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A CAMELS-BASED INTEGRATED MCDM MODEL FOR FINANCIAL PERFORMANCE ASSESSMENT IN THE BANKING SECTOR

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Abstract

This study aims to evaluate the financial performances of BIST-listed deposit banks from a multidimensional and objective point of view within the scope of the CAMELS assessment system. It attempts to fill this gap by presenting an integrated model as a contribution to the literature which is in fact another step towards overcoming limitations arising from performance assessments based on a single technique or indicator. The Criterion Importance based on Sum of Squares (CRISUS) and Maximum of Criterion (MAXC) procedures are jointly used for weighting, while finding final weights are integrated with Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS) procedure in order to define relative performance among banks. Validity and applicability tests for the developed model were carried out through an application on eight banks operating on BIST using annual data covering 2020-2024. Results indicated that banking performance is mostly determined by income structure, profitability, and risk management dimensions. Specifically, the ratio of net non-interest income to total assets, return on average assets, and the ratio of non-performing loans to total loans emerge as the most important criteria. The rankings obtained via the MARCOS approach show that Garanti, Akbank, and Yapı ve Kredi are the top-performing banks during the examined period. Sensitivity analyses further confirm that the offered framework produces stable, robust, and method-independent findings. Overall, the results highlight the significance of multicriteria and integrated approaches in banking performance assessment, present both methodological contributions to the academic literature and practical decision-support and policy implications for bank managers and regulatory authorities.

Keywords
Banking sector, CAMELS, Financial Performance, MCDM, CRISUS, MAXC, MARCOS

JEL Classification
C54, G17, G21, G32, G53.

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1. INTRODUCTION

As the structural backbone of any modern financial system, the banking sector performs functions that extend well beyond simple financial intermediation. By channeling savings into productive investments, regulating the allocation of credit, and sustaining the uninterrupted operation of payment systems, banks occupy a uniquely central position in economic activity (Jabari, A ğa & Samour, 2022; Bayar, 2023). In economies where bank-based financial structures predominate, the stability and operational efficiency of this sector are widely regarded as preconditions for macroeconomic equilibrium — not merely as desirable attributes, but as systemic necessities. The channels through which banks influence resource allocation, financial intermediation costs, and the transmission of monetary policy underscore the broader significance of their performance for both institutional and macroeconomic outcomes (Ulusoy, Demirel & Özbilge, 2023; Kartal, 2018). Against this backdrop, the systematic, multidimensional, and objective evaluation of banking sector performance represents a critical analytical imperative — one that carries implications far beyond academic inquiry, extending to regulatory oversight, investment decision-making, and financial stability monitoring.

The Turkish banking system has undergone a profound structural transformation following the wide-ranging institutional and regulatory reforms enacted in the aftermath of the 2001 financial crisis. These reforms substantially expanded the supervisory mandate of the Banking Regulation and Supervision Agency (BRSA), aligned risk management standards with prevailing international regulatory frameworks, and considerably strengthened the balance sheet resilience of the sector (Alper & Öniş, 2012; Kesebir, 2018). The structural soundness that emerged from this process enabled Turkish banks to weather subsequent external shocks with relative resilience — most notably the 2008 global financial crisis. Nevertheless, the sector today confronts a markedly more demanding operating environment shaped by heightened market volatility, evolving regulatory requirements, and fundamental shifts in revenue composition. These developments collectively point to an urgent need for performance monitoring tools that move beyond conventional profitability metrics and capture the full structural complexity of modern banking operations.

As of September 2025, the Turkish banking landscape comprises 38 deposit banks, nine participation banks, and 21 development and investment banks, with deposit banks accounting for the dominant share of total sector assets (TBB, 2025; Çalış & Sakarya, 2020; Atukalp, 2021). Within this institutional landscape, deposit banks listed on Borsa Istanbul (BIST) occupy a position of particular analytical salience. They serve not only as representative indicators of broader sectoral performance but also maintain direct and consequential linkages with capital markets — making their financial condition a matter of relevance to regulators, investors, and policymakers alike. A rigorous assessment of the financial performance of these institutions must therefore extend across structurally interconnected dimensions, encompassing capital adequacy, asset quality, management efficiency, earnings capacity, liquidity management, and sensitivity to market risk (Al-Najjar & Assous, 2021; Dash & Das, 2009).

A critical review of the existing literature on bank performance evaluation reveals that the overwhelming majority of studies rely either on a single weighting technique or on a standalone ranking method. The fundamental limitation of single-method weighting approaches lies in their capacity to capture inter-criterion dispersion only along one analytical dimension, thereby introducing a tangible risk of incomplete or systematically biased estimation of criterion importance. Studies focusing specifically on the Turkish banking sector have, in large part, treated the CAMELS framework and multi-criteria decision-making methods as parallel but largely separate analytical traditions; empirical work that rigorously integrates these two frameworks within a unified objective weighting structure remains notably scarce. Beyond this methodological gap, the predominant tendency in the literature to rely on short-horizon cross-sectional data or to adopt a narrowly profitability-centred evaluative perspective further constrains the analytical scope of existing assessments — an approach that falls meaningfully short of capturing the inherently multidimensional character of banking performance. Departing from these limitations, the present study proposes a comprehensive and fully objective bank performance evaluation framework that integrates the CRISUS and MAXC objective weighting procedures with the MARCOS ranking method under the CAMELS assessment criteria.

Accordingly, the present research aimed to recommend a novel integrated MCDM framework for the systematic, objective, and multidimensional evaluation of performance in the banking sector based on the CAMELS assessment criteria. The proposed decision-making framework was constructed through the integration of CRiterion Importance based on the SUm of Squares (CRISUS), MAXimum of Criterion (MAXC), and Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS) methodologies. Within this integrated structure, objective criterion weights were first derived by jointly employing the CRISUS and MAXC procedures. Then, the MARCOS method was used to find out how well banks were performing financially compared to each other by using the final objective weights in the ranking process. The real-world case study tested whether the integrated decision model could be practically used and was valid empirically. This case study used yearly data from eight commercial banks that operate within BIST during the 2020-2024 period. Within this framework, the study is guided by the following research questions:

* Does the joint application of the CRISUS and MAXC procedures yield more balanced and reliable estimates of CAMELS criterion importance weights compared with single-method weighting approaches?
* Which CAMELS criteria demonstrate the greatest discriminatory power in explaining cross-bank variation in financial performance among BIST-listed deposit banks over the 2020–2024 period?
* Does the proposed integrated framework produce consistent and method-independent ranking outcomes under alternative weighting scenarios and across competing MCDM approaches?
* How can the empirical findings be interpreted within the structural and regulatory context of the Turkish banking sector, and what actionable analytical insights do they offer for key industry stake-

holders?

The contributions of this study to the existing literature can be summarized as follows:

* To the best of the authors' knowledge, the joint application of the CRISUS and MAXC procedures has not previously been attempted within a CAMELS-based bank performance evaluation framework. By combining these two objective weighting approaches for the first time in this context, the study directly addresses the well-documented limitation of single-method weighting — namely, its tendency to capture inter-criterion dispersion only partially — and thereby produces more balanced and structurally reliable criterion importance estimates.
* In contrast to prior studies that either focus narrowly on profitability or employ a restricted set of performance indicators, this study simultaneously incorporates capital adequacy, asset quality, management efficiency, earnings capacity, liquidity management, and sensitivity to market risk — offering a genuinely holistic assessment that reflects the multidimensional nature of banking performance more faithfully than existing single-dimension approaches.
* The entire analytical process, from criterion weighting through to final ranking, is grounded exclusively in objective procedures, effectively eliminating the subjectivity bias inherent in judgement-based weighting approaches that remain prevalent in the literature.
* The robustness, consistency, and method independence of the proposed framework are systematically verified through sensitivity analyses and cross-method comparisons, providing formal evidence of the structural stability of the resulting rankings.
* Beyond its methodological contributions, the study generates empirically grounded analytical insights and policy-relevant implications for bank managers, regulatory authorities, and investors operating within the Turkish banking sector.

The remainder of the paper is structured as follows. Section 2 presents a review of the relevant literature on banking performance measurement using MCDM approaches. Section 3 provides a detailed exposition of the proposed integrated methodological framework. Section 4 describes the data set and sample selection procedure. Section 5 reports the empirical findings derived from the application of the model. Section 6 presents sensitivity and comparative analyses conducted to assess the robustness and reliability of the framework. Section 7 concludes the paper with a summary of findings, theoretical and managerial implications, and directions for future research.

2. LITERATURE REVIEW

Academic interest in the financial performance evaluation of banking institutions has grown considerably over the past decade, with multi-criteria decision-making methods emerging as an increasingly prominent analytical tradition in this field. A closer examination of the existing body of work reveals that research efforts have tended to cluster around several recurrent themes: the selection and classification of performance indicators, the choice of criterion weighting procedures, and the comparative effectiveness of alternative ranking techniques. Viewed as a whole, however, the literature displays a number of methodological limitations that remain insufficiently addressed. Chief among these are the reliability concerns associated with single-method weighting approaches, the tendency to adopt a unidimensional — and predominantly profitability-centred — perspective in selecting evaluation criteria, and the fragmented analytical frameworks that treat the CAMELS rating system and MCDM methodologies as largely independent traditions rather than complementary components of an integrated assessment structure. Table 1 below presents a systematic overview of the studies most directly relevant to the present research.

