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A Hybrid Multi-Criteria Decision-Making Model for Performance Assessment in the Banking Industry

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ABSTRACT

This work presents a novel hybrid multi-criteria decision-making (MCDM) framework designed to assess the financial and non-financial Environmental, Social, and Governance (ESG) performance of the banking sector. To demonstrate its applicability, a longitudinal case study was conducted on a major Turkish bank using annual data from 2012 to 2022. The proposed framework integrates two complementary methodologies: Maximum of Criterion (MAXC) and Range of Value (ROV). The MAXC method was utilized to objectively compute the weights of financial and non-financial performance indicators, while the ROV procedure enabled the ranking of annual performance across both dimensions. The evaluation followed a two-stage structure. In the first phase, MAXC revealed that the most influential financial indicators were return on average assets, return on average equity, and the ratio of non-performing loans to total loans. For the non-financial dimension, community engagement, governance quality, and human rights emerged as the most impactful criteria. In the second phase, the ROV method was employed to calculate composite performance scores and derive annual rankings. The results indicate that 2022, 2012, and 2014 marked the strongest years in terms of financial performance, while 2021, 2022, and 2020 demonstrated the highest ESG-related performance. Finally, a series of sensitivity analyses confirmed the robustness and reliability of the proposed hybrid model, thereby validating its suitability for comprehensive performance evaluation in the banking sector.

1. Introduction

The banking industry plays a pivotal role in modern economies and financial systems. Its function extends beyond merely facilitating the circulation of money; it is central to capital formation and serves as a key driver of economic growth [1]. As global economies become more interconnected, banks must adapt to dynamic economic conditions and evolving regulatory policies [2]. Performance evaluations assist banking institutions in identifying areas for improvement, optimizing resource allocation and adjusting their products and services to meet changing customer expectations [3]. This

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process of adaptation, underpinned by robust performance analysis, is vital for gaining a competitive edge in volatile financial environments and safeguarding operational sustainability [4].

Regular assessment and interpretation of bank performance data is crucial for several reasons. A stable and profitable banking industry is essential for fostering economic stability and growth. Banks act as a protective buffer against financial crises, enabling national economies to withstand sudden shocks and maintain continuity of core financial services, even during economic downturns [5]. Furthermore, as banks play a pivotal role in directing funds from economic agents towards productive investment opportunities, the health of the banking sector is intricately linked to the broader economic and financial landscape [6]-[7].

Conducting performance analysis using financial indicators is essential in the financial sector as it provides a quantitative foundation for evaluating firms' stability, profitability, and operational efficiency. Financial metrics such as liquidity ratios, leverage ratios, return on assets, and return on equity serve as objective measures of financial health, enabling stakeholders-including investors, regulators, and policymakers-to make informed decisions regarding asset allocation, credit risk assessment, and regulatory compliance [8]-[9]. Furthermore, financial analysis supports risk management strategies, helping financial institutions mitigate potential systemic vulnerabilities and enhance resilience in dynamic market environments.

Simultaneously, the integration of Environmental, Social, and Governance (ESG) indicators into performance assessments has gained strategic importance, particularly in the context of sustainable finance and long-term value creation [10]. ESG dimensions-such as carbon emissions reduction, corporate social responsibility (CSR), and transparent governance practices—contribute to institutional reputation, stakeholder confidence, and regulatory alignment, thereby shaping both investment appeal and systemic financial stability. Embedding ESG metrics into evaluation frameworks enables financial institutions to synchronize their operational strategies with global sustainability agendas, reduce exposure to climate-related and compliance risks, and foster responsible investment behaviors. Moreover, ESG-based assessments offer critical insight into firms' resilience to non-financial risks, including reputational damage and legal liabilities, reinforcing their adaptive capacity and long-term viability in an increasingly sustainability-oriented economic ecosystem [11].

On the other hand, gauging and evaluating firm performance from different perspectives is an inherently complex decision-making problem, as it involves multiple and often conflicting criteria that affect corporate success [12]-[13]. In this context, multi-criteria decision-making (MCDM) techniques offer a structured and robust approach to overcome these challenges by integrating various performance indicators, allowing for a holistic assessment and rational prioritization [14]-[15].

This existing manuscript introduces a hybrid Multi-Criteria Decision-Making (MCDM) methodology for assessing the financial and non-financial (ESG) performance in baking industry. The suggested hybrid approach integrates Maximum of Criterion (MAXC) and Range of Value (ROV) procedures. The MAXC method is used to objectively determine the weights of the chosen financial and non-financial performance indicators, and the ROV method is employed to rank the decision alternatives. The effectiveness of the suggested decision-making model was applied to a real-world case study evaluating the multidimensional performance of İş bank, one of the leading commercial banks in the Turkish banking industry, for the period 2012-2022.

The MAXC method was selected over other objective methods like Entropy, CRITIC, or CRISUS due to its capacity to identify dominant criteria through the contrast between normalized and maximal values-a particularly important feature when dealing with heterogeneous performance indicators. In addition, ROV method was preferred over more commonly employed ranking techniques such as TOPSIS and PROMETHEE owing to its robustness against outliers and its ability to simultaneously incorporate both beneficial and non-beneficial criteria without requiring a distance-to-ideal solution concept. Moreover, both methods are computationally efficient and well-suited for use with limited expert input, making them ideal for data-rich, expertise-scarce environments such as ESG evaluation.

