, with the market value of the company exceeding the book value significantly, and the possibility of a correction in the price in the future, while a low M/B ratio suggests that the company is undervalued or asset-backed, and has a higher margin of safety (Fama & French, 1992). Similarly, a high P/E ratio could signal that a stock has gone too far ahead of its earnings potential and is in need of a sharp reappraisal (Damodaran, 2012). If earnings are negative, the P/E ratio is also negative, which is mathematically undefined for valuation purposes and is typically a sign of serious financial distress.

2.2. Data Preprocessing

The raw data contain negative values in financial criteria such as profitability, solvency and market-based ratios. Such inputs are incompatible with the basic mathematical operations in this work, which are based on logarithmic transformations, scaling with ratios, and exponential aggregations, which are undefined or numerically unstable for non-positive inputs. To do so, and to preserve the distributional shape and the relative distances between firms fully, we follow the approach of Gopisetty and Sama (2025), and take a constant shift for every criterion that contains negative values. The shift is applied separately to each year's decision matrix. Let x_{ij} denote the raw value of firm i ($i = 1, \dots, m$) on criterion j ($j = 1, \dots, n$). The transformed value, $\tilde{x}_{ij}$, is calculated in Equation (2) and guaranteed to be strictly positive. This ensures that all subsequent normalization and aggregation steps are carried out on a positive decision matrix. This transformation is uniformly applied to all criteria with at least one negative value, irrespective of whether the criteria are benefit or cost oriented. It is there just to make sure that the following logarithmic and exponential operations have strictly positive inputs. The transformation is important in that it maintains the relative distances between the firms and the distributional shape of each criterion. The final dataset consists of 157 non-financial firms for each fiscal year, and the same 157 firms are present in all three years, forming a balanced panel.

$$\tilde{x}_{ij} = x_{ij} + \left| \min_i(x_{ij}) \right| + 1, \quad \forall i, j \quad (2)$$

2.3. Criteria Weighting Methods

The weights for the objective criteria are obtained from three methods, LOPCOW, MEREC and SITDE. This procedure is carried out independently for each of the three years. The final weight w_j for criterion j is the arithmetic mean of the three objective weight vectors for that year, as shown in Equation (3). This aggregation reduces the idiosyncratic biases of individual weighting methods and provides a solid basis for the ranking stage.

$$w_j = \frac{w_j^{\text{LOPCOW}} + w_j^{\text{MEREC}} + w_j^{\text{SITDE}}}{3} \quad (3)$$

2.3.1. LOPCOW

LOPCOW, introduced to the literature by Ecer and Pamučar (2022), subjects the root mean squared and standard deviation of normalized data to a comparative analysis in determining weights. This approach minimizes scale bias and demonstrates

methodological fit in the presence of negative inputs. The steps for applying the method are presented below:

Step 1: Normalize the decision matrix:

$$r_{ij} = \begin{cases} \frac{\tilde{x}_{ij} - \min_i \tilde{x}_{ij}}{\max_i \tilde{x}_{ij} - \min_i \tilde{x}_{ij}}, & j \in \text{Benefit} \\ \frac{\max_i \tilde{x}_{ij} - \tilde{x}_{ij}}{\max_i \tilde{x}_{ij} - \min_i \tilde{x}_{ij}}, & j \in \text{Cost} \end{cases} \quad (4)$$

Step 2: Compute the percentage value of each criterion where σ_j denotes the standard deviation of the normalized values of criterion j :

$$PV_j = \left| \ln \left(\frac{1}{\sigma_j} \times \sqrt{\frac{1}{m} \sum_{i=1}^m r_{ij}^2} \right) \times 100 \right| \quad (5)$$

Step 3: The objective weight is obtained by normalizing the percentage values:

$$w_j^{\text{LOPCOW}} = \frac{PV_j}{\sum_{j=1}^n PV_j} \quad (6)$$

2.3.2. MEREC

MEREC (Keshavarz-Ghorabae et al., 2021) quantifies the importance of a criterion by measuring how much the overall performance score of the alternatives changes when that criterion is removed.

Step 1: Normalize the decision matrix:

$$n_{ij} = \begin{cases} \frac{\min_k \tilde{x}_{kj}}{\tilde{x}_{ij}}, & j \in \text{Benefit} \\ \frac{\tilde{x}_{ij}}{\max_k \tilde{x}_{kj}}, & j \in \text{Cost} \end{cases} \quad (7)$$

Step 2: Calculate the overall performance of each alternative:

$$OP_i = \ln \left(1 + \frac{1}{n} \sum_{j=1}^n |\ln(n_{ij})| \right) \quad (8)$$

Step 3: Compute the performance of each alternative after removing criterion j :

$$OP'_{ij} = \ln \left(1 + \frac{1}{n} \sum_{k \neq j} |\ln(n_{ik})| \right) \quad (9)$$

Step 4: The removal effect of criterion j is the sum of absolute deviations and the final weights are obtained via linear normalization:

$$w_j^{\text{MEREC}} = \frac{\sum_{i=1}^m |OP'_{ij} - OP_i|}{\sum_{j=1}^n \sum_{i=1}^m |OP'_{ij} - OP_i|} \quad (10)$$

2.3.3. SITDE

SITDE (Gopisetty and Sama, 2025) is an objective weighting method that incorporates the skewness of criterion distributions into the weighting process. Criteria with asymmetric distributions receive higher weights, allowing extreme values commonly observed

in financial data to be more realistically reflected in the decision-making process. Step 1 of SITDE is same as MEREC, hence n_{ij} 's are calculated as in Equation (7).