Table 1
Literature Review

Author(s)	Method(s)	Period(s)	Results
Ahsan (2016)	CAMELS	2007-2014	All selected Islamic banks were found to be in a strong position within the composite rating system; they were determined to have a generally sound structure in terms of capital adequacy, asset quality, governance quality, profitability, and liquidity.
Wanke, Azad & Barros (2016)	TOPSIS	2004-2013	The results show that the effects of a bank's ownership structure, orientation, and origin can be high or low, depending on the bank's efficiency level.
Akbulut (2020)	PSI, ARAS and Grey Entropy	2018	The study concluded that Ziraat Bank was the most successful bank in terms of performance during the period in question.
Marjanovic & Popovic	CRITIC, TOPSIS	2012-2017	To conduct an analysis, the data from balance sheets and income statements of the specified 25 banks, which operated in Serbia during the period from 2012 to 2017, were used to analyse financial performance.
Karadağ Ak, Babuşçu & Hazar (2021)	COPRAS	2009-2019	While the analysis period shows that banks exhibit variable performance rankings in terms of financial performance, it can be said that T. Garanti Bankası A.Ş. and Akbank T.A.Ş. consistently ranked in the top three for all years except 2013, while Şekerbank T.A.Ş. consistently ranked in the bottom three for all years. In conclusion, it can be said that banks with high liquidity and profitability ratios also perform well.
Gupta et al. (2021)	CRITIC, TOPSIS, IV-TOPSIS	2013-2014 and 2017-2018	The financial performance of public sector undertaking (PSU) banks, forming part of PSU bank nifty index, those who operate in the Indian capital market was examined.
Abdel-Basset et al. (2021)	AHP, TOPSIS, VIKOR and COPRAS	-	According to results, CIB has the best performance while Faisal Islamic Bank and Bank Audi have the least performance among the top 10 CBs in Egypt.
Nguyen et al. (2021)	CRITIC, DEMATEL and TOPSIS	2019-Q3/2020	The findings show that the COVID-19 pandemic had significant impacts on banks' asset quality, liquidity levels, and growth rates.
Maredza et al. (2022)	COPRAS, TOPSIS, SWARA	-	This study evaluates the endogenous relationships between banking performance and social welfare in Southern African Development Community (SADC) countries using a comprehensive three-stage (MCDM) approach.
Wanke et al. (2022)	CAMELS, Fuzzy TOPSIS, Z-Numbers	2015–2019	The proposed framework effectively handled expert preference uncertainties in banking performance evaluation; findings demonstrated that information reliability methodologies improve the robustness of CAMELS-based bank rankings across ASEAN member countries.

Ünlü et al. (2022)	SWARA II, MEREC and MARCOS	2015–2020	Foreign-capital banks achieved higher efficiency and productivity than other bank groups; state-owned banks recorded a marked decline in productivity during the COVID-19 period, underscoring the importance of ownership structure in performance outcomes.
Zorkirişçi & Rençber (2023)	BWM-based TOPSIS, PROMETHEE, and COPRAS	2009-2020	The study concluded that public banks had higher performance, and while the findings of all three methods were similar in terms of methodology, the PROMETHEE method was more applicable due to its ease of application and the useful information it provided.
Bulut & Şimşek (2024)	CRITIC - CAMELS	2023	According to ARAS, TOPSIS, and COPRAS methods, EMLAK Katılım Bank has the highest performance.
Goel et al. (2024)	Equal Weighting and GIA	2018-2023	This study examines the changes in performance over time of 10 deposit banks operating in India.
Akbulut and Aydın (2024)	MSD, MPSI and RAWEC	2022	This paper compared the multi-dimensional sustainability performance of commercial banks traded on the BIST.
Boubaker et al. (2024)	DEA and Shannon Entropy	2002–2020	The proposed composite performance index, constructed directly from CAMELS ratios through objective weighting, yielded robust and internally consistent bank stability assessments for Vietnamese banks, demonstrating the viability of fully objective CAMELS-based evaluation frameworks.
Mastilo et al. (2024)	MEREC and MARCOS	-	By analyzing the performance of 21 banks operating in Bosnia and Herzegovina, the study demonstrated the validity of multi-faceted creditworthiness (MCDM) applications in different financial systems.
Hussain et al. (2024)	AHP, TOPSIS and GRA	2017–2022	Both AHP-TOPSIS and AHP-GRA models produced consistent bank rankings across China, India, Pakistan, and Thailand, confirming the reliability and cross-market applicability of integrated MCDM frameworks in emerging economy banking.
Kumar & Sharma (2024)	CRITIC and TOPSIS	2015–2021	Operating expenses to total assets emerged as the most influential performance criterion; CRITIC-based objective weighting produced stable and consistent rankings across the examined Indian private sector banks.
Akbulut (2025a)	CRISUS and RAM	2020-2024	Findings from the CRISUS approach show that the profitability performance of foreign-owned deposit banks differs significantly, particularly in terms of capital efficiency and revenue diversification. RAM results show that the profitability performance of foreign-owned deposit banks differs significantly in terms of the contribution of stability and balanced criteria.
Peci et al. (2025)	Fuzzy AHP and Fuzzy TOPSIS	2020-2022	According to the FAHP method, the most important indicators were determined to be equity and pre-tax profit. The TOPSIS method findings revealed that Banka Kombëtare Tregtare (BKT) was the bank with the best indicators for the years examined.

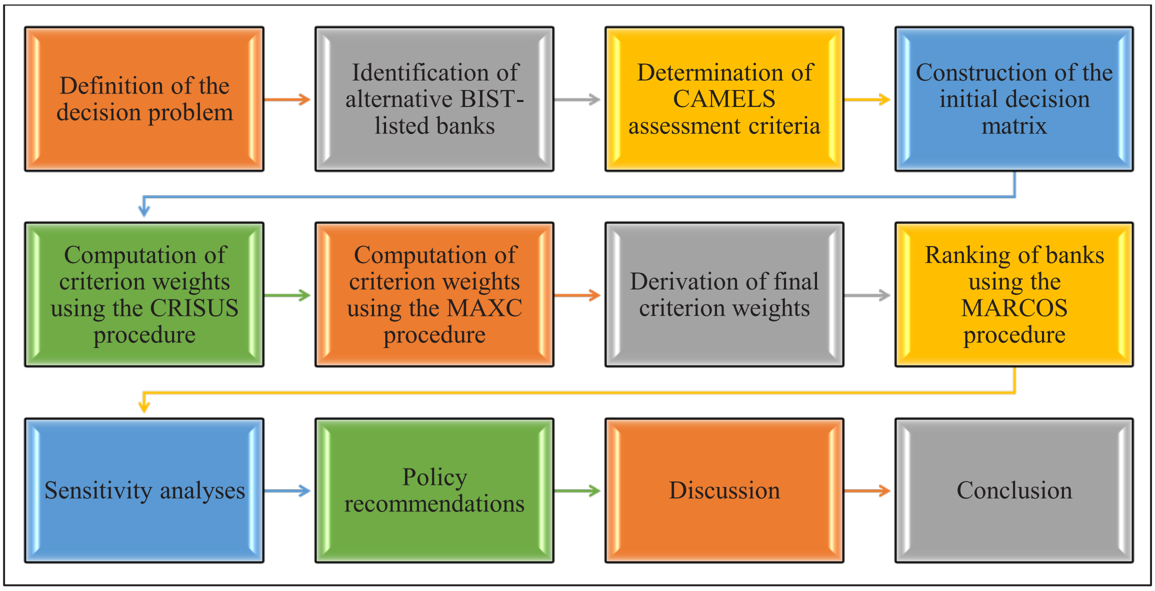
Tekgün (2025)	Grey LOPCOW and Grey MSD	-	The ESG performance of banks traded on BIST was examined within the scope of this study.
Demir (2025)	MPSI and RAWEC	-	This study analyzes the multidimensional ESG performance of commercial banks traded on the BIST.
Işık et al. (2025)	Fuzzy LBWA, Fuzzy LBWA and MARCOS	-	The relative performance of 15 deposit banks registered in Pakistan's banking sector was compared.
Durmuş et al. (2025)	PSI & CODAS	-	This study proposes an integrated decision-making framework that combines Type-2 Neutrosophic Fuzzy numbers-based Preference Selection Index (PSI) and the Combinative Distance-based Assessment (CODAS) methods to assess the financial performance of banks operating in Balkan countries.
Karki et al. (2025)	R-SWARA, CoCoSo	-	This study employs an integrated MCDM framework using R-SWARA and CoCoSo methods to evaluate the ESG-based sustainability performance of five major commercial banks, drawing on the assessments of 15 banking experts.
Wanke et al. (2026)	QI-MCDM	2015-2024	The relative performance of 43 Chinese commercial banks was examineed.
Taher Khani et al. (2026)	TOPSIS, Fuzzy TOPSIS	2000-2013 and 2014-2018	One of these studies examined the performance of 19 Bangladeshi banks. Also, another study examined the performance of the top seven banks in Turkey.
Katı (2026)	CRITIC, MARCOS	2012-2022	the financial performance of 8 Turkish private capital deposit banks was evaluated.

Taken together, the studies compiled in Table 1 reveal several discernible patterns in the banking performance literature that are worth examining in some detail. To begin with, the majority of existing contributions place considerable emphasis on ranking methods such as TOPSIS, COPRAS, and MARCOS, while treating the criterion weighting process as a relatively secondary concern; weights are frequently determined either through equal distribution assumptions or by means of a single objective technique (Hussain et al., 2024; Kumar & Sharma, 2024). Studies that bring the CAMELS framework and MCDM methodologies into dialogue do exist (Wanke et al., 2022; Boubaker et al., 2024), yet work that rigorously integrates these two analytical traditions within a unified structure employing multiple objective weighting procedures remains notably scarce. A related limitation concerns the Turkish banking sector specifically: while a number of studies have examined this context, they tend either to rely on short-horizon data or to focus on particular banking subgroups in isolation (Ünlü et al., 2022), leaving a clear gap for research offering a comprehensive, objective, and multidimensional assessment of BIST-listed deposit banks as a whole. Finally, robustness testing is either absent or confined to limited sensitivity checks in a large share of the reviewed studies — an omission that raises legitimate questions about the structural stability of the proposed frameworks. The present study addresses these gaps directly by proposing a CAMELS-based bank performance evaluation framework that integrates the CRISUS and MAXC objective weighting procedures with the MARCOS ranking method, and whose validity is systematically verified through both sensitivity and cross-method comparative analyses.