The remainder of the paper is structured as follows: Following the introduction, a literature review is presented in alignment with the research objective. Section 2 outlines the methodological framework of the study. Section 3 introduces the sample and dataset used, along with the empirical results derived from implementing the proposed model. Section 4 conducts a series of sensitivity and comparative analyses to evaluate the model's robustness. Section 5 provides practical and managerial implications for various stakeholder groups based on the findings. Finally, Section 6 concludes the study by discussing the results and offering directions for future research.

1.1 Literature Review

In recent years, academic research on performance assessment in the banking sector has grown and diversified, particularly with regard to the increasing focus on incorporating financial and non-financial ESG-based performance indicators. This reflects a growing recognition of the multidimensional nature of bank performance. Table 1 provides an overview of selected studies that exemplify this evolving research landscape.

A critical review of the literature summarized in Table 1 reveals that existing studies on banking performance have predominantly focused either on traditional financial indicators or on a narrow selection of ESG-based metrics. Most applications employ conventional MCDM frameworks without systematically distinguishing between financial and non-financial performance dimensions. Moreover, although various hybrid methods have been explored, no prior research to our knowledge has implemented an integrated MAXC-ROV framework in a comparative, dimensionally bifurcated context. This study responds to this gap by offering a methodological advancement through the novel integration of the MAXC objective weighting technique and the ROV ranking method. Conceptually, the study advances the literature by introducing a dual-perspective evaluation model that treats financial and non-financial performance streams as analytically distinct yet complementary components. This dual-structured framework facilitates a more nuanced and multidimensional understanding of banking performance, particularly relevant in ESG-sensitive institutional environments.

Table 1
Literature review the adopted MCDM models

Author(s)	Weighting Procedure	Ranking Procedure	Country	Period	Sample
Chaudhuri & Ghosh [16]	Equal Weight	TOPSIS & M-TOPSIS	India	2007-2013	29 banks
Akbulut [17]	CRITIC	EDAS	Turkey	2009-2018	1 bank
Marjanović & Popović [18]	CRITIC	TOPSIS	Serbia	2012-2017	25 banks
Bayram [19]	SWARA	CODAS	Turkey	2019-2021	10 banks
Guru & Mahalik [20]	AHP	TOPSIS	India	2014	26 banks
Yılmaz & Yakut [21]	F- Entropy	F-TOPSIS & F-VIKOR	Turkey	2009-2018	22 banks
Avşarlıgil *et al.* [22]	Entropy	MOOSRA ARAS, & MOORA	Turkey	2019-2020	13 banks
Rao and Shukla [23]	MEREC	MARCOS	India	2021-2022	20 banks
Akbulut & Aydın [24]	MSD and MPSI	RAWEC	Turkey	2022	6 banks
Hussain *et al.* [25]	AHP	GRA and TOPSIS	China, India, Pakistan and Thailand	2019-2022	38 banks
Mastilo *et al.* [26]	MEREC	MARCOS	Bosnia & Herzegovina	2022	21 banks
Goel *et al.* [27]	Equal Weight	GIA	India	2018-2023	10 banks
Akbulut [28]	LOPCOW-G	PIV-G	Turkey	-	6 banks
Kumar & Sharma [29]	CRITIC	TOPSIS	India	2015-2016 & 2020-2021	9 banks
Ali *et al.* [30]	CRITIC	RAFSI	Iraq	2007-2020	19 banks
Karki *et al.* [31]	R-SWARA	CoCoSo	India	-	5 banks
Işık *et al.* [32]	F-LBWA & F-LMAW	MARCOS	Pakistan	-	15 banks
Peci *et al,* [33]	F-AHP	F-TOPSI	Albania	2020-2022	11 banks
Işık *et al.* [34]	Spherical F-SWARA and SPC	Spherical F-AROMAN	Turkey	-	6 banks

2. Methodological Framework

In multi-criteria decision-making (MCDM) frameworks, the determination of criteria weights is a critical step that directly influences the robustness, transparency, and interpretability of the final decision. Since decision problems often involve multiple, and sometimes conflicting, criteria, assigning appropriate weights is essential for reflecting both the informational structure of the data and the preferences of decision-makers.

Subjective weighting techniques rely on expert judgment to capture contextual knowledge and value-based preferences. Notable examples include the Level-Based Weight Assessment (LBWA) method Žižović & Pamučar [35], the Best-Worst Method (BWM) Rezaei [36], and the RANCOM

(Ranking Comparison) method Więckowski et al., [37], which accounts for inaccuracies in expert rankings to derive more reliable weights. These approaches are especially valuable when qualitative insights are essential to the decision context.

In contrast, objective weighting methods, such as MEREC (Method based on the Removal Effects of Criteria) Keshavarz Ghorabaee et al., [38], CRITIC (Criteria Importance Through Intercriteria Correlation) Diakoulaki et al., [39], CRISUS (CRiterion Importance based on the SUm of Squares) Adalar & Işık, [40], and the MAXC (MAXimum of Criterion) Gligorić et al., [41], derive weights from the decision matrix. These methods are particularly useful when expert input is limited or when a data-driven perspective is prioritized.