Step 2: Skewness coefficient for each criterion:

$$S_j = \frac{m}{(m-1)(m-2)} \sum_{i=1}^m \left(\frac{n_{ij} - \bar{n}_j}{\sigma_j} \right)^3 \quad (11)$$

Step 3: Logarithmic transformation of skewness:

$$LS_j = \ln \left| (S_j + 1) + \left(\min_k S_k + 1 \right) \right| \quad (12)$$

Step 4: Final weights:

$$w_j^{\text{SITDE}} = \frac{LS_j}{\sum_{k=1}^n LS_k} \quad (13)$$

2.4. Ranking Methods

Three recently proposed ranking algorithms DOBI, ALWAS, and SWEM are employed in this study. All three methods are applied to each year's preprocessed decision matrix, using the weight vector derived for that same year. Because the three ranking methods may produce non-identical orderings within a single year, a consensus ranking across the three years is constructed using an extended Borda count. The procedure operates in three steps. First, each firm is given a Borda score for each method and each year equal to the number of firms below it in the ranking, i.e., $(m - R_{ikt})$, where the higher the score the better the performance. Second, these method-specific scores are aggregated across the three methods to obtain an annual Borda score per firm each year. Third, the annual scores for 2022, 2023 and 2024 are summed to give a single multi-year Borda score. Formally, if R_{ikt} denotes the rank of firm i under method k ($k = 1, 2, 3$) in year t , the multi-year Borda score, B_i , is calculated as the sum of the annual scores in Equation (14), where $m = 157$. The final consensus ranking is obtained by ranking firms in descending order of B_i (highest score = best performance). All methods operate on the same preprocessed decision matrix $\tilde{X} = [\tilde{x}_{ij}]_{m \times n}$ and use the aggregated weight vector w of the corresponding year.

$$B_i = \sum_{t=2022}^{2024} \sum_{k=1}^3 (m - R_{ikt} + 1) \quad (14)$$

2.4.1. DOBI (Dombi–Bonferroni)

The DOBI method (Ecer and Pamučar, 2022) employs nonlinear aggregation based on Dombi norms combined with the Bonferroni mean operator.

Step 1: Standardize the decision matrix using the inverse sorting algorithm, as shown in Equation (15). The standardized value $\hat{\partial}_{ij}$ is obtained through the following formula, where $\tilde{x}_j^+ = \max_{1 \leq i \leq m} (\tilde{x}_{ij})$ represents the highest value observed among all alternatives in the context of criterion j . This reverse ranking procedure allows the original trends of cost-oriented attributes to be preserved throughout the normalization process. In other words, higher original values in the cost criteria correspond to lower standardized scores, with all standardized values remaining within the $[0, 1]$ range.

$$\hat{\partial}_{ij} = \begin{cases} \frac{\tilde{x}_{ij}}{\tilde{x}_j^+}, & j \in \text{Benefit} \\ -\frac{\tilde{x}_{ij}}{\tilde{x}_j^+} + \max_{1 \leq i \leq m} \left(\frac{\tilde{x}_{ij}}{\tilde{x}_j^+} \right) + \min_{1 \leq i \leq m} \left(\frac{\tilde{x}_{ij}}{\tilde{x}_j^+} \right), & j \in \text{Cost} \end{cases} \quad (15)$$

Step 2: Define the DOBI weighted averaging ($Z_i^{(1)}$) and geometric ($Z_i^{(2)}$) strategies where $f(\hat{\partial}_{ij}) = \hat{\partial}_{ij} / \sum_{k=1}^n \hat{\partial}_{ik}$ and $\psi_1 = \psi_2 = \xi = 1$ for the baseline configuration:

$$Z_i^{(1)} = \frac{\sum_{j=1}^n \hat{\partial}_{ij}}{1 + \left\{ \frac{1}{\psi_1 + \psi_2 - w_i} \sum_{j=1}^n \left[\psi_1 \left(\frac{1 - f(\hat{\partial}_{ij})}{f(\hat{\partial}_{ij})} \right)^\xi + \psi_2 \left(\frac{1 - f(\hat{\partial}_{ij})}{f(\hat{\partial}_{ij})} \right)^\xi \right] \right\}^{1/\xi}} \quad (16)$$

$$Z_i^{(2)} = \sum_{j=1}^n \hat{\partial}_{ij} - \frac{\sum_{j=1}^n \hat{\partial}_{ij}}{1 + \left\{ \frac{1}{\psi_1 + \psi_2 - w_i} \sum_{j=1}^n \left[\psi_1 \left(\frac{f(\hat{\partial}_{ij})}{1 - f(\hat{\partial}_{ij})} \right)^\xi + \psi_2 \left(\frac{f(\hat{\partial}_{ij})}{1 - f(\hat{\partial}_{ij})} \right)^\xi \right] \right\}^{1/\xi}} \quad (17)$$

Step 3: Compute the integrated DOBI score with $\delta = 1$. Firms are ranked in descending order of $\Re_i$:

$$\Re_i = \frac{Z_i^{(1)} + Z_i^{(2)}}{1 + \frac{1}{2} \left[\left(\frac{1 - Z_i^{(1)}}{Z_i^{(1)}} \right)^\delta + \left(\frac{1 - Z_i^{(2)}}{Z_i^{(2)}} \right)^\delta \right]} \quad (18)$$

2.4.2. ALWAS

The ALWAS method (Pamučar et al., 2024a) combines two different nonlinear aggregation strategies derived from Aczél–Alsina triangular norms into a single structure. The first step of the ALWAS methodology has a structure identical to that of the initial step of the DOBI method presented in Equation (15).