3. METHODOLOGICAL FRAMEWORK

The reliability and analytical integrity of MCDM-based performance evaluation frameworks depend, to a considerable degree, on the quality of the criterion weighting process and the structural soundness of the ranking procedure employed. Approaches that rely on a single weighting technique capture inter-criterion dispersion from only one analytical perspective, and are therefore susceptible to incomplete or systematically biased estimation of criterion importance — a limitation that directly undermines the credibility of the resulting rankings (Işık et al., 2024; Tekgün, 2025; Durdu et al., 2025). To address this methodological shortcoming, the present study proposes an integrated decision support framework that systematically combines two objective weighting procedures grounded in complementary but distinct dispersional logics — CRISUS (Adalar & Işık, 2025) and MAXC (Gligorić et al., 2024) — with the MARCOS ranking method (Stević et al., 2020). Within this structure, CRISUS and MAXC estimate criterion importance weights from analytically complementary perspectives, while MARCOS draws on the resulting integrated weight set to determine the relative financial performance rankings of the sampled banks. The theoretical foundations, computational procedures, and functional roles of each component within the proposed framework are discussed in detail in the sections that follow. The overall architecture of the integrated decision-making framework developed for the present study is illustrated in Figure 1.

Figure 1
Methodological Framework



3.1. CRISUS Procedure

The CRISUS objective criterion weighting procedure was presented to the decision-making literature as a novel methodological approach by Adalar and Işık (2025). This procedure was analytically developed by drawing upon the fundamental assumptions of the Statistical Variance (SV) technique (Rao & Patel, 2010), which has a well-established background in objective weighting literature, and the Entropy method originally presented by Shannon (1948). By employing a two-stage normalization mechanism, the CRISUS procedure assesses inter-criterion dispersion through the sum of squares measure, thereby enabling the objective and systematic estimation of criterion importance weights. The computational framework of the CRISUS objective weighting procedure consists of the following six steps:

Step 1. In order to solve the decision problem, the decision matrix is created in accordance with Eq. (1).

$$\tilde{X} = \left(\begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{bmatrix}\right) \quad (1)$$

Step 2. A first normalization process based on the sum of Euclidean distances is executed. Accordingly, Eq. (2) is applied for beneficial performance criteria, whereas Eq. (3) is used for non-beneficial performance criteria.

$$x_{ij} = \frac{\tilde{x}_{ij}}{\sqrt{\sum_{i=1}^{m} \tilde{x}_{ij}^2}} \tag{2}$$

$$x_{ij} = 1 - \frac{\tilde{x}_{ij}}{\sqrt{\sum_{i=1}^{m} \tilde{x}_{ij}^2}} \tag{3}$$

Step 3. The second normalization process is executed by utilizing Eq. (4) without differentiating between the types of criteria.

$$s_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{4}$$

Step 4. For each performance criterion, the corresponding sum of squares values are calculated by means of Eq. (5).

$$\rho_j = \sum_{i=1}^{m} s_{ij}^2 \tag{5}$$

Step 5. The standard deviation scores associated with the assessment criteria $(\sigma_j,\ j = 1,2,\ldots,n)$ are determined.

$$w_j = \frac{\sigma_j \rho_j}{\sum_{j=1}^{n} \sigma_j \rho_j} \tag{6}$$

Step 6. In the final stage of the CRISUS procedure, the importance weights of each performance indicators are computed in accordance with Eq. (6).

The CRISUS procedure evaluates inter-criterion dispersion through a sum-of-squares measure applied within a two-stage normalization mechanism, thereby enabling a systematic and fully objective assessment of the information content embedded in each criterion. By combining dispersion-based estimates with standard deviation scores, the procedure allows criterion importance weights to be derived from a perspective that simultaneously accounts for both variance magnitude and distributional concentration — dimensions that single-stage normalization approaches tend to conflate or overlook. In the present study, CRISUS serves as the primary objective weighting procedure for the selected CAMELS indicators, capturing the variance-based dimension of inter-criterion dispersion and contributing the first of two complementary analytical perspectives to the integrated weight estimation process.

3.2. MAXC Procedure

The MAXC procedure was presented into the decision-making literature by Gligorić et al. (2024) as a relatively recent and innovative objective criterion weighting technique. The MAXC procedure seeks to quantify, in a fully objective manner, both the marginal and aggregate contributions of individual assessment criteria to overall system performance by explicitly accounting for their cumulative effects. In this view, the MAXC method offers a framework that captures implicitly interactions between criteria while at the same time highlighting those criteria that have a dominant effect on performance results. Some of the most significant benefits associated with using MAXC include its ability to generate statistically sensitive, transparent, and objective results with respect to weightings, especially when it is used with large-scale and high-dimensional data Dündar (2025). The simplicity associated with using MAXC, especially from a mathematical point of view, ensures that it can effectively and conveniently be used as an alternative tool for theoretical research as well as for use in practical evaluation problems. The use of the MAXC procedure involves a set of six steps, as outlined by Gligorić et al. (2024).

Step 1. Forming an initial decision matrix for alternative decisions with respect to evaluation criteria, as outlined in Eq. (1).
Step 2. Application of a linear normalization transformation on an initial matrix, as outlined in Eq. (7).

$$r_{ij} = \frac{\tilde{x}_{ij}}{\sum_{i=1}^{m} \tilde{x}_{ij}} \quad (7)$$

Step 3. The maximum value for each criterion is identified from the normalized matrix using the formulation provided by Eq. (8).

$$r_{ij}(\max) = \max(r_{ij}) \quad (8)$$

Step 4. The distance measure between the maximum value for assessment criterion and normalized values is computed using Eq. (9).

$$d_{ij} = r_{ij}(\max) - r_{ij} \quad (9)$$

Step 5. The estimated value for distance measure, as applicable for assessment criterion, is computed using Eq. (10).

$$E_j = \frac{\sum_{i=1}^{m} d_{ij}}{m} \quad (10)$$

Step 6. The last step of the MAXC method involves computation of objective weights for each assessment criterion using Eq. (11).

$$w_j = \frac{E_j}{\sum_{i=1}^{m} E_j} \quad (11)$$

The MAXC procedure approaches criterion importance estimation from a fundamentally different but analytically complementary angle: rather than focusing on the distributional spread of observed values, it quantifies the distance of each criterion's normalized scores from their respective maximum, thereby capturing the marginal and cumulative contributions of individual criteria to overall system performance. This distance-based logic is particularly well-suited to identifying criteria whose influence on cross-alternative differentiation would be underweighted — or missed entirely — by variance-centred approaches alone. In the present study, MAXC functions as the second objective weighting procedure, operating on the same decision matrix as CRISUS but extracting a structurally distinct dimension of inter-criterion dispersion. The deliberate pairing of these two procedures ensures that the final weight estimates reflect a richer and more balanced characterization of criterion importance than either method could produce independently.

3.3. Final Weighting Procedure

To correctly judge the levels of importance of the evaluation criteria, the application of the single weighting technique might not correctly reveal the underlying information content and the structure of the data's dispersion. Therefore, more balanced, stable, and dependable weight structures in the decision process might be obtained using the results of the application of multiple objective weighting techniques (Işık et al., 2024; Tekgün, 2025; Durdu et al., 2025). The results of the weighting process using the CRISUS and MAXC methods are analyzed together in the case study under consideration. The aggregation operator expressed in Eq. (12) is used to obtain the final weight for each of the assessment criteria. The final weight for each of the assessment criteria is obtained using the aggregation operator expressed in Eq. (12). The criteria weight obtained using the CRISUS and MAXC methods is expressed as the terms $w_j^{(CRISUS)}$ and $w_j^{(MAXC)}$ in the above equation, respectively.

$$w_j^{(Final)} = \Psi w_j^{(CRISUS)} + (1-\Psi) w_j^{(MAXC)} \tag{12}$$

The parameter Ψ in Eq. (12) is a constant coefficient with values ranging between 0 and 1. The existing literature has shown that the parameter is usually set to 0.5, thus ensuring the results obtained in both objective approaches have equal weight. In the present study, the aggregation parameter Ψ is set to 0.5, assigning equal weight to the outputs of the CRISUS and MAXC procedures in the construction of the final criterion importance scores. This choice rests on three interconnected grounds. First, since both procedures are grounded exclusively in objective, data-driven logic and capture analytically distinct but equivalent dimensions of inter-criterion dispersion, no empirical or theoretical basis exists for systematically privileging one over the other. To impose an asymmetric weighting in the absence of such justification would itself introduce a form of subjectivity inconsistent with the fully objective orientation of the proposed framework. Second, equal aggregation of multiple objective weighting results is a well-established practice in the MCDM literature, recognized for its capacity to reduce dependence on any single technique and to produce more balanced, bias-resistant criterion importance estimates (Işık et al., 2024; Tekgün, 2025; Durdu et al., 2025). Third, and most importantly, the sensitivity of the final rankings to this parametric assumption is not simply asserted but empirically examined: the robustness analyses presented in Section 6 systematically test the stability of the results under alternative weighting configurations, providing formal evidence that the $\Psi = 0.5$ assumption does not compromise the structural integrity of the proposed framework.