In this manuscript, we chose to use the MAXC method, which focuses on measuring the distance between the maximum values and normalized values of the criteria, as it effectively captures both the discriminative power and the relative dominance of each criterion across the decision matrix. This approach, as proposed by Gligorić et al. [41], emphasizes the criteria that contribute most significantly to differentiation among decision alternatives, thereby enhancing the robustness and transparency of the weighting process.

This study examined the financial and non-financial performance of Türkiye İş Bankası by applying a hybrid decision-making procedure. During the analysis, MAXC method was first applied to objectively calculate the weights of the chosen financial and non-financial performance indicators. Based on these calculated weights, the ROV method was then employed to rank the bank's annual performance across the assessment period. Figure 1 below illustrates the proposed decision-making framework developed within the scope of this study.

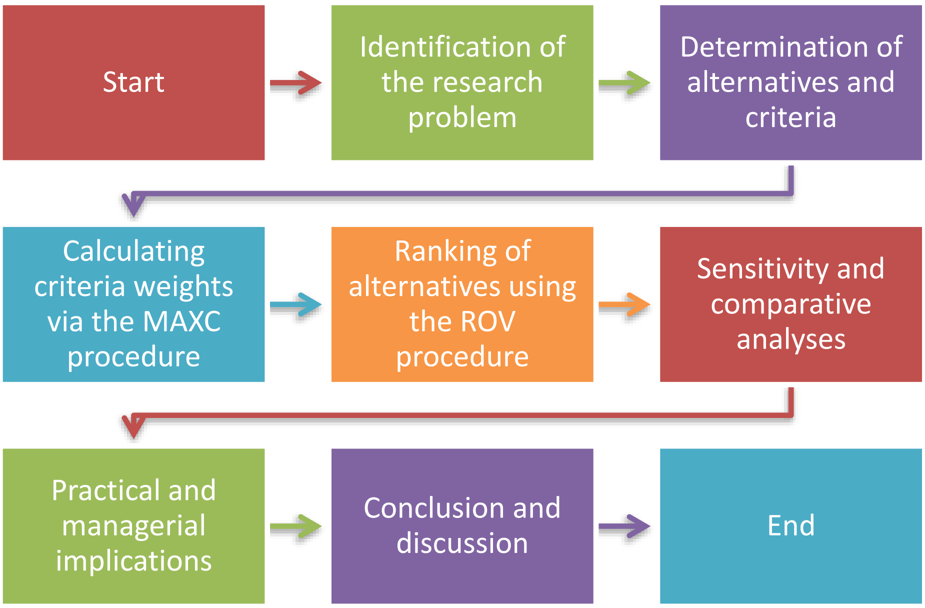

Fig. 1. The proposed Methodological Decision-Making Framework

2.1 MAXC Objective Weighting Procedure

The MAXC procedure is a relatively new, objective weighting approach that was introduced to decision-making literature by Gligorić et al., [41]. MAXC approach quantifies the cumulative influence of each assessment criterion on overall performance, providing an objective measure of its impact. It offers two significant advantages: it provides statistically sensitive and objective results, particularly for large data sets, and it is mathematically straightforward and easy to implement. MAXC procedure application consists of six sequential steps, as illustrated below [41]-[42].

Step 1. Construct the initial decision matrix including the alternatives and evaluation criteria, as shown in Eq. (1).

$$D = \left[x_{ij}\right]_{m\times n} = \begin{bmatrix} A/C & C_1 & C_2 & \cdots & C_n \\ A_1 & x_{11} & x_{12} & \cdots & x_{1j} \\ A_2 & x_{21} & x_{22} & \cdots & x_{2j} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

Step 2. Normalize the initial matrix using the linear normalization technique defined in Eq. (2).

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

Step 3. Identify the maximum value for each performance criterion in the normalized matrix, in accordance with Eq. (3).

$$r_{ij}(max) = max\ (r_{ij}) \tag{3}$$

Step 4. Calculate the distance between the normalized values and their respective maximum values using Eq. (4).

$$d_{ij} = r_{ij}(max) - r_{ij} \tag{4}$$

Step 5. Compute the expected distance value for each criterion based on Eq. (5).

$$E_j = \frac{\sum_{i=1}^{m} d_{ij}}{m} \tag{5}$$

Step 6. Finally, derive the objective importance weights of the criteria by using Eq. (6). This constitutes the final step of the MAXC procedure.

$$w_j = \frac{E_j}{\sum_{i=1}^{m} E_j} \tag{6}$$

2.2 ROV Ranking Procedure

The ROV procedure was originally introduced to the field of decision-making by Yakowitz *et al.,* [43], as an alternative ranking approach. It assesses each decision option based on its proximity to ideal and anti-ideal solutions [44]. Unlike many other ranking methods, the ROV procedure has the unique advantage of simultaneously accounting for both positive and negative contributions to performance. This feature reduces sensitivity to extreme values, yielding more stable and consistent ranking results [45]. Implementing the ROV procedure involves four sequential steps, as outlined below [43]-[46].

Step 1. Initial decision matrix construction, as shown in Eq. (1).