Step 2: Compute the Aczél–Alsina strategies:

$$\mathbb{R}_i^{(1)\xi} = \sum_{j=1}^n \hat{\partial}_{ij} \left(1 - e^{-\left(\sum_{j=1}^n w_j (-\ln(1-f(\hat{\partial}_{ij})))\xi\right)^{1/\xi}} \right) \quad (19)$$

$$\mathbb{R}_i^{(2)\xi} = \sum_{j=1}^n \hat{\partial}_{ij} \cdot e^{-\left(\sum_{j=1}^n w_j (-\ln(f(\hat{\partial}_{ij})))\xi\right)^{1/\xi}} \quad (20)$$

Step 3: Integrate the two strategies into the final ALWAS score with $\theta = 1$ and $\phi = 0.5$ where higher values of $\mathfrak{S}_i$ indicate better-performing firms:

$$\mathfrak{S}_i = \frac{\mathbb{R}_i^{(1)\xi} + \mathbb{R}_i^{(2)\xi}}{1 + \left\{ \phi \left(\frac{1-f(\mathbb{R}_i^{(1)\xi})}{f(\mathbb{R}_i^{(1)\xi})} \right)^\theta + (1-\phi) \left(\frac{1-f(\mathbb{R}_i^{(2)\xi})}{f(\mathbb{R}_i^{(2)\xi})} \right)^\theta \right\}^{1/\theta}} \quad (21)$$

2.4.3. SWEM

The SWEM approach (Ecer et al., 2026) offers a high level of stability, especially under extreme data conditions, by extending the aggregation logic based on Schweizer–Sklar norms. The initial stage of the SWEM method parallels the first step of the DOBI methodology in Equation (15). The third step of SWEM, however, is identical to that of the ALWAS method (Equation (21)) in all processes except for the weighted average and weighted geometric strategies calculated in Equations (22) and (23).

Step 2: Define the fuzzy Schweizer–Sklar strategies with $\alpha = 2$:

$$\Omega_i^{(1)\alpha} = \sum_{j=1}^n \hat{\partial}_{ij} \cdot \left(1 - \sum_{j=1}^n w_j (1 - f(\hat{\partial}_{ij}))^\alpha \right)^{1/\alpha} \quad (22)$$

$$\Omega_i^{(2)\alpha} = \sum_{j=1}^n \hat{\partial}_{ij} \cdot \left(\sum_{j=1}^n w_j (f(\hat{\partial}_{ij}))^\alpha \right)^{1/\alpha} \quad (23)$$

2.5. Robustness and Sensitivity Analysis

A large sub-literature has developed around the methodological question of how to assess the robustness of MCDM rankings. In MCDM, sensitivity analysis generally investigates the change of rankings due to the perturbation of criterion weights (Triantaphyllou and Sánchez, 1997), performance scores (Lahdelma and Salminen, 2001), the normalization procedure used (Jahan and Edwards, 2015) or the specific method used (Mardani et al., 2015). Multiple methods' results are often combined by rank aggregation techniques such as Borda count (Borda, 1781) and Kemeny optimal aggregation (Dwork et al., 2001), leading to more robust aggregated rankings than the output of a single method. The Spearman rank correlation coefficient and the WS coefficient are classical statistical methods used to assess inter-method agreement in ranking studies. In line with these well-established practices, the present research adopts three complementary robustness procedures, detailed in the following subsections, to assess the stability of the proposed framework under different conditions.

We first examine rank reversal by sequentially dropping the lowest-ranked firm and recomputing the rankings for the remaining 156 firms. The procedure is carried out over five iterations, with a single firm removed in each. A method has rank reversal resistance (RRR) if the relative ranking of the surviving firms does not change over iterations. Second, we progressively reduce the weight of the dominating criterion from its original value to 10% of that value across 20 equally spaced scenarios. The remaining weight is then proportionally distributed among the other criteria to assess sensitivity. We report the average Spearman rank correlation between the perturbed rankings and the baseline ones.

Third, financial ratios often contain outliers that can disproportionately affect the weighting and ranking algorithms, particularly those that use logarithmic, exponential, or power-based scaling. To assess the sensitivity of the results to such outliers, the entire weighting and ranking pipeline is repeated on a winsorized version of the data set. For each criterion j , the observations below the 1st and above the 99th percentile are pulled back to the respective threshold. The winsorized value $\tilde{x}_{ij}^W$ is defined in Equation (24). Let $P_j(\alpha)$ be the α^{th} percentile of criterion j . The MCDM framework is then applied to this winsorized matrix and the rankings are compared with the rankings obtained from the original (non-winsorized) data. The comparison shows how much the final rankings are driven by the extreme observations, and whether the consensus ordering is robust to the removal of outliers.

$$\tilde{x}_{ij}^W = \begin{cases} P_j(0.01), & \text{if } \tilde{x}_{ij} < P_j(0.01) \\ \tilde{x}_{ij}, & \text{if } P_j(0.01) \leq \tilde{x}_{ij} \leq P_j(0.99) \\ P_j(0.99), & \text{if } \tilde{x}_{ij} > P_j(0.99) \end{cases} \quad (24)$$

3. Findings

This section presents the empirical findings from the multi-criteria evaluation of financial performance. Objective criteria weights are obtained through LOPCOW, MEREC, and SITDE for each year; the firm rankings are computed via DOBI, ALWAS, and SWEM

for each year; comparative performance evaluations across methods and years as well as robustness checks are reported. All analyses are performed in Python 3.9 using the NumPy, pandas, SciPy, Matplotlib, and Seaborn libraries.