3.4. MARCOS Procedure

Since its emergence in the decision-making literature by Stević et al. in 2020, the MARCOS method has been extensively applied in MCDM studies. An analytical assessment reasoning process that identifies the relative relationships between reference values defined by ideal and anti-ideal solutions with respect to decision alternatives constitutes the MARCOS approach (Akbulut, 2025b; Durdu, 2025). The MARCOS approach asserts that the best solution is the one that indicates the maximum distance from the anti-ideal solution and the minimum approach to the ideal solution simultaneously. According to Yalman et al. (2023) and Işık et al. (2025), one of the most important advantages of the MARCOS method is its ability to assess solutions simultaneously with respect to both ideal and anti-ideal reference solutions and among themselves, which enables the construction of effective comparison frameworks. This dual-reference assessment mechanism allows Decision Makers not only to perceive decision outcomes more transparently but also internally consistently improving interpretability of resulting rankings. Further on, due to systematic and transparent computational steps easy compatibility with different weighting procedures and capability for generating stable results over large scale data sets the MARCOS approach is considered a reliable as well as efficient ranking tool for practical performance evaluation problems (Stević & Brković, 2020; Işık et al., 2023). In line with methodological frameworks in relevant literature, this case study applies the MARCOS procedure through following stepwise process.

Step 1. Form a decision matrix comprising the performance indicators and decision alternatives according to Eq. (1).
Step 2. The extended decision matrix which is shown in Eq. (13) is generated by merging ideal (AI) and anti-ideal (AAI) solutions into the initial matrix.

$$X = \begin{array}{c} AAI \\ A_1 \\ A_2 \\ \dots \\ A_m \\ AI \end{array} \begin{bmatrix} x_{aa1} & x_{aa2} & \dots & x_{aan} \\ x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \\ x_{ai1} & x_{ai2} & \dots & x_{ain} \end{bmatrix} \tag{13}$$

In this framework, the anti-ideal solution (AAI) denotes the worst-performing alternative, whereas the ideal solution (AI) corresponds to the best-performing alternative. The AAI and AI values are defined by considering the beneficial and non-beneficial characteristics of the criteria, as expressed in Eq. (14) and Eq. (15), respectively.

$$AAI = \min_i x_{ij} \ \text{ if } j \in B \text{ and } \max_i x_{ij} \ \text{ if } j \in NB \tag{14}$$

$$AI = \max_i x_{ij} \ \text{ if } j \in B \text{ and } \min_i x_{ij} \ \text{ if } j \in NB \tag{15}$$

Step 3. At this stage, the extended decision matrix is normalized by accounting for the beneficial and non-beneficial orientations of the indicators. Eq. (16) is applied to beneficial criteria, while Eq. (17) is employed for non-beneficial criteria.

$$n_{ij} = \frac{x_{ij}}{x_{ai}} \tag{16}$$

$$n_{ij} = \frac{x_{ai}}{x_{ij}} \tag{17}$$

Step 4. The weighted normalized matrix is obtained through the application of Eq. (18).

$$v_{ij} = n_{ij} \times w_j \tag{18}$$

Step 5. Based on the ideal and anti-ideal reference solutions, the utility degrees of the alternatives are determined. For each alternative, the utility degrees are determined conducting Eq. (19) and Eq. (20).

$$K_i^- = \frac{S_i}{S_{aai}} \tag{19}$$

$$K_i^+ = \frac{S_i}{S_{ai}} \tag{20}$$

In this context, the term S_i represents the sum of the weighted values for each alternative, as defined in Eq. (21).

$$S_i = \sum_{i=1}^{n} v_{ij} \tag{21}$$

Step 6. The utility functions of the alternatives are computed according to Eq. (22). More explicitly, the utility function reflects the degree of compromise of each alternative relative to the ideal and anti-ideal solutions.

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}} \tag{22}$$

The terms $f(K_i^+)$ and $f(K_i^-)$ reflect the utility functions with respect to the ideal and anti-ideal solutions, respectively, which are determined applying Eq. (23) and Eq. (24).

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{23}$$

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{24}$$

Step 7. At this stage, the decision alternatives are ranked based on the final values of the utility function. The alternative with the highest value of the utility function is considered the best. The design of the CRISUS–MAXC–MARCOS integrated framework rests on the principle that each methodological component contributes a distinct but structurally compatible function to the overall analytical architecture. CRISUS approaches the weighting problem through a sum-of-squares dispersion measure applied across two normalization stages, while MAXC introduces a complementary perspective by quantifying distance from maximum values — a logic that foregrounds marginal criterion contributions rather than distributional spread. Combining the weight outputs of these two procedures yields a final criterion importance set that is more balanced, more resistant to the idiosyncrasies of any single method, and more reflective of the multidimensional structure of the underlying data than either approach could produce in isolation. The MARCOS ranking method is particularly well-suited to receiving this integrated weight set: its dual-reference evaluation mechanism — which simultaneously assesses alternatives against both ideal and anti-ideal solutions — exploits the full informational content of the criterion weights while producing rankings that are internally consistent and transparent in their interpretive logic (Stević et al., 2020; Stević & Brković, 2020). Taken together, these structural compatibilities render the proposed CRISUS–MAXC–MARCOS framework a methodologically coherent and analytically reliable instrument for the multidimensional assessment of banking performance under the CAMELS criteria.

4. CASE STUDY

The primary objective of this study is to provide a systematic, objective, and multidimensional assessment of the financial performance of commercial banks listed on BIST within the CAMELS evaluation framework. To this end, the analysis encompasses six performance dimensions of critical relevance to the banking sector: capital adequacy, asset quality, management efficiency, earnings capacity, liquidity management, and sensitivity to market risk. The study sample comprises eight deposit banks listed on BIST whose financial data were continuously available and reliably accessible throughout the observation period. Participation banks and development and investment banks were excluded from the sample on the grounds that their balance sheet structures, revenue models, business activities, and regulatory frameworks differ fundamentally from those of conventional deposit banks — an exclusion that safeguards the analytical validity and internal consistency of the cross-bank performance comparisons. Detailed information on the sampled banks is provided in Table 2. All financial data were sourced from the publicly accessible database of the Banks Association of Turkey (BAT) and the annual reports of the respective banks.

Table 2
Alternative Banks

Rank	Banks	Code
1	Türkiye Halk Bankası A.Ş.	HB
2	Türkiye Vakıflar Bankası T.A.O.	VB
3	Akbank T.A.Ş.	AB
4	Şekerbank T.A.Ş.	ŞB
5	Türkiye İş Bankası A.Ş.	İB
6	Yapı ve Kredi Bankası A.Ş.	YB
7	ICBC Turkey Bank A.Ş.	IB
8	Türkiye Garanti Bankası A.Ş.	GB

The 2020–2024 observation period was determined on both conceptual and practical grounds. Conceptually, the study is designed not to capture a static performance snapshot at a single point in time, but rather to conduct a medium-term performance analysis and to propose a replicable evaluation model for use by decision-makers — an objective for which a five-year data horizon provides both adequate analytical depth and a time frame meaningfully aligned with managerial planning cycles. On practical grounds, this period encompasses a series of exceptional macroeconomic conditions specific to the Turkish context, including the economic pressures of the COVID-19 pandemic, persistently elevated inflation, pronounced exchange rate volatility, and a structural shift in monetary policy. To minimize the distorting influence of these conjunctural fluctuations on the measurement process and to ensure a fairer basis for cross-bank comparison, five-year period averages were employed in place of individual annual observations — a choice that attenuates the impact of transitory shocks while preserving the informational content of the underlying data. It is nonetheless acknowledged, as a substantive limitation of this study, that the exceptional macroeconomic conditions characterizing this period may partly be reflected in the empirical findings, and that the results should be interpreted with this caveat in mind.

The twelve financial indicators employed in this study were selected to represent each of the six dimensions of the CAMELS evaluation framework. Three guiding criteria governed the selection process: the prevalence and recurrence of the indicators in the CAMELS-based bank performance evaluation literature; the reliable and complete accessibility of the corresponding data for all sampled banks through the BAT's publicly available database; and the capacity of each selected indicator to provide an analytically meaningful and representative measure of its assigned CAMELS dimension. Detailed information on all selected criteria — including their classification and optimization directions — is presented in Table 3.

The capital adequacy (C) dimension is measured through the capital adequacy ratio (C1) and the equity to total assets ratio (C2), both of which reflect the bank's capacity to absorb potential losses and its overall financial resilience, and are among the most consistently employed indicators in the banking performance literature (Hayajneh & Yassine, 2011; Mili et al., 2017; Buallay et al., 2021; Akbulut & Aydın, 2024). Asset quality (A) is represented by the total loans to total assets ratio (A1) and the total loans to total deposits ratio (A2), which together capture the structural weight of the credit portfolio within the bank's asset base and the efficiency of resource utilization — dimensions that are widely recognized as structural indicators of asset quality (Prabowo et al., 2018; Zakaria & Purhanudin, 2017; Mehzabin et al., 2023; Cui et al., 2023). Management efficiency (M) is assessed through the non-performing loans to total loans ratio (M1) and the other operating expenses to total assets ratio (M2): the former reflects management's effectiveness in controlling credit risk, while the latter captures operational cost management performance (Wang et al., 2020; Brei et al., 2024; Hayajneh & Yassine, 2011; Akbulut & Aydın, 2024). The earnings (E) dimension is evaluated using return on average assets (E1) and return on average equity (E2), which rank among the most established profitability measures in the banking literature (Mili et al., 2017; Buallay et al., 2021; Mehzabin et al., 2023; Cui et al., 2023). Liquidity (L) is examined through the liquid assets to total assets ratio (L1) and the liquid assets to short-term liabilities ratio (L2), both of which gauge the bank's capacity to meet its short-term obligations and the adequacy of its liquidity buffer (Prabowo et al., 2018; Wang et al., 2020; Zakaria & Purhanudin, 2017; Brei et al., 2024).