Step 2. Normalize the decision matrix based on the properties of the assessment criteria. Specifically, use Eq. (7) for beneficial (benefit-type) criteria and Eq. (8) for non-beneficial (cost-type) criteria.

$$r_{ij} = \frac{x_{ij} - min\,(x_{ij})}{max(x_{ij}) - min\,(x_{ij})} \tag{7}$$

$$r_{ij} = \frac{max(x_{ij}) - x_{ij}}{max(x_{ij}) - min\,(x_{ij})} \tag{8}$$

Step 3. Calculate the best (u_i^+) and worst (u_i^-) utility function values for each alternative, incorporating the weight coefficients assigned to each criterion. The utility and cost characteristics of the criteria must be considered. Accordingly, Eq. (9) is applied to beneficial criteria to find the best utility values, while Eq. (10) is used to find the worst utility values for non-beneficial criteria.

$$u_i^+ = \sum_{j=1}^{n} r_{ij} \times w_j \tag{9}$$

$$u_i^- = \sum_{j=1}^{n} r_{ij} \times w_j \tag{10}$$

Step 4. In the final step of the ROV procedure, the performance scores and corresponding rankings of the alternatives are computed using Eq. (11).

$$u_i = \frac{u_i^+ + u_i^-}{2} \tag{11}$$

The alternative with the highest score is considered the best-performing option.

3. Sample, Data, and Findings

The objective of this paper is to propose a novel, integrated algorithm for making decisions and assessing the performance of Türkiye İş Bankası between 2012 and 2022, taking into account both financial and non-financial factors. To this end, a thorough case study was carried out using a robust dataset to test the applicability and practical relevance of the proposed algorithm. To enable a comparative assessment of the bank's performance, annual data relating to nine financial and ten non-financial performance indicators was retrieved from the widely recognized, internationally reliable Refinitiv Eikon database. Two separate datasets were constructed for use in the performance assessment process. The first dataset consists of financial indicators reflecting the bank's financial soundness, profitability, asset quality and liquidity structure. Detailed descriptions of these indicators are provided in Table 2. The second dataset encompasses non-financial (ESG-based) indicators that capture dimensions such as corporate governance quality, environmental responsibility, and social sustainability. Comprehensive explanations of these non-financial indicators are presented in Table 3. This dual-framework approach enables multidimensional evaluation of the bank's performance, providing a more holistic and analytically grounded perspective.

Table 2
Financial Performance Indicators

Rank	Assessment Criterion	Objective	Code
1	Capital Adequacy Ratio	Max	FI1
2	Deposit - to - Asset Ratio	Max	FI2
3	Credit - to - Asset Ratio	Max	FI3
4	Liquidity Ratio	Max	FI4
5	Return on Average Assets	Max	FI5
6	Return on Average Equity	Max	FI6
7	Personnel Expense - to - Other Operating Expenses Ratio	Min	FI7
8	Non-Performing Loans - to - Total Loans Ratio	Min	FI8
9	Price Volume	Min	FI9

Table 3
ESG-Based Non-Financial Performance Indicators

Rank	Assessment Criterion	Objective	Code
1	Resource Use	Max	SI1
2	Emissions	Max	SI2
3	İnnovation	Max	SI3
4	Workforce	Max	SI4
5	Human Rights	Max	SI5
6	Community	Max	SI6
7	Product Responsibility	Max	SI7
8	Management	Max	SI8
9	Shareholders	Max	SI9
10	Corporate Social Responsibility	Max	SI10

3.1 Results of MAXC Procedure

The assessment process began with calculating the objective weight scores for the chosen financial and non-financial performance indicators. To this end, the MAXC procedure was initially applied to derive the weights of the indicators. The first stage of the MAXC procedure involved constructing separate decision matrices for the financial and non-financial criteria based on Eq. (1). These matrices are presented in Tables 4 and 5, respectively.

Table 4
Decision Matrix (For Financial Criteria)

	FI1	FI2	FI3	FI4	FI5	FI6	FI7	FI8	FI9
2012	16.3283	60.0666	61.0690	25.7124	1.9639	16.2907	40.6117	1.8903	34.4200
2013	14.3793	57.4702	64.2665	26.1789	1.6393	13.6652	45.8547	1.6542	33.5700
2014	16.0217	56.1678	65.5562	27.9798	1.5091	12.7904	43.1256	1.5529	32.0900
2015	15.6466	55.7826	64.5348	27.4276	1.2007	10.0502	40.8994	2.0253	31.3100
2016	15.1726	56.9144	65.5457	26.4957	1.6008	13.8279	45.4581	2.4207	30.0700
2017	16.6563	56.2303	66.2796	24.9033	1.5751	13.4285	45.9594	2.2499	26.6000
2018	16.4896	58.9040	62.4887	11.6524	1.7385	14.5864	84.2197	4.3013	26.2500
2019	17.8652	63.2232	61.7963	14.1408	1.3721	11.1748	77.7618	6.5286	27.6300
2020	18.6839	62.1106	61.5457	14.2176	1.2827	10.7551	78.6070	5.5733	26.4300
2021	20.3595	64.2832	55.4960	22.2382	1.7715	17.4206	66.7017	4.0510	26.4900
2022	24.3639	66.1125	55.5571	15.7609	5.2712	44.2376	79.7293	2.9567	27.6900

Table 5
Decision Matrix (For Non-Financial Criteria)