3.1. Criteria Weights

The weight profiles show a clear hierarchy among the 13 financial criteria, that largely corresponds to the theoretical expectations of corporate finance. Risk, profitability and market valuation indicators have consistently been given the highest weights, whereas short-term liquidity and growth indicators have been allocated the lowest weights over the three years and across the three methods. The qualified audit opinion is by far the most influential criterion under MEREC, implying its decisive role in differentiating firms' overall performance scores when it is excluded from the decision matrix. This high weight doesn't mean that the final rankings can be decided only by the audit opinion. Rather, the MEREC method quantifies how much the overall performance of all firms deteriorates if a criterion is removed. Thus the criterion is a strong binary discriminator of clearly healthy and clearly problematic firms. The residual criteria, especially profitability, leverage and market valuation, determine finer ranking distinctions for firms with clean audit opinions. The consistently high weight during 2022–2024 signals that audit quality is a structurally significant risk signal in the Turkish capital market, rather than a year-specific aberration.

LOPCOW and SITDE, in addition to distributing the weights more evenly, also converge towards profitability and market valuation as main sources of discriminatory power. Specifically, both M/B and the leverage ratio are consistently and significantly present across the methods, highlighting the importance of both market perception and capital structure in determining rankings of financial performance. At the other extreme, the current ratio, share price growth, and sales growth rate rarely exceed a weight of 0.05, indicating that they provide relatively little incremental information beyond what is already captured by profitability and solvency measures.

Table 3. Criteria weights obtained from LOPCOW, MEREC, SITDE

	LOPCOW 2022	MEREC	SITDE	LOPCOW 2023	MEREC	SITDE	LOPCOW 2024	MEREC	SITDE
Current ratio	0.0176	0.0365	0.0759	0.0055	0.0312	0.0772	0.0095	0.0351	0.0631
Operating cash flow ratio	0.0733	0.0141	0.0530	0.0997	0.0141	0.0764	0.0620	0.0263	0.0812
Leverage ratio	0.0606	0.0198	0.0531	0.0640	0.0196	0.0708	0.1415	0.1037	0.1012
Receivables turnover ratio	0.0015	0.1082	0.1032	0.0260	0.0831	0.0909	0.0037	0.0818	0.1016
Asset turnover ratio	0.0395	0.0985	0.0961	0.0357	0.1392	0.0909	0.0285	0.0712	0.0828
Net profit margin	0.0010	0.0177	0.0252	0.1640	0.1213	0.0909	0.1255	0.0384	0.1014
ROE	0.1745	0.0442	0.1033	0.1177	0.0188	0.0824	0.1270	0.0465	0.1005
Sales growth rate	0.0553	0.0266	0.0691	0.0006	0.0214	0.0726	0.0317	0.0157	0.0288
Qualified audit opinion	0.0910	0.4291	0.0745	0.0834	0.3791	0.0774	0.0700	0.3982	0.0622
Altman Z'' score	0.1284	0.0649	0.1034	0.1538	0.0717	0.0909	0.1050	0.0576	0.1019
M/B	0.1617	0.0885	0.0925	0.1614	0.0725	0.0893	0.1364	0.0883	0.0949
Share price growth	0.0506	0.0253	0.0686	0.0291	0.0169	0.0707	0.0429	0.0169	0.0351
P/E	0.1450	0.0266	0.0820	0.0594	0.0109	0.0196	0.1164	0.0202	0.0453

The temporal evolution of the weights shows several interesting changes. The MEREC weight of the qualified audit opinion decreased only slightly from 0.4291 in 2022 to 0.3982 in 2024, and the LOPCOW and SITDE weight of the qualified audit opinion remained low and steady, suggesting that the marginal discriminating power of audit quality, albeit still dominant, slightly reduced over time. The biggest change is for the leverage ratio. The weight of LOPCOW increased from 0.0606 in 2022 to 0.1415 in 2024, and the weight of MEREC increased from 0.0198 to 0.1037. It is almost as important as the market-to-book ratio. This sharp increase probably reflects the increased market sensitivity to corporate indebtedness over the sample period. The net profit margin displayed a significant peak in 2023 with LOPCOW and MEREC weights of 0.1640 and 0.1213, respectively and reverted to more moderate levels in 2024. On the contrary, the weights of the M/B and Altman Z'' score were stable for all years and methods, which shows that their use as discriminators is structural and not period-specific. Liquidity and growth criteria remained low throughout the entire period, with no discernible upward or downward trend.

3.2. Firm Rankings

Table 5 shows the top-five and bottom-five firms based on the multi-year Borda consensus, the three method-specific multi-year rankings (DOBI, ALWAS, SWEM), and the annual Borda rankings for 2022, 2023, and 2024. There are a few obvious patterns. First,

the consensus ranking as a whole is surprisingly robust at the edges. In the aggregate ordering, ARSAN and ESCOM are in the first two places as the only two firms that appear in the top five of each individual method and in all the years. The aggregate top five comprises MGROS, FMIZP, and TUPRS and they feature in almost all method-specific and annual top-fives, confirming their structurally sound financial profiles. At the other extreme, MARTI and AKSUE are consistently the poorest performers, finishing last or second-last in the aggregate, in each method, and in each year. KUVVA, DGNMO and EGGUB are also in the bottom five consistently, with only slight changes in positions across methods and years. The high degree of agreement between the aggregate, method-specific and yearly rankings underscores the robustness of the nonlinear MCDM framework: the best and worst firms are almost unanimously identified regardless of the aggregation operator and time period.