The sensitivity to market risk (S) dimension is represented by the net non-interest income to total assets ratio (S1) and the foreign currency assets to total assets ratio (S2). Within the CAMELS framework, this dimension measures the degree to which changes in interest rates, exchange rates, and broader market conditions can adversely affect a bank's earnings and financial soundness (Stackhouse, 2019). S2 directly quantifies the bank's exposure to currency risk by capturing the share of foreign currency-denominated assets within total assets (Mili et al., 2017; Akbulut & Aydın, 2024). S1, in turn, expresses the ratio of net non-interest income — encompassing fee and commission revenues, service charges, and trading gains, all of which are directly sensitive to interest rate movements and prevailing market conditions — relative to total assets. Stiroh (2004) demonstrated empirically that non-interest income exhibits substantially greater volatility than traditional interest income, and that reliance on such revenue streams amplifies banks' exposure to market-driven risk. Accordingly, S1 is treated in this study as a direct proxy for a bank's structural dependence on market-sensitive revenue sources beyond conventional intermediation activities — and, by extension, for its sensitivity to fluctuations in market conditions (Stiroh, 2004; Chronopoulos et al., 2023).

Table 3
Chosen CAMELS Assessment Measures

Rank	Type	Indicators	Code	Optimization
1	C	Capital Adequacy Ratio	C1	Max.
2		Equity to Total Assets Ratio	C2	Max.
3	A	Total Loans to Total Assets Ratio	A1	Max.
4		Total Loans to Total Deposits Ratio	A2	Max.
5	M	Non-Performing Loans to Total Loans Ratio	M1	Min.
6		Other Operating Expenses to Total Assets Ratio	M2	Min.
7	E	Return on Average Assets	E1	Max.
8		Return on Average Equity	E2	Max.
9	L	Liquid Assets to Total Assets Ratio	L1	Max.
10		Liquid Assets to Short-Term Liabilities Ratio	L2	Max.
11	S	Net Non-Interest Income to Total Assets Ratio	S1	Max.
12		Foreign Currency Assets to Total Assets Ratio	S2	Min.

5. EMPIRICAL FINDINGS OF THE RESEARCH

In this section, the findings derived from implementing the offered CRISUS–MAXC–MARCOS integrated decision-making framework for assessing the financial performance of deposit banks listed on BIST are reported.

5.1. Findings of the CRISUS Procedure

The assessment process was initiated with the determination of criterion weights associated with the chosen CAMELS indicators. In this context, the relative importance levels of the performance indicators were first estimated utilizing the CRISUS approach. The decision matrix comprising the bank alternatives and the assessment criteria was created in accordance with Eq. (1) and is reported in Table 4. To ensure temporal comparability of the data and to mitigate the effect of short-term fluctuations on the analysis results, the arithmetic means of annual observations covering the 2020–2024 time period were calculated for all performance indicators. Accordingly, a representative and single decision matrix, free from period-specific volatility, was obtained for each bank based on these average values.

Subsequently, a first normalization process was employed to the decision matrix by considering the benefit and cost orientations of the criteria, by means of Eq. (2) and (3). The findings derived from this stage are showed in Table 5. This was followed by a secondary normalization procedure conducted with Eq. (4), and the corresponding results are displayed in Table 6. In the final stage of the CRISUS method, the sum of squares values associated with the chosen performance indicators (ρ_j) were first calculated by applying Eq. (5). In the subsequent step, the standard deviation values (σ_j) for each criterion were obtained. Finally, the objective weights (w_j) of the criteria were determined by means of Eq. (6). The aggregated outcomes of these computations are summarized in Table 7.

Table 4

Decision Matrix

	C1	C2	A1	A2	M1	M2	E1	E2	L1	L2	S1	S2
HB	14.663	5.861	61.103	82.956	2.612	0.812	0.625	10.452	12.216	17.704	0.218	32.360
VB	15.391	6.076	58.178	92.084	2.623	0.831	1.073	17.325	16.947	28.008	1.553	41.861
AB	22.633	12.727	51.845	83.437	4.315	1.190	3.756	29.223	16.802	31.507	2.464	40.204
ŞB	19.770	7.420	59.660	80.297	5.688	2.032	1.687	22.556	19.555	33.267	1.569	41.119
İB	21.251	11.322	55.093	84.996	3.677	1.350	3.017	25.972	18.829	29.391	1.557	43.960
YB	19.630	10.161	56.362	98.407	4.365	1.190	3.362	32.629	16.640	28.840	2.343	41.649
IB	27.609	4.627	41.647	95.554	0.304	0.809	1.230	27.104	21.417	52.590	1.414	80.098
GB	19.506	12.236	58.335	85.623	3.252	1.284	3.824	30.947	21.197	33.924	3.323	39.614

Table 5

Fist Normalized Decision Matrix

	C1	C2	A1	A2	M1	M2	E1	E2	L1	L2	S1	S2
HB	0.254	0.223	0.389	0.333	0.749	0.770	0.084	0.145	0.238	0.189	0.038	0.757
VB	0.267	0.231	0.370	0.369	0.747	0.764	0.145	0.240	0.330	0.298	0.275	0.686
AB	0.392	0.484	0.330	0.335	0.585	0.663	0.506	0.405	0.327	0.336	0.436	0.698
ŞB	0.342	0.282	0.379	0.322	0.452	0.424	0.227	0.313	0.381	0.354	0.278	0.691
İB	0.368	0.431	0.350	0.341	0.646	0.617	0.407	0.360	0.366	0.313	0.275	0.670
YB	0.340	0.387	0.359	0.395	0.580	0.663	0.453	0.452	0.324	0.307	0.414	0.687
IB	0.478	0.176	0.265	0.383	0.971	0.771	0.166	0.376	0.417	0.560	0.250	0.399
GB	0.338	0.466	0.371	0.343	0.687	0.636	0.515	0.429	0.413	0.361	0.588	0.703

Table 6

Second Normalized Decision Matrix

	C1	C2	A1	A2	M1	M2	E1	E2	L1	L2	S1	S2
HB	0.091	0.083	0.138	0.118	0.138	0.145	0.034	0.053	0.085	0.069	0.015	0.143
VB	0.096	0.086	0.132	0.131	0.138	0.144	0.058	0.088	0.118	0.110	0.108	0.130
AB	0.141	0.181	0.117	0.119	0.108	0.125	0.202	0.149	0.117	0.123	0.171	0.132
ŞB	0.123	0.105	0.135	0.114	0.084	0.080	0.091	0.115	0.136	0.130	0.109	0.131
İB	0.132	0.161	0.125	0.121	0.119	0.116	0.162	0.132	0.131	0.115	0.108	0.127
YB	0.122	0.144	0.127	0.140	0.107	0.125	0.181	0.166	0.116	0.113	0.162	0.130
IB	0.172	0.066	0.094	0.136	0.179	0.145	0.066	0.138	0.149	0.206	0.098	0.075
GB	0.122	0.174	0.132	0.122	0.127	0.120	0.206	0.158	0.148	0.133	0.230	0.133

Table 7

Findings of CRISUS

	ρ_j	σ_j	$\rho_j \times \sigma_j$	w_j	Rank
C1	0.130	0.071	0.009	0.053	9
C2	0.139	0.121	0.017	0.098	4
A1	0.126	0.039	0.005	0.029	11
A2	0.126	0.026	0.003	0.019	12
M1	0.131	0.154	0.020	0.117	3
M2	0.128	0.115	0.015	0.086	5
E1	0.160	0.176	0.028	0.163	1
E2	0.135	0.104	0.014	0.082	7
L1	0.128	0.058	0.007	0.043	10
L2	0.135	0.104	0.014	0.082	6
S1	0.153	0.162	0.025	0.145	2
S2	0.128	0.109	0.014	0.081	8

5.2. Findings of the MAXC Procedure

In this section, the weight scores of the CAMELS indicators are calculated based on the MAXC method. To this end, the analysis begins with the decision matrix made in accordance with Eq. (1) and displayed in Table 4. All entries of the decision matrix are subsequently subjected to a linear normalization process with Eq. (7). Following normalization, the maximum values associated with each assessment criterion are determined by applying Eq. (8). The outcomes obtained at this stage are showed in Table 8. Based on these maximum values, a distance-from-maximum matrix is then calculated by means of Eq. (9), and the finding values are reported in Table 9. In the final of the MAXC approach, the expected distance measures for the performance criteria (E_j) are first calculated by employing Eq. (10). Subsequently, the criterion importance weights (w_j) are computed in accordance with Eq. (11). The consolidated consequences derived from these computations are summarized in Table 10.