	SI1	SI2	SI3	SI4	SI5	SI6	SI7	SI8	SI9	SI10
2012	15.2500	31.1300	56.5800	43.6700	31.5500	18.9500	37.7100	86.0000	78.0000	13.1600
2013	40.0500	54.8200	85.9300	69.8400	30.7300	22.4900	40.2900	54.0000	66.0000	86.3600
2014	48.6400	51.9900	87.2100	69.4400	30.4800	22.3800	39.4800	78.8500	55.7700	84.0900
2015	51.7600	50.2200	89.2000	73.1800	31.1500	22.0000	44.9800	24.0700	38.8900	86.0000
2016	49.8000	50.8000	89.0100	75.1200	58.3300	24.4100	57.7500	44.2300	40.3800	88.0000
2017	88.9500	83.7100	87.5600	91.7400	53.2900	25.1300	86.7200	32.6900	65.3800	78.0000
2018	85.6900	85.7800	85.8100	94.1500	48.9400	27.9600	87.6200	11.2900	85.4800	93.5500
2019	78.6300	86.5900	83.8400	95.5200	95.5400	24.1300	68.0300	28.9500	85.0900	91.8400
2020	79.5100	87.5500	83.4400	93.9500	95.6600	27.6900	63.8100	83.3300	83.3300	91.3800
2021	97.6000	99.1900	96.4800	98.6800	95.7000	99.1400	99.5700	82.3900	71.5900	82.9300
2022	99.7900	99.3000	96.7200	99.3900	95.4500	99.1100	99.7500	43.6300	60.7800	81.3800

The criterion values included in the decision matrices were normalized with the help of Eq. (2). The findings obtained from the normalization process are presented in Tables 6 and 7.

Table 6
Normalized Decision Matrix (For Financial Criteria)

	FI1	FI2	FI3	FI4	FI5	FI6	FI7	FI8	FI9
2012	0.0851	0.0914	0.0893	0.1086	0.0939	0.0914	0.0626	0.0537	0.1067
2013	0.0749	0.0874	0.0939	0.1106	0.0783	0.0767	0.0707	0.0470	0.1041
2014	0.0835	0.0855	0.0958	0.1182	0.0721	0.0718	0.0665	0.0441	0.0995
2015	0.0815	0.0849	0.0943	0.1159	0.0574	0.0564	0.0630	0.0575	0.0971
2016	0.0790	0.0866	0.0958	0.1119	0.0765	0.0776	0.0701	0.0688	0.0932
2017	0.0868	0.0856	0.0969	0.1052	0.0753	0.0753	0.0708	0.0639	0.0825
2018	0.0859	0.0896	0.0913	0.0492	0.0831	0.0818	0.1298	0.1222	0.0814
2019	0.0931	0.0962	0.0903	0.0597	0.0656	0.0627	0.1198	0.1854	0.0857
2020	0.0973	0.0945	0.0900	0.0601	0.0613	0.0603	0.1211	0.1583	0.0819
2021	0.1061	0.0978	0.0811	0.0939	0.0847	0.0977	0.1028	0.1151	0.0821
2022	0.1269	0.1006	0.0812	0.0666	0.2519	0.2482	0.1229	0.0840	0.0858

Table 7
Normalized Decision Matrix (For Non-Financial Criteria)

	SI1	SI2	SI3	SI4	SI5	SI6	SI7	SI8	SI9	SI10
2012	0.0207	0.0399	0.0601	0.0483	0.0473	0.0458	0.0520	0.1510	0.1067	0.0150
2013	0.0544	0.0702	0.0912	0.0772	0.0461	0.0544	0.0555	0.0948	0.0903	0.0985
2014	0.0661	0.0666	0.0926	0.0768	0.0457	0.0541	0.0544	0.1385	0.0763	0.0959
2015	0.0704	0.0643	0.0947	0.0809	0.0467	0.0532	0.0620	0.0423	0.0532	0.0981
2016	0.0677	0.0650	0.0945	0.0830	0.0875	0.0590	0.0796	0.0777	0.0553	0.1004
2017	0.1209	0.1072	0.0930	0.1014	0.0799	0.0608	0.1195	0.0574	0.0895	0.0890
2018	0.1165	0.1098	0.0911	0.1041	0.0734	0.0676	0.1207	0.0198	0.1170	0.1067
2019	0.1069	0.1109	0.0890	0.1056	0.1433	0.0584	0.0937	0.0508	0.1165	0.1048
2020	0.1081	0.1121	0.0886	0.1038	0.1435	0.0670	0.0879	0.1463	0.1140	0.1042
2021	0.1327	0.1270	0.1024	0.1091	0.1435	0.2398	0.1372	0.1447	0.0980	0.0946
2022	0.1356	0.1271	0.1027	0.1099	0.1431	0.2397	0.1375	0.0766	0.0832	0.0928

The corresponding distance matrices were derived using Eq. (4) following the identification of the maximum values for each assessment criterion in the normalized matrices, as specified in Eq. (3). The results relating to these distance matrices are reported in Tables 8 and 9.