Table 4. Final consensus ranking (Borda count) – top 5 and bottom 5

Ranking	Aggregate	DOBI	ALWAS	SWEM	2022	2023	2024
1	ARSAN	ESCOM	ARSAN	ARSAN	ARSAN	ESCOM	ARSAN
2	ESCOM	ARSAN	ESCOM	MGROS	DOGUB	DOAS	BURVA
3	MGROS	FMIZP	MGROS	FMIZP	ESCOM	TUPRS	MGROS
4	FMIZP	TUPRS	FMIZP	TUPRS	TUPRS	TTRAK	FMIZP
5	TUPRS	DOAS	TUPRS	ESCOM	VAKKO	SANKO	USAK
153	MARTI	MARTI	MARTI	MARTI	AKSUE	MARTI	MARTI
154	AKSUE	AKSUE	AKSUE	AKSUE	SONME	AKSUE	LYDHO
155	DGNMO	DGNMO	DGNMO	DGNMO	MARTI	TRMET	TEKTU
156	KUVVA	KUVVA	KUVVA	KUVVA	EMNIS	KUVVA	KUVVA
157	EGGUB	EGGUB	TRENJ	TRMET	GUBRF	SONME	AKSUE

Second, the multi-year rankings specific to the method show small but informative variation. FMIZP and TUPRS are ranked third and forth by DOBI, whereas ALWAS and SWEM prefer MGROS and FMIZP. DOAS is only in the top five of ALWAS, which is consistent with the particular sensitivity of this method to operational efficiency indicators captured by the Aczél–Alsina norms. SWEM ranks ESCOM fifth, a little lower than the other methods which rank it first or second, implying a slightly different treatment of extreme observations by the Schweizer-Sklar operator. In the lower tail the match is nearly perfect. The only difference is that SWEM has TRMET and ALWAS has TRENJ in the bottom five instead of EGGUB, and DOBI and the aggregate rank has EGGUB in the very bottom.

Third, there is a high degree of temporal persistence in the annual rankings, although some turnover is observed in the intermediate positions of the top five. ARSAN is the only company to be ranked first on two different years (2022 and 2024), while ESCOM is leading in 2023. DOGUB, VAKKO, TTRAK, SANKO, BURVA, and USAK are only in the annual top five once, which indicates their extraordinary performances were period-specific to some extent. But the fact they were able to break into the top five at least one year shows real, if perhaps temporary, financial muscle. In the lower tail the picture is more static: Over the years, MARTI and AKSUE are the worst or second-worst, and KUVVA, SONME, LYDHO and TEKTU are continuously among the weakest firms, exposing deep-rooted financial vulnerabilities that persisted all over the sample period.

3.3. Performance Comparison Across Methods

To evaluate the overall agreement of the three ranking algorithms across the whole 2022-2024 time period, we computed the Spearman rank correlation and the WS similarity coefficient between the method-specific multiyear Borda rankings (i.e. the aggregated rankings generated by each method separately). These matrices are provided in Table 5. The three methods agree very well. The Spearman correlation between ALWAS and SWEM is almost perfect (0.9907), which confirms that the Aczél–Alsina and the Schweizer-Sklar operators, despite their different mathematical structures, produce almost identical composite rankings. DOBI also has a high correlation with both ALWAS (0.9244) and SWEM (0.9345), indicating that the Dombi-Bonferroni operator generates a very similar ranking to the two norm-based methods. This is further supported by the WS coefficients, which penalize the disagreements in the distant rank more. ALWAS and SWEM have the highest similarity (0.3037), while DOBI has lower similarity with ALWAS (0.1368) and SWEM (0.1178). This is expected, since the Spearman coefficients capture the slight variation in the ranks. Overall, the methods give a very consistent picture of financial performance with the strongest agreement at the extremes of the rankings.

Table 5. Spearman correlation (upper triangle) and WS coefficient (lower triangle) between method-specific multi-year Borda rankings

Method	DOBI	ALWAS	SWEM
DOBI	1.0000	0.9244	0.9345

ALWAS	0.1368	1.0000	0.9907
SWEM	0.1178	0.3037	1.0000

We assessed temporal stability by computing the Spearman and WS coefficients between the annual rankings of each method for each pair of years. The results for Spearman and WS coefficients are reported separately in Table 6. All three methods produce positive and statistically significant year-to-year correlations, suggesting that relative performance ranks are stable and not random. All methods show the highest correlation for 2023–2024, indicating an increase in temporal consistency towards the end of the sample period.

ALWAS consistently has the largest year-to-year correlations (Spearman: 0.5953 for 2022–2023, 0.6598 for 2023–2024) with SWEM in hot pursuit. DOBI exhibits moderate but statistically significant persistence. Spearman coefficients range from 0.3696 (2022–2024) to 0.5880 (2023–2024). The WS coefficients, albeit small in terms of numbers given the high number of alternatives, mirror these patterns: the maximum WS values are for ALWAS and SWEM, especially for the pair 2023–2024. The 2022–2024 WS coefficients are also still well above zero, meaning the rankings are not driven by transient factors. The high consistency from year to year, particularly at the tails, lends credence to the reliability of the multi-year consensus ranking as a stable indicator of underlying financial health.