Table 8

Normalized Decision Matrix

	C1	C2	A1	A2	M1	M2	E1	E2	L1	L2	S1	S2
HB	0.091	0.083	0.138	0.118	0.097	0.085	0.034	0.053	0.085	0.069	0.015	0.090
VB	0.096	0.086	0.132	0.131	0.098	0.088	0.058	0.088	0.118	0.110	0.108	0.116
AB	0.141	0.181	0.117	0.119	0.161	0.125	0.202	0.149	0.117	0.123	0.171	0.111
ŞB	0.123	0.105	0.135	0.114	0.212	0.214	0.091	0.115	0.136	0.130	0.109	0.114
İB	0.132	0.161	0.125	0.121	0.137	0.142	0.162	0.132	0.131	0.115	0.108	0.122
YB	0.122	0.144	0.127	0.140	0.163	0.125	0.181	0.166	0.116	0.113	0.162	0.115
IB	0.172	0.066	0.094	0.136	0.011	0.085	0.066	0.138	0.149	0.206	0.098	0.222
GB	0.122	0.174	0.132	0.122	0.121	0.135	0.206	0.158	0.148	0.133	0.230	0.110
max (r_{ij})	0.172	0.181	0.138	0.140	0.212	0.214	0.206	0.166	0.149	0.206	0.230	0.222

Table 9

Distance Matrix from Maximum Values

	C1	C2	A1	A2	M1	M2	E1	E2	L1	L2	S1	S2
HB	0.081	0.097	0.000	0.022	0.115	0.128	0.172	0.113	0.064	0.137	0.215	0.132
VB	0.076	0.094	0.007	0.009	0.114	0.126	0.148	0.078	0.031	0.096	0.123	0.106
AB	0.031	0.000	0.021	0.021	0.051	0.089	0.004	0.017	0.032	0.083	0.060	0.111
ŞB	0.049	0.075	0.003	0.026	0.000	0.000	0.115	0.051	0.013	0.076	0.121	0.108
İB	0.040	0.020	0.014	0.019	0.075	0.072	0.043	0.034	0.018	0.091	0.122	0.100
YB	0.050	0.036	0.011	0.000	0.049	0.089	0.025	0.000	0.033	0.093	0.068	0.107
IB	0.000	0.115	0.044	0.004	0.201	0.129	0.140	0.028	0.000	0.000	0.132	0.000
GB	0.051	0.007	0.006	0.018	0.091	0.079	0.000	0.009	0.002	0.073	0.000	0.112

Table 10

Findings of MAXC

	C1	C2	A1	A2	M1	M2	E1	E2	L1	L2	S1	S2
E_j	0.047	0.056	0.013	0.015	0.087	0.089	0.081	0.041	0.024	0.081	0.105	0.097
w_j	0.064	0.076	0.018	0.020	0.118	0.121	0.110	0.056	0.033	0.110	0.143	0.132
Rank	8	7	12	11	4	3	6	9	10	5	1	2

5.3. Findings of the Final Weighting Procedure

This section presents the final weights of the selected performance indicators by using an aggregation operator that simultaneously reflects the different decision-making procedures on criterion importance levels. In this frame, results obtained through Eq. (12) are provided in Table 11, thus giving integrated importance levels of the criteria.

Table 11
Final Weighting Results

	w_j^{CRISUS}	w_j^{MAXC}	w_j^{Final}	Rank
C1	0.053	0.064	0.059	9
C2	0.098	0.076	0.087	7
A1	0.029	0.018	0.023	11
A2	0.019	0.020	0.020	12
M1	0.117	0.118	0.118	3
M2	0.086	0.121	0.104	5
E1	0.163	0.110	0.137	2
E2	0.082	0.056	0.069	8
L1	0.043	0.033	0.038	10
L2	0.082	0.110	0.096	6
S1	0.145	0.143	0.144	1
S2	0.081	0.132	0.107	4

The final criterion importance weights reported in Table 11 reveal a clear hierarchy of discriminatory power among the twelve CAMELS indicators. The net non-interest income to total assets ratio (S1) emerges as the single most influential criterion, commanding the highest final weight across both objective procedures. This finding is not incidental — it reflects a structural shift in the competitive dynamics of the Turkish banking sector during the 2020–2024 period. Sustained interest rate volatility and persistently elevated inflation compelled banks to diversify their revenue base beyond traditional intermediation activities, making fee and commission income, service charges, and capital market revenues increasingly decisive determinants of relative financial performance. The empirical literature lends considerable support to this interpretation: non-interest income has been shown to exhibit substantially greater volatility than interest-based revenues, and banks with higher exposure to such income streams face amplified sensitivity to prevailing market conditions (Stiroh, 2004; Chronopoulos et al., 2023). That S1 should rank first under both CRISUS and MAXC — two methodologically distinct procedures — further reinforces the robustness of this finding.

Return on average assets (E1) ranks second, reflecting the enduring centrality of asset utilization efficiency as a performance differentiator in bank-based financial systems. The non-performing loans to total loans ratio (M1) follows closely in third place, underscoring the critical role of credit risk management in a period marked by rapid credit expansion and mounting asset quality pressures in the Turkish banking sector. Taken together, these three criteria — S1, E1, and M1 — account for a disproportionate share of the total explanatory weight, pointing to an underlying performance dynamic shaped by the interdependence of income structure, profitability, and credit risk management.

At the other end of the weight spectrum, the credit concentration indicators within the asset quality dimension — total loans to total assets (A1) and total loans to total deposits (A2) — receive the lowest importance weights, suggesting limited discriminatory power in explaining cross-bank performance differences over the analysis period. This outcome is at least partly attributable to the balance sheet homogeneity that the BRSA-led structural reforms instilled across the Turkish banking sector in the aftermath of the 2001 financial crisis — a convergence that may have compressed the interbank variance in these indicators sufficiently to render them less analytically distinguishing within the present sample.

5.4. Findings of the MARCOS Procedure

The final weights derived from the CRISUS and MAXC procedures are now incorporated into the MARCOS process to rank the deposit banks as per their relative performances. Therefore, the application of the MARCOS method starts with the construction of an initial matrix expressed in Eq. (1) and shown in Table 4. For reference-based evaluation of alternatives, ideal and anti-ideal values defined by Eq. (14) and (15) are then merged with this initial matrix. Thus an extended initial decision matrix is formed according to Eq. (13). The numerical values related to this extended matrix can be seen in Table 12.

In the next step, performance criteria contained in the extended matrix are normalized considering whether they are beneficial or non-beneficial using Eqs. (16) and (17). This normalization procedure makes criteria measured on different scales comparable; normalized values are given in Table 13. After normalization, entries of the normalized matrix are multiplied by final weights according to Eq. (18), resulting in a weighted normalized matrix whose empirical findings at this stage are illustrated in Table 14. In the last phase of MARCOS procedure, utility degrees of banks will be found conducting Eqs. (19)- (21). Based on these utility degrees, corresponding utility functions and therefore final rankings will be determined by means of Eqs. (22)- (24). The consolidated and final findings that clearly reveal relative performance positions among banks are displayed in Table 15.

Table 12
Extended Decision Matrix

	C1	C2	A1	A2	M1	M2	E1	E2	L1	L2	S1	S2
HB	14.663	5.861	61.103	82.956	2.612	0.812	0.625	10.452	12.216	17.704	0.218	32.360
VB	15.391	6.076	58.178	92.084	2.623	0.831	1.073	17.325	16.947	28.008	1.553	41.861
AB	22.633	12.727	51.845	83.437	4.315	1.190	3.756	29.223	16.802	31.507	2.464	40.204
ŞB	19.770	7.420	59.660	80.297	5.688	2.032	1.687	22.556	19.555	33.267	1.569	41.119
İB	21.251	11.322	55.093	84.996	3.677	1.350	3.017	25.972	18.829	29.391	1.557	43.960
YB	19.630	10.161	56.362	98.407	4.365	1.190	3.362	32.629	16.640	28.840	2.343	41.649
IB	27.609	4.627	41.647	95.554	0.304	0.809	1.230	27.104	21.417	52.590	1.414	80.098
GB	19.506	12.236	58.335	85.623	3.252	1.284	3.824	30.947	21.197	33.924	3.323	39.614
AI	27.609	12.727	61.103	98.407	0.304	0.809	3.824	32.629	21.417	52.590	3.323	32.360
AAI	14.663	4.627	41.647	80.297	5.688	2.032	0.625	10.452	12.216	17.704	0.218	80.098

Table 13
Normalized Decision Matrix

	C1	C2	A1	A2	M1	M2	E1	E2	L1	L2	S1	S2
HB	0.531	0.460	1.000	0.843	0.116	0.996	0.163	0.320	0.570	0.337	0.065	1.000
VB	0.557	0.477	0.952	0.936	0.116	0.973	0.281	0.531	0.791	0.533	0.467	0.773
AB	0.820	1.000	0.848	0.848	0.070	0.680	0.982	0.896	0.785	0.599	0.741	0.805
ŞB	0.716	0.583	0.976	0.816	0.053	0.398	0.441	0.691	0.913	0.633	0.472	0.787
İB	0.770	0.890	0.902	0.864	0.083	0.599	0.789	0.796	0.879	0.559	0.469	0.736
YB	0.711	0.798	0.922	1.000	0.070	0.680	0.879	1.000	0.777	0.548	0.705	0.777
IB	1.000	0.364	0.682	0.971	1.000	1.000	0.322	0.831	1.000	1.000	0.426	0.404
GB	0.706	0.961	0.955	0.870	0.094	0.630	1.000	0.948	0.990	0.645	1.000	0.817
AI	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
AAI	0.531	0.364	0.682	0.816	0.053	0.398	0.163	0.320	0.570	0.337	0.065	0.404

Table 14

Weighted Normalized Matrix

	C1	C2	A1	A2	M1	M2	E1	E2	L1	L2	S1	S2
HB	0.031	0.040	0.023	0.017	0.014	0.103	0.022	0.022	0.022	0.032	0.009	0.107
VB	0.033	0.042	0.022	0.019	0.014	0.101	0.038	0.037	0.030	0.051	0.067	0.082
AB	0.048	0.087	0.020	0.017	0.008	0.070	0.134	0.062	0.030	0.058	0.107	0.086
ŞB	0.042	0.051	0.023	0.016	0.006	0.041	0.060	0.048	0.035	0.061	0.068	0.084
İB	0.045	0.077	0.021	0.017	0.010	0.062	0.108	0.055	0.034	0.054	0.067	0.078
YB	0.042	0.069	0.022	0.020	0.008	0.070	0.120	0.069	0.030	0.053	0.101	0.083
IB	0.059	0.032	0.016	0.019	0.118	0.104	0.044	0.057	0.038	0.096	0.061	0.043
GB	0.041	0.084	0.022	0.017	0.011	0.065	0.137	0.065	0.038	0.062	0.144	0.087
AI	0.059	0.087	0.023	0.020	0.118	0.104	0.137	0.069	0.038	0.096	0.144	0.107
AAI	0.031	0.032	0.016	0.016	0.006	0.041	0.022	0.022	0.022	0.032	0.009	0.043

Table 15

Findings of MARCOS

	S_i	K_i^-	K_i^+	$f(K_i^+)$	$f(K_i^-)$	$f(K_i)$	Rank
HB (Halk Bankası)	0.443	0.443	1.509	0.227	0.773	0.415	8
VB (Vakıflar Bankası)	0.535	0.535	1.825	0.227	0.773	0.502	6
AB (Akbank)	0.726	0.726	2.476	0.227	0.773	0.681	2
ŞB (Şekerbank)	0.534	0.534	1.822	0.227	0.773	0.501	7
İB (İş Bankası)	0.628	0.628	2.141	0.227	0.773	0.589	5
YB (Yapı ve Kredi)	0.687	0.687	2.341	0.227	0.773	0.644	3
IB (ICBC Turkey)	0.686	0.686	2.339	0.227	0.773	0.643	4
GB (Garanti Bankası)	0.773	0.773	2.637	0.227	0.773	0.725	1
AI	1.000						
AII	0.293						

The MARCOS results presented in Table 15 provide a comparative mapping of the relative financial performance positions of the eight sampled deposit banks over the 2020–2024 period within the CAMELS evaluation framework. Before turning to the substantive findings, a methodological qualification is in order: the rankings derived from any MCDM-based framework are inherently conditional on the criteria selected, the normalization procedure applied, and the weighting structure employed. The results reported here should therefore be interpreted as relative performance positions obtained under the specific analytical parameters of the proposed framework, rather than as absolute or unconditional performance rankings.