Table 8
Distance Matrix (For Financial Criteria)

	FI1	FI2	FI3	FI4	FI5	FI6	FI7	FI8	FI9
2012	0.0419	0.0092	0.0076	0.0096	0.1581	0.1568	0.0672	0.1318	0.0000
2013	0.0520	0.0131	0.0029	0.0076	0.1736	0.1715	0.0591	0.1385	0.0026
2014	0.0435	0.0151	0.0011	0.0000	0.1798	0.1764	0.0633	0.1413	0.0072
2015	0.0454	0.0157	0.0026	0.0023	0.1945	0.1918	0.0668	0.1279	0.0096
2016	0.0479	0.0140	0.0011	0.0063	0.1754	0.1706	0.0597	0.1167	0.0135
2017	0.0402	0.0150	0.0000	0.0130	0.1766	0.1729	0.0590	0.1215	0.0242
2018	0.0410	0.0110	0.0055	0.0690	0.1688	0.1664	0.0000	0.0633	0.0253
2019	0.0339	0.0044	0.0066	0.0585	0.1863	0.1855	0.0100	0.0000	0.0211
2020	0.0296	0.0061	0.0069	0.0581	0.1906	0.1879	0.0086	0.0271	0.0248
2021	0.0209	0.0028	0.0158	0.0243	0.1672	0.1505	0.0270	0.0704	0.0246
2022	0.0000	0.0000	0.0157	0.0516	0.0000	0.0000	0.0069	0.1015	0.0209

Table 9
Distance Matrix (For Non-Financial Criteria)

	SI1	SI2	SI3	SI4	SI5	SI6	SI7	SI8	SI9	SI10
2012	0.1149	0.0873	0.0426	0.0616	0.0962	0.1940	0.0855	0.0000	0.0102	0.0917
2013	0.0812	0.0569	0.0115	0.0327	0.0974	0.1854	0.0819	0.0562	0.0267	0.0082
2014	0.0695	0.0606	0.0101	0.0331	0.0978	0.1857	0.0830	0.0126	0.0407	0.0108
2015	0.0653	0.0628	0.0080	0.0290	0.0968	0.1866	0.0755	0.1088	0.0638	0.0086
2016	0.0680	0.0621	0.0082	0.0268	0.0560	0.1808	0.0579	0.0734	0.0617	0.0063
2017	0.0147	0.0200	0.0097	0.0085	0.0636	0.1790	0.0180	0.0936	0.0275	0.0177
2018	0.0192	0.0173	0.0116	0.0058	0.0701	0.1722	0.0167	0.1312	0.0000	0.0000
2019	0.0288	0.0163	0.0137	0.0043	0.0002	0.1815	0.0437	0.1002	0.0005	0.0020
2020	0.0276	0.0150	0.0141	0.0060	0.0001	0.1728	0.0495	0.0047	0.0029	0.0025
2021	0.0030	0.0001	0.0003	0.0008	0.0000	0.0000	0.0002	0.0063	0.0190	0.0121
2022	0.0000	0.0000	0.0000	0.0000	0.0004	0.0001	0.0000	0.0744	0.0338	0.0139

In the final stage of the MAXC procedure, the expected distance values (E_j) for each performance indicator were obtained by solving Eq. (5). Then, the importance weight scores (w_j) for the financial and non-financial performance indicators were computed using Eq. (6). The results obtained by applying these equations are presented in Table 10.

The weighting findings obtained through the MAXC procedure objectively reveal the relative importance of the criteria that influence İşbank's financial performance. Based on the empirical findings for financial indicators, the top three performance criteria with the highest weight values were identified as follows: FI5 (return on average assets); FI6 (return on average equity); and FI8 (the ratio of non-performing loans to total loans). These findings suggest that İşbank's financial performance is primarily influenced by profitability metrics and credit quality, as reflected in the ratio of non-performing loans. Conversely, the financial performance indicators with the lowest weights were found to be FI3 (credit-to-asset ratio), FI2 (deposit-to-asset ratio) and FI9 (price volume), in that order. This suggests that these structural balance sheet indicators play a relatively minor role in shaping the bank's financial outcomes.

Table 10
Results of MAXC Procedure

For Financial Criteria				For Non-Financial Criteria			
	E_j	w_j	Rank		E_j	w_j	Rank
FI1	0.0360	0.0659	5	SI1	0.0447	0.0969	5
FI2	0.0097	0.0177	8	SI2	0.0362	0.0784	6
FI3	0.0060	0.0109	9	SI3	0.0118	0.0255	10
FI4	0.0273	0.0499	6	SI4	0.0190	0.0410	8
FI5	0.1610	0.2946	1	SI5	0.0526	0.1139	3
FI6	0.1573	0.2878	2	SI6	0.1489	0.3225	1
FI7	0.0389	0.0711	4	SI7	0.0465	0.1008	4
FI8	0.0945	0.1730	3	SI8	0.0601	0.1302	2
FI9	0.0158	0.0289	7	SI9	0.0261	0.0565	7
				SI10	0.0158	0.0342	9

Regarding the findings of the MAXC-based objective weighting of non-financial ESG indicators, the three factors with the greatest influence on the bank's performance were identified as SI6 (community), SI8 (management) and SI5 (human rights). These results highlight that the bank's corporate performance is more strongly associated with social impact, governance quality and human rights responsibilities than with other sustainability dimensions. Conversely, sustainability-related indicators such as SI3 (innovation), SI10 (corporate social responsibility) and SI4 (workforce) were found to have the lowest weight values. This implies that areas such as innovation and workforce management have a relatively limited impact on İşbank's non-financial sustainability performance.