Table 6. Year-to-year Spearman and WS coefficients for each method

Year Pair	Spearman rank correlations			WS similarity coefficients		
	DOBI	ALWAS	SWEM	DOBI	ALWAS	SWEM
2022 vs 2023	0.5553	0.5953	0.5649	0.0393	0.0658	0.0798
2022 vs 2024	0.3696	0.5087	0.4597	0.0576	0.0506	0.0565
2023 vs 2024	0.588	0.6598	0.6253	0.0551	0.0724	0.048

3.4. Robustness and Sensitivity Analysis

We use three complementary procedures to examine the stability of the rankings. The tests are conducted on the 2024 dataset, which serves as a representative year reflecting the most recent financial conditions. The results of robustness checks are presented in Table 6. RRR is determined by iteratively removing the lowest-ranked firm and recomputing the rankings. DOBI and ALWAS exhibit full immunity and preserve relative orderings among all surviving firms, which remain invariant. The SWEM shows 90% resistance, with only minor rank changes when the lowest-ranked firm is removed, a slight sensitivity arising from the impact of extreme observations have an impact on the Schweizer–Sklar aggregation functions.

Table 6. Robustness test results.

Method	RRR	Perturbed Avg. Spearman	Winsorized Avg. Spearman	Winsorized RRR
DOBI	100 %	0.9922	0.9656	100 %
ALWAS	100 %	0.9999	0.9979	100 %
SWEM	90 %	0.9976	0.9990	100 %

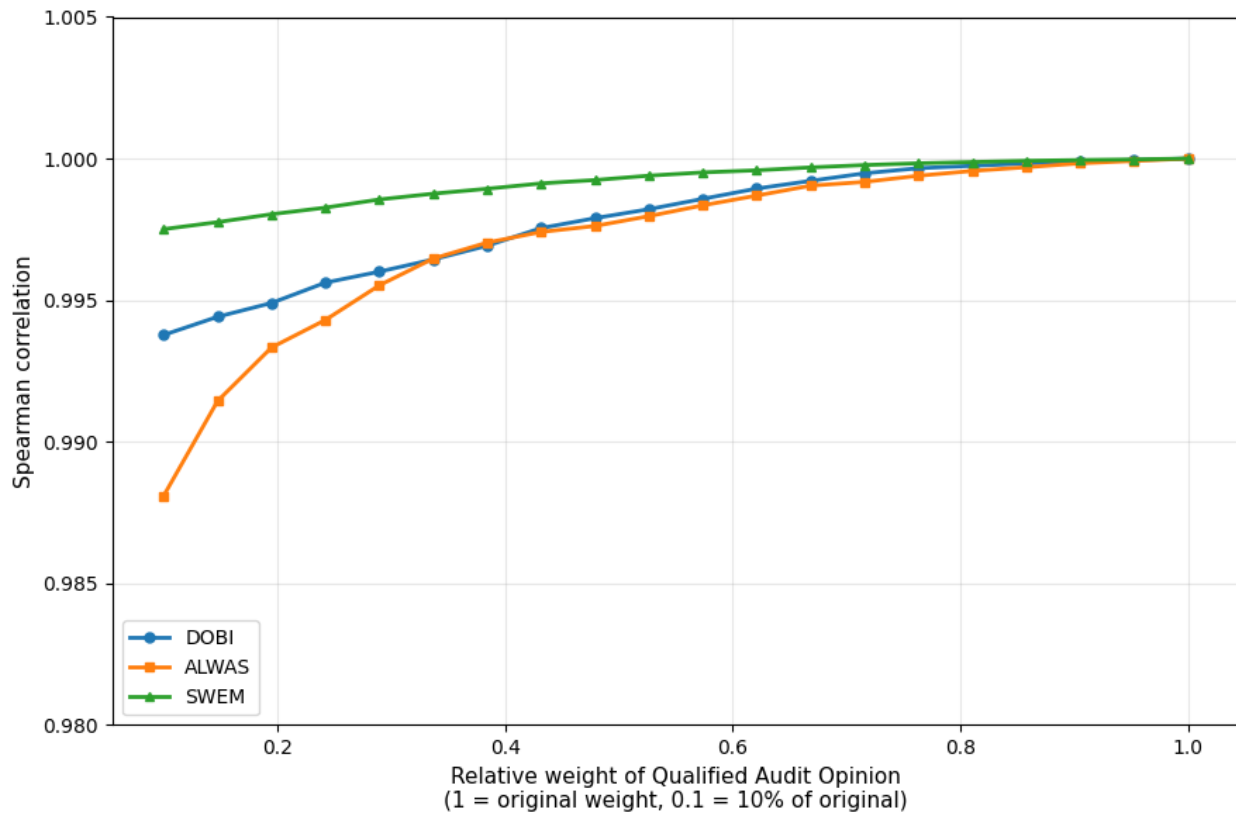
Figure 1. Sensitivity to Weight Perturbations

Figure 1 shows the Spearman's rank correlation coefficient between the original ranking, which contains the full weight of the qualified audit opinion criterion, and the perturbed rankings, where the weight of this dominant criterion is gradually reduced from its original value to 10% across 20 equally spaced scenarios. The horizontal axis represents the relative weight of the audit opinion criterion, ranging from 0.1 to 1.0. The three nonlinear ranking methods exhibit strong correlations, even under the most extreme perturbations, confirming the robustness of the consensus ordering. On close inspection, a systematic ordering of the methods is evident. SWEM consistently exhibits the highest correlation, starting at 0.9975 for a relative weight of 0.1 and gradually rising to 1.0. DOBI has an intermediate course, where the first correlation of 0.9938 at the same perturbation level. ALWAS has the lowest initial value (0.9881), but all three methods converge to a near-perfect correlation as the weight approaches its original value. This pattern shows that the three aggregation operators produce nearly identical rankings under practical weightings, although ALWAS is slightly more sensitive to large weight reductions. Moreover, the convergence suggests that no single criterion that dominates the final ordering; instead, the multi-criteria framework distributes influence across the entire set of financial ratios, providing a stable, reliable evaluation that is highly resilient to subjective weight choices.