Within this frame of reference, Garanti Bankası (GB) achieves the highest utility function value, positioning it closest to the ideal solution among all sampled banks. Akbank (AB) and Yapı ve Kredi Bankası (YB) follow in second and third place, respectively. A common thread running through the top-ranked institutions is their capacity to combine strong income diversification, sustained asset profitability, and a relatively balanced risk profile — a configuration that, under the weighting structure derived in this study, translates into pronounced proximity to the ideal solution. A noteworthy finding is the fourth-place ranking of ICBC Turkey (IB), a foreign-capital bank. This result suggests that foreign-owned institutions may leverage more selective credit portfolio management strategies and structurally distinct revenue compositions to achieve competitive performance outcomes within the particular conditions of the Turkish banking sector — an observation consistent with broader evidence on ownership effects in emerging market banking.

At the lower end of the rankings, Halk Bankası (HB) and Şekerbank (ŞB) are positioned furthest from the ideal solution. The last-place ranking of Halk Bankası — a state-owned institution — is consistent with the well-documented structural constraints facing public banks in Turkey: the burden of policy-directed lending and subsidised credit programmes tends to compress profitability margins and exert downward pressure on asset quality indicators, irrespective of operational competence (Ulusoy et al., 2023; Kartal, 2018). It bears emphasis, however, that these ranking differentials reflect not only structural performance characteristics but also the particular conjunctural conditions of the observation period, and should be interpreted accordingly.

6. SENSITIVITY ANALYSES

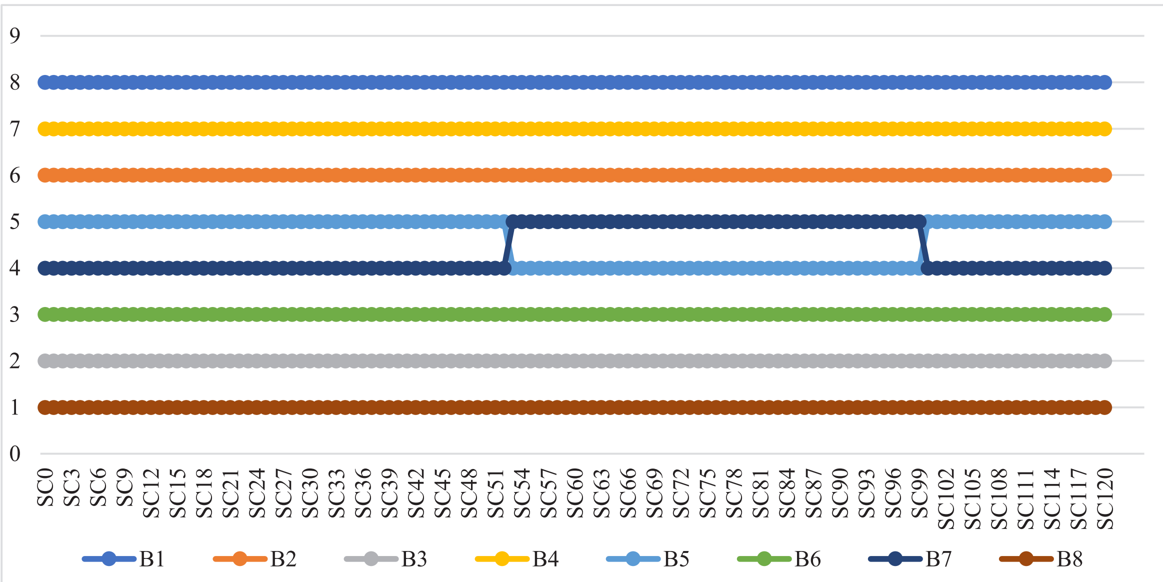
In this part, a number of sensitivity investigations will be used to demonstrate the validity and reliability of the decision model developed in the context of assessing the financial performance of the banking industry. These investigations are important in assessing the validity of the methodological approach of the proposed framework in decision-making, as well as the stability of the empirical evidence generated from the research.

6.1. Impact of Changes in Criterion Weights on the Final Ranking

Several sensitivity analysis approaches have been developed in the literature of decision making for evaluating the extent of impact of criterion weights on final ranking results. In this case study, the robustness of the proposed integrated model in terms of criterion weight variations is explored by using the methodological framework as presented in Akbulut (2025c) and Işık et al. (2025). According to this framework, the weight of the most effective criterion in the final weight set (S1) is decreased by 5% in all scenarios, and this weight difference is equally allocated among all other 11 criteria, resulting in 120 different scenarios in total. For every single one of these cases, MARCOS is re-run, and any potential changes in the final ranking of alternative banks are carefully monitored. The results show that these weight variations do not result in any significant changes in the final ranking of alternative banks, thereby showing that the offered methodological framework is highly robust, stable, and reliable. The results of this sensitivity analysis are presented in Figure 2.

Figure 2

Rankings Based on the New Weight Sets



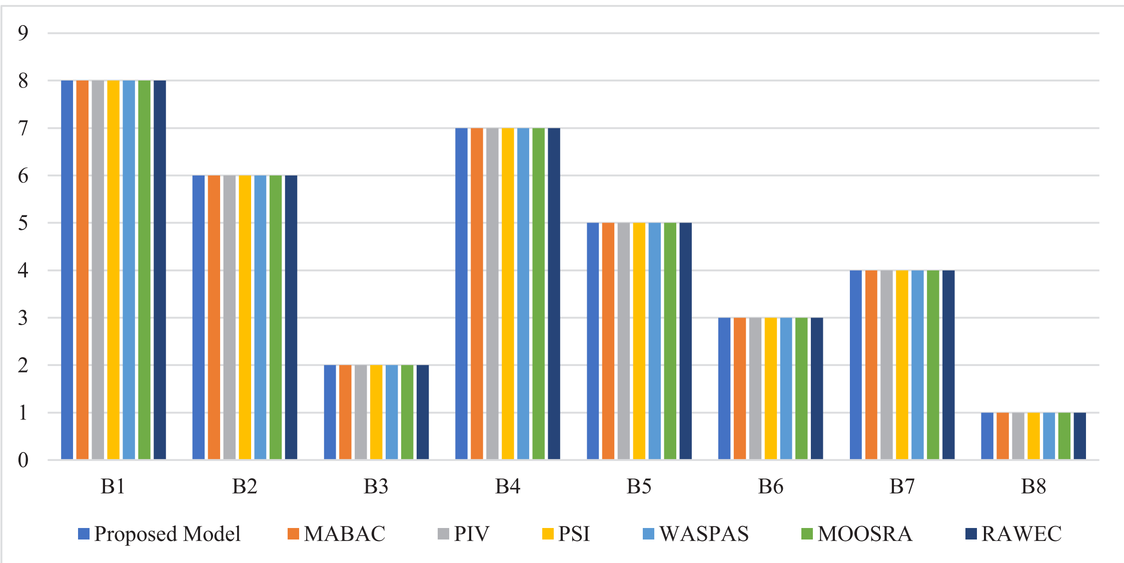
A careful examination of the sensitivity profiles displayed in Figure 2 reveals that the proposed framework produces highly stable ranking outcomes across the vast majority of the 120 weight scenarios tested. Rank shifts are confined exclusively to the fourth and fifth positions — involving ICBC Turkey (IB) and İş Bankası (İB) — and occur only within a specific subset of scenarios, approximately between SC54 and SC99. The remaining six banks, including first-ranked Garanti Bankası (GB) and last-ranked Halk Bankası (HB), retain their positions without exception across all 120 scenarios. This pattern of results demonstrates that the proposed framework is highly resilient to perturbations in the criterion weighting structure, and that the derived rankings are, to a substantial degree, independent of any particular weight configuration. The limited rank interchange observed between IB and İB warrants no methodological concern: with utility function values of 0.643 and 0.589 respectively, these two institutions occupy closely adjacent performance positions, and the occasional reversal between them is a natural consequence of their similar overall profiles rather than an indication of structural fragility in the model. Taken as a whole, the consistency of the sensitivity results constitutes meaningful empirical evidence that the integrated weight set derived from the joint application of CRISUS and MAXC effectively mitigates the vulnerability to arbitrary weighting choices that characterizes single-method approaches.