3.2 Results of ROV Procedure

In the second and final stage of the assessment, the weight scores obtained from the MAXC procedure for each performance indicator were incorporated into the ROV procedure. This enabled annual performance scores and corresponding rankings of İşbank in terms of financial and non-financial performance to be calculated. In the initial step of the ROV approach, the decision matrices constructed in accordance with Eq. (1) and presented in Tables 4 and 5 were utilized. After that, normalization was performed based on the type of each performance criterion. Specifically, Eq. (7) was applied to beneficial indicators and Eq. (8) to non-beneficial indicators. The results obtained from these calculations are reported in Tables 11 and 12.

Table 11
Normalized Matrix (For Financial Criteria)

	FI1	FI2	FI3	FI4	FI5	FI6	FI7	FI8	FI9
2012	0.1952	0.4147	0.5168	0.8611	0.1875	0.1825	1.0000	0.9322	0.0000
2013	0.0000	0.1634	0.8133	0.8897	0.1078	0.1057	0.8798	0.9796	0.1040
2014	0.1645	0.0373	0.9329	1.0000	0.0758	0.0802	0.9424	1.0000	0.2852
2015	0.1269	0.0000	0.8382	0.9662	0.0000	0.0000	0.9934	0.9051	0.3807
2016	0.0795	0.1096	0.9319	0.9091	0.0983	0.1105	0.8889	0.8256	0.5324
2017	0.2281	0.0433	1.0000	0.8116	0.0920	0.0988	0.8774	0.8599	0.9572
2018	0.2114	0.3022	0.6485	0.0000	0.1321	0.1327	0.0000	0.4476	1.0000
2019	0.3491	0.7203	0.5843	0.1524	0.0421	0.0329	0.1481	0.0000	0.8311
2020	0.4311	0.6126	0.5610	0.1571	0.0202	0.0206	0.1287	0.1920	0.9780
2021	0.5989	0.8229	0.0000	0.6483	0.1402	0.2156	0.4017	0.4979	0.9706
2022	1.0000	1.0000	0.0057	0.2516	1.0000	1.0000	0.1030	0.7179	0.8237

Table 12
Normalized Matrix (For Non-Financial Criteria)

	SI1	SI2	SI3	SI4	SI5	SI6	SI7	SI8	SI9	SI10
2012	0.0000	0.0000	0.0000	0.0000	0.0164	0.0000	0.0000	1.0000	0.8395	0.0000
2013	0.2934	0.3475	0.7312	0.4697	0.0038	0.0441	0.0416	0.5717	0.5819	0.9106
2014	0.3950	0.3060	0.7631	0.4625	0.0000	0.0428	0.0285	0.9043	0.3623	0.8823
2015	0.4319	0.2800	0.8127	0.5296	0.0103	0.0380	0.1172	0.1711	0.0000	0.9061
2016	0.4087	0.2885	0.8079	0.5644	0.4270	0.0681	0.3230	0.4409	0.0320	0.9310
2017	0.8718	0.7713	0.7718	0.8627	0.3497	0.0771	0.7900	0.2864	0.5686	0.8066
2018	0.8332	0.8017	0.7282	0.9060	0.2830	0.1124	0.8045	0.0000	1.0000	1.0000
2019	0.7497	0.8136	0.6791	0.9305	0.9975	0.0646	0.4887	0.2364	0.9916	0.9787
2020	0.7601	0.8276	0.6692	0.9024	0.9994	0.1090	0.4207	0.9643	0.9539	0.9730
2021	0.9741	0.9984	0.9940	0.9873	1.0000	1.0000	0.9971	0.9517	0.7019	0.8679
2022	1.0000	1.0000	1.0000	1.0000	0.9962	0.9996	1.0000	0.4329	0.4698	0.8486

At this step, the weight values obtained from the MAXC procedure were incorporated into the ROV approach, leading to the development of weighted normalized matrices. The results relating to these matrices are displayed in Tables 13 and 14.

Table 13
Weighted Normalized Matrix (For Financial Criteria)

	FI1	FI2	FI3	FI4	FI5	FI6	FI7	FI8	FI9
2012	0.0129	0.0073	0.0056	0.0430	0.0552	0.0525	0.0711	0.1613	0.0000
2013	0.0000	0.0029	0.0089	0.0444	0.0317	0.0304	0.0626	0.1695	0.0030
2014	0.0108	0.0007	0.0102	0.0499	0.0223	0.0231	0.0670	0.1730	0.0082
2015	0.0084	0.0000	0.0092	0.0483	0.0000	0.0000	0.0707	0.1566	0.0110
2016	0.0052	0.0019	0.0102	0.0454	0.0290	0.0318	0.0632	0.1428	0.0154
2017	0.0150	0.0008	0.0109	0.0405	0.0271	0.0284	0.0624	0.1488	0.0277
2018	0.0139	0.0054	0.0071	0.0000	0.0389	0.0382	0.0000	0.0774	0.0289
2019	0.0230	0.0128	0.0064	0.0076	0.0124	0.0095	0.0105	0.0000	0.0240
2020	0.0284	0.0108	0.0061	0.0078	0.0059	0.0059	0.0092	0.0332	0.0283
2021	0.0395	0.0146	0.0000	0.0324	0.0413	0.0621	0.0286	0.0861	0.0281
2022	0.0659	0.0177	0.0001	0.0126	0.2946	0.2878	0.0073	0.1242	0.0238