Next, the whole MCDM pipeline is repeated on a winsorized data set, where the values below the 1st percentile and above the 99th percentile are replaced by the respective percentile. The structure of criteria weights is qualitatively similar, and the inter-method correlation pattern is preserved. Furthermore, for all approaches, the sensitivity correlations are higher than 0.96, and SWEM's rank-reversal resistance increases to 100%, indicating that the weak sensitivity observed with SWEM is due to a small number of extreme observations in the bottom tail. These results show that the consensus ranking is robust to the suppression of outliers.

Conclusion and Discussion

The evaluation of the financial performance of corporations is crucial for the efficient allocation of capital, particularly in the dynamic and high-potential environment of emerging markets. Investors, creditors and policymakers are always looking for robust transparent ways to deal with the inherent complexity of companies where real financial health is not a single figure but a multi-dimensional concept that embraces profitability, solvency, operational efficiency and the perception of the market. The problem is aggravated in real world financial data with extreme outliers, heaviness of tails and non-linear inter-dependencies where linear models can mislead. In this study, we directly address this issue by moving away from the traditional linear MCDM frameworks and using a new generation of non-linear aggregation operators, which provide a more robust and realistic perspective for financial ranking.

The research developed an integrated three-stage methodological framework. First, 13 financial measures were adopted for 157 non-financial companies listed on BIST for the fiscal years 2022, 2023, and 2024, and a constant-shift transformation was applied to negative values in each year independently to ensure mathematical suitability while preserving the shape of the data's distribution. In the second phase, the objective criterion weights were calculated for each year using an ensemble of three different methods, LOPCOW, MEREC, and SITDE, each exploiting different statistical properties of the data, from dispersion and removal effects to distributional asymmetry. This ensemble approach resulted in a robust averaged weight vectors that identified the qualified audit opinion, leverage ratio and M/B ratio as the main discriminators of financial performance, with remarkable temporal stability over the three years. Finally, three non-linear ranking algorithms, DOBI, ALWAS and SWEM, based on Dombi, Aczél–Alsina and Schweizer–Sklar triangular norms, respectively, were used for each year separately. The individual rankings were combined into a final consensus ordering using an extended Borda count that aggregates annual Borda scores across 2022, 2023, and 2024.

The results show a high level of methodological consistency and stability of results. The integration of LOPCOW, MEREC, and SITDE weighting with DOBI, ALWAS, and SWEM ranking yielded a coherent and highly stable evaluation of BIST non-financial firms, and the resulting multi-year Borda consensus ranking provides a robust investment screening benchmark that is less sensitive to single-year anomalies. According to the consensus ranking, the firms with the strongest financial strength over the three years were identified as ARSAN, ESCOM and MGROS. Strong profitability, moderate leverage and clean audit opinions were indicative of this. MARTI, AKSUE and KUVVA are always at the bottom of the rankings. LYDHO, TEKUT, DGNMO and EGGUB are also repeatedly among the weakest performers. This indicates there are persistent problems of high leverage, weak profitability and qualified audit opinions.

Spearman correlation analysis demonstrated a near perfect alignment between ALWAS and SWEM (0.99 in both annual means and method-specific multi-year rankings) and very strong correlations for both with DOBI, confirming that these mathematically distinct non-linear operators are converging on a consistent and reliable ordering. The Spearman correlations from year to year for adjacent years ranged from 0.56 to 0.66, suggesting that the rankings are driven by structural corporate fundamentals rather than transient noise. The robustness check was extensive covering weight perturbation sensitivity, winsorized outlier treatment and rank reversal tests on the 2024 data which revealed the outstanding stability of the framework and confirmed that no single criterion or extreme observation has undue influence on the final rankings.

The findings of this study have some practical implications for different stakeholder groups in the Turkish capital market. The consistently high weight assigned to the qualified audit opinion across all three years provides strong empirical evidence to the regulatory authorities such as Capital Markets Board of Türkiye on the importance of independent auditing in signaling corporate health. It further stresses the need for aggressive enforcement of audit standards and for extending mandatory independent audit to a larger number of listed companies for enhanced market transparency and investor protection.

The research offers a powerful, data-driven screening tool for investors and portfolio managers. Market participants can use the multi-year Borda consensus ranking as part of their analytical process to go beyond simple, often misleading, single metric screens such as P/E ratios and to holistically find financially resilient companies that perform consistently over time. The rankings are robust to extreme weight perturbations, suggesting that the model is a robust anchor for long-term investment decisions and not an artifact of a particular weighting assumption. The better performance of the firms with conservative leverage and strong operating profitability confirms the robustness of the value-oriented investment strategies in the high-inflation environment in Türkiye.

The benchmarking capability of the framework gives corporate managers a clear diagnosis of the competitive position of a firm. The low rank can be broken down into its criteria, which focus on certain operational weaknesses (excessive leverage, poor cash-flow management, inefficient asset turnover) that require strategic attention. The methodology therefore becomes a tool of strategic management for improving internal performance by focusing resource allocation on the most critical value drivers identified by the objective weighting scheme.