6.2. Comparison of the Proposed Model with Different MCDM Approaches

At this level, the reliability, robustness, and consistency of the ranking results obtained through the integrated model proposed in this study are critically examined. To achieve this, the ranking results obtained through the MARCOS approach are comprehensively compared with the ranking results obtained through several other ranking techniques commonly applied in the MCDM literature, such as the MABAC method (Pamučar & Ćirović, 2015), the PIV method (Mufazzal & Muzakkir, 2018), the PSI method (Maniya & Bhatt, 2010), the WASPAS method (Zavadskas et al., 2012), the MOOSRA method (Das et al., 2012), the RAWEC method (Puška et al., 2024), etc. The results of the comparison studies are presented in Figure 3. An analysis of the results presented in Figure 3 reveals that the proposed model produces stable, robust, and method-independent ranking results in the evaluation of the performance of banks.

Figure 3

Re-Ranking of Alternatives across Different MCDM Approaches



The comparative results presented in Figure 3 reveal a striking degree of convergence: the bank rankings produced by the MARCOS method are in complete agreement with those generated by each of the six alternative MCDM approaches examined — MABAC, PIV, PSI, WASPAS, MOOSRA, and RAWEC. To move beyond this descriptive observation and establish the consistency of rankings on a statistically rigorous footing, Spearman rank correlation coefficients were computed between the MARCOS rankings and those yielded by each alternative method. The resulting coefficients uniformly attain a value of ρ = 1.000 across all method pairs, providing formal statistical confirmation that the proposed framework generates rankings that are entirely independent of the particular scoring and aggregation logic of any single MCDM technique. A degree of cross-method consistency of this magnitude represents a notably strong robustness signal in the MCDM literature, and constitutes compelling evidence for the structural validity and method-independence of the proposed integrated framework.

Considered jointly, the sensitivity and comparative analyses presented in Sections 6.1 and 6.2 paint a coherent and mutually reinforcing picture of the robustness properties of the proposed CRISUS–MAXC–MARCOS framework. Across 120 criterion weight scenarios, only a narrow and localized rank interchange between two closely matched banks was observed, while all remaining positions held firm; across seven competing MCDM methods, perfect rank correlation (ρ = 1.000) was obtained without exception. Together, these results establish that the proposed framework is resilient along two analytically distinct robustness dimensions — parameter sensitivity and method dependence — simultaneously. The evidence supports the conclusion that the integrated framework not only produces rankings that are stable under perturbation, but does so in a manner that is transparent, replicable, and independent of the idiosyncrasies of any individual methodological component — attributes that collectively position it as a analytically reliable decision support instrument for the multidimensional performance evaluation of BIST-listed deposit banks.

7. CONCLUSION AND RECOMMENDATIONS

This structural element emphasizes the need for constant, comprehensive, and frequent evaluations of the performance of banks. The evaluation of performance in terms of conventional profitability measures alone is no longer adequate in the face of increasing market volatility, mounting regulatory burdens, and evolving patterns of revenue for banks. There is a need to have a system that considers income diversification, liquidity, and risk simultaneously. It is, therefore, important that there be objective and comparable performance analysis by appropriate means. This study set out to evaluate the financial performance of eight BIST-listed deposit banks over the 2020–2024 period through an integrated decision support framework combining the CRISUS and MAXC objective weighting procedures with the MARCOS ranking method, using the CAMELS criteria as the analytical foundation. The findings reported below are discussed with respect to their theoretical, empirical, and practical implications.

The final criterion importance weights derived from the joint application of CRISUS and MAXC point to a discernible hierarchy among the performance determinants of BIST-listed deposit banks over the 2020–2024 period. The net non-interest income to total assets ratio (S1) emerges as the single most influential criterion — a finding that acquires particular interpretive resonance when situated within the structural conditions of the Turkish banking sector during this period. Sustained interest rate volatility and persistently elevated inflation compelled banks to diversify their revenue base beyond traditional intermediation, elevating income diversification to a decisive competitive differentiator. Return on average assets (E1) and the non-performing loans to total loans ratio (M1) follow in second and third place respectively; taken together, these three criteria suggest that banking performance over the observation period was shaped primarily by the interdependent dynamics of income structure, asset utilization efficiency, and credit risk management. At the other end of the weight spectrum, the credit concentration indicators within the asset quality dimension (A1, A2) receive the lowest importance weights — an outcome that points to the balance sheet homogeneity instilled by the post-2001 BRSA-led structural reforms, which appears to have compressed inter-bank variance in these indicators sufficiently to limit their discriminatory power within the present sample. This finding carries a broader methodological implication: performance evaluations anchored exclusively in balance sheet composition risk overlooking the dimensions of banking performance that prove most consequential in differentiating institutions under conditions of structural convergence.

The ranking results derived from the MARCOS procedure reveal meaningful differentiation in the relative financial performance positions of the sampled banks. Before turning to the substantive findings, a methodological qualification bears restatement: the rankings reported here are inherently conditional on the criteria selected, the normalization procedure applied, and the weighting structure employed, and should accordingly be understood as relative performance positions obtained under the specific analytical parameters of the proposed framework rather than as absolute or unconditional performance verdicts.

Within this frame of reference, Garanti Bankası, Akbank, and Yapı ve Kredi Bankası occupy the top three positions. A common thread running through these institutions is their capacity to combine strong income diversification, sustained asset profitability, and a relatively balanced risk profile — a configuration that, under the weighting structure derived in this study, translates into pronounced proximity to the ideal solution. A noteworthy finding is the fourth-place ranking of ICBC Turkey, a foreign-capital institution. This result suggests that foreign-owned banks may leverage more selective credit portfolio management strategies and structurally distinct revenue compositions to achieve competitive performance outcomes within the particular conditions of the Turkish banking sector.

At the lower end of the rankings, Halk Bankası, Şekerbank, and Vakıflar Bankası are positioned furthest from the ideal solution. Their relative performance positions may be understood as a reflection of structural factors including limited non-interest income diversification, comparatively subdued asset profitability, and pressure on credit quality indicators. The last-place ranking of Halk Bankası — a state-owned institution — is consistent with the well-documented structural constraints facing public banks in Turkey: the burden of policy-directed lending and subsidized credit programmers tends to compress profitability margins and exert downward pressure on asset quality indicators, irrespective of operational competence (Ulusoy et al., 2023; Kartal, 2018). It bears emphasis, nonetheless, that the observed ranking differentials reflect not only structural performance characteristics but also the particular conjunctural conditions of the observation period, and should be interpreted with this caveat firmly in mind.

Considered jointly, the sensitivity and comparative analyses provide consistent and mutually reinforcing evidence of the robustness properties of the proposed framework across multiple analytical dimensions. Across 120 criterion weight scenarios, the rankings of six out of eight banks remained entirely stable; the sole exception involved a limited and localized interchange between the fourth and fifth positions — two institutions with near-identical utility function values — observed within a specific subset of scenarios, and attributable to the proximity of their overall performance profiles rather than to any structural fragility in the model. The cross-method comparison yielded perfect rank correlation between the MARCOS rankings and those produced by each of the six alternative MCDM approaches examined (Spearman $\rho = 1.000$), providing formal statistical confirmation that the proposed framework generates consistent and stable rankings independently of the particular scoring and aggregation logic of any individual ranking technique. Together, these results establish that the proposed framework is resilient along two analytically distinct dimensions simultaneously — parameter sensitivity and method dependence — and that its outputs are both stable under perturbation and independent of idiosyncratic methodological choices..

On a theoretical level, this study strengthens the conceptual foundations of MCDM-based bank performance evaluation by integrating the weighting and ranking processes within a unified objective framework — an approach that addresses a methodological gap that has remained insufficiently resolved in the existing literature. On a practical level, the findings highlight the centrality of non-interest income diversification, asset utilization efficiency, and credit risk management as performance differentiators, and point to these dimensions as priority areas for institutions seeking to strengthen their competitive positioning. From a managerial and regulatory standpoint, the study demonstrates how CAMELS indicators can be operationalized within an integrated model structure to serve as effective instruments for early warning systems, continuous performance monitoring, and evidence-based policy intervention. In this respect, the proposed framework contributes not only a methodological advance to the academic literature but also an analytically grounded decision support instrument with direct applicability to strategic planning and regulatory oversight processes within the banking sector.

The contributions of this study should be situated within a set of methodological and contextual limitations. First, the sample is restricted to eight deposit banks listed on BIST over the 2020–2024 period, which constrains the generalisability of the findings to the broader Turkish banking sector, to other national contexts, and to banking systems with different ownership structures. Second, the use of five-year period averages — while effective in attenuating the influence of short-term conjunctural fluctuations — necessarily suppresses year-on-year performance dynamics and precludes a longitudinal analysis of performance trajectories over the observation window. Third, the 2020–2024 period encompasses a series of exceptional macroeconomic conditions specific to the Turkish context, including the economic disruptions of the COVID-19 pandemic, persistently elevated inflation, and pronounced exchange rate volatility; the empirical findings may partly reflect these period-specific dynamics, and should be interpreted with this caveat in mind. Finally, as is inherent to all MCDM-based evaluation frameworks, the ranking outcomes reported in this study are conditional on the criteria selected, the normalisation procedure applied, and the weighting structure employed, and should be understood as relative performance positions within the specific analytical parameters of the proposed model rather than as unconditional performance verdicts.

Several directions present themselves for future research. Extending the sample to include banks from different countries or ownership structures would enhance the comparative scope and generalizability of the findings. Adopting a longitudinal design — whether through an extended observation window, the use of panel data approaches, or the substitution of annual averages with individual yearly observations — would enable a more granular examination of performance dynamics over time. The integration of ESG-related indicators into the CAMELS structure would yield a more comprehensive analytical framework for the multidimensional sustainability assessment of banking institutions. Finally, applying the CRISUS–MAXC–MARCOS framework to non-banking financial sectors and to other emerging market contexts would provide further evidence on the broader methodological transferability of the proposed approach.

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