This study contributes to the literature as the first large scale application of non-linear MCDM to BIST firms with a longitudinal dimension, but has some limitations that pave the way for future research. The biggest issue is the data pre-processing step. For negative values, a constant-shift transformation is applied, which is mathematically necessary for logarithmic and exponential aggregation operators, but introduces a dependence on the minimum values of the sample. This means that the calculated normalized scores are strictly relative to the sample and cannot be directly compared with rankings from a different sample or time period. In addition, the interpretation of financial ratios varies from sector to sector (e.g. acceptable leverage levels differ between manufacturing and service industries; profit margins differ systematically across sectors). In the present study, all 157 non-financial firms are treated equally without adjustment for the sector and this should be borne in mind when interpreting the consensus ranking. In order to handle the negative and high volatility financial data without such shifts, other extensions of design

interval-valued fuzzy MCDM or transformations should be studied.

Second, while the study spans three fiscal years, a longer panel would enable more advanced dynamic analyses, such as trend assessment and predictive validity tests. Future research should extend the time horizon to examine the temporal stability of the rankings over a complete business cycle and to assess the framework's capacity to predict future bankruptcy, financial distress or persistent market outperformance. Third, the study was limited to comparing the three recently developed nonlinear methods. There is a need for a more comprehensive comparative meta-analysis that systematically examines how these methods perform when compared to their classical linear counterparts (TOPSIS, VIKOR, COPRAS) and to other new-generation methods (MUNRA, ALPAS, DEPART). Such a study would more conclusively quantify the marginal benefit of using nonlinear operators across different financial data conditions in terms of metrics such as rank-reversal probability and algorithmic complexity.

The objective weighting ensemble reduces subjective bias, but it does not incorporate the qualitative and forward-looking preferences of the domain experts. The omission of subjective weights is a conceptual limitation. The most promising frontier is a hybrid framework that forms a new mathematically rigorous interface for integrating objective statistical weights with subjective expert judgments (acquired from methods such as FUCOM or LBWA). Furthermore, extending this framework to other emerging markets (e.g., BRICS countries) and sensitive sectors (e.g., banking and energy) would provide cross-national validation by testing whether the finding that nonlinear aggregation operators confer a fundamental advantage in financial performance evaluation is transferable.



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Author Contributions

The author has not declared any other contributors.

Acknowledgments

The author(s) did not provide acknowledgment.

Funding and Support

The author(s) did not report any funding or support information.

Conflict of Interests

The author(s) did not report any conflict of interest.

Ethics Statement

The author(s) did not report ethical committee approval as the research content does not require.

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Appendices

Appendix A. Borda-based consensus ranking of all firms

Firm	Ranking	Firm	Ranking	Firm	Ranking	Firm	Ranking	Firm	Ranking
ARSAN	1	AKCNS	33	KRTEK	65	BFREN	97	GUBRF	129
ESCOM	2	GENTS	34	KENT	66	BAKAB	98	HEKTS	130
MGROS	3	TBORG	35	KRDMD	67	DEVA	98	TATGD	131
FMIZP	4	GSDDE	36	RYSAS	68	VESBE	100	DITAS	132
TUPRS	5	YATAS	37	EGSER	68	TCCELL	101	SKTAS	133
DOAS	6	CCOLA	38	GOODY	70	PNSUT	102	MNDRS	134
BIMAS	7	CLEBI	39	AKENR	71	BRISA	103	KLMSN	135
VAKKO	8	ARENA	40	TUKAS	72	BTCIM	104	YYAPI	136
PKART	9	AKSA	41	CIMSA	73	DMSAS	105	KARSN	137
ALKA	10	USAK	42	FRIGO	74	PRKME	106	PARSN	138
CEMTS	10	ERBOS	43	ALCAR	75	PETKM	107	ATEKS	139
TTRAK	12	YUNSA	44	DESA	76	AYCES	108	BIGTK	140
SANKO	13	BURVA	45	BUCIM	77	PETUN	109	BSOKE	140
AYGAZ	14	DUNYH	46	SILVR	78	ARCLK	110	VKING	142
FROTO	15	ADEL	47	INGRM	79	ASELS	111	SONME	143
KRSTL	16	BAGFS	48	MERKO	80	PINSU	112	LYDHO	144
SARKY	17	GOLTS	49	BOSSA	81	CELHA	113	ZOREN	145
IHEVA	18	LINK	50	MNDTR	82	PENGD	114	SNPAM	146
OYAKC	19	IZMDC	51	AEFES	82	EMNIS	115	HURGZ	147
DGATE	20	RUZYE	52	ENKAI	84	KAREL	116	TEKTU	148
ALKIM	21	KONYA	53	DURDO	85	SASA	117	BRMEN	149
CMBTN	22	PKENT	53	DOGUB	86	VESTL	118	NETAS	150

İNDES	23	ALCTL	55	ULKER	87	KORDS	119	TRMET	151
SELEC	24	KNFRT	56	DARDL	88	LUKSK	119	EGGUB	152
NUHCM	25	BESLR	57	AYEN	89	DOKTA	121	TRENJ	152
DERIM	26	BURCE	58	PRKAB	90	EDIP	122	KUVVA	154
CMENT	27	EGPRO	59	KAPLM	91	EMKEL	123	DGNMO	155
TOASO	28	KUTPO	60	MAKTK	92	OTKAR	123	AKSUE	156
BANVT	29	GEREL	61	DYOBY	93	MAALT	125	MARTI	157
EGEEN	29	BRSAN	62	ASUZU	94	LOGO	126		
AFYON	31	THYAO	63	EREGL	94	INTEM	127		
KARTN	32	ERSU	64	MRSHL	96	IHLGM	128		