Table 14
Weighted Normalized Matrix (For Non-Financial Criteria)

	SI1	SI2	SI3	SI4	SI5	SI6	SI7	SI8	SI9	SI10
2012	0.0000	0.0000	0.0000	0.0000	0.0019	0.0000	0.0000	0.1302	0.0474	0.0000
2013	0.0284	0.0273	0.0187	0.0193	0.0004	0.0142	0.0042	0.0744	0.0329	0.0312
2014	0.0383	0.0240	0.0195	0.0190	0.0000	0.0138	0.0029	0.1177	0.0205	0.0302
2015	0.0418	0.0220	0.0207	0.0217	0.0012	0.0123	0.0118	0.0223	0.0000	0.0310
2016	0.0396	0.0226	0.0206	0.0232	0.0486	0.0220	0.0326	0.0574	0.0018	0.0319
2017	0.0845	0.0605	0.0197	0.0354	0.0398	0.0249	0.0796	0.0373	0.0321	0.0276
2018	0.0807	0.0629	0.0186	0.0372	0.0322	0.0362	0.0811	0.0000	0.0565	0.0342
2019	0.0726	0.0638	0.0173	0.0382	0.1136	0.0208	0.0493	0.0308	0.0560	0.0335
2020	0.0736	0.0649	0.0171	0.0370	0.1139	0.0351	0.0424	0.1255	0.0539	0.0333
2021	0.0944	0.0783	0.0254	0.0405	0.1139	0.3225	0.1005	0.1239	0.0396	0.0297
2022	0.0969	0.0784	0.0255	0.0410	0.1135	0.3224	0.1008	0.0564	0.0265	0.0290

In the closing stages of the ROV procedure, the best (u_i^+) and worst (u_i^-) utility function values for each alternative year were found by applying Eqs. (8) and (9), respectively. The performance scores for the alternative years were then calculated in accordance with Eq. (10). The ranking results obtained from these calculations, together with the corresponding performance rankings, are reported in Table 15.

Table 15
Results of ROV Procedure

For Financial Criteria					For Non-Financial Criteria				
	u_i^+	u_i^-	u_i	Rank		u_i^+	u_i^-	u_i	Rank
2012	0.1767	0.2324	0.2045	2	2012	0.1795	0.0000	0.0897	11
2013	0.1184	0.2351	0.1767	5	2013	0.2509	0.0000	0.1255	9
2014	0.1170	0.2483	0.1827	3	2014	0.2858	0.0000	0.1429	8
2015	0.0658	0.2383	0.1520	8	2015	0.1848	0.0000	0.0924	10
2016	0.1235	0.2215	0.1725	6	2016	0.3003	0.0000	0.1501	7
2017	0.1228	0.2389	0.1808	4	2017	0.4414	0.0000	0.2207	5
2018	0.1035	0.1064	0.1049	9	2018	0.4396	0.0000	0.2198	6
2019	0.0716	0.0346	0.0531	11	2019	0.496	0.0000	0.248	4
2020	0.0651	0.0707	0.0679	10	2020	0.5968	0.0000	0.2984	3
2021	0.1898	0.1428	0.1663	7	2021	0.9687	0.0000	0.4844	1
2022	0.6787	0.1553	0.4170	1	2022	0.8905	0.0000	0.4452	2
Observation					11				
Spearman's Rho					-0.2364				
Prob.					0.4841				

According to the performance rankings obtained through the ROV procedure and reported in Table 15, there have been substantial fluctuations in both the financial and non-financial performance of Türkiye İş Bankası across the years under assessment. Findings based on financial performance indicators show that the bank achieved its highest financial performance in 2022, 2012 and 2014 respectively. Conversely, the years in which the bank demonstrated the worst financial outcomes were 2019, 2020 and 2018. The outstanding performance in 2022 appears to have been driven by notable improvements in key financial metrics, particularly return on assets, return on equity, and the non-performing loans ratio. Conversely, the poor performance rankings in 2019 and 2020 may be attributed to macroeconomic uncertainty in Turkey, heightened volatility in monetary and capital markets, and increased credit risk-factors that likely had an adverse effect on the bank's financial outcomes during these periods.

With respect to non-financial ESG indicators, the empirical findings show that the bank performed best in 2021, 2022 and 2020. During these periods, notable advancements in environmental sustainability initiatives, governance practices, and social responsibility programmers contributed to accelerating the bank's ESG-driven strategic transformation. In contrast, the worst ESG performance was recorded in 2012, 2015 and 2013. The relatively low scores in these years may be explained by the limited maturity or partial implementation of sustainability-oriented policies and practices during the early stages of the bank's ESG evolution.

Finally, a Spearman rank correlation test was carried out to establish whether there was a statistically significant relationship between İşbank's financial and non-financial performance rankings. This statistical analysis approach was chosen due to its robustness under small sample sizes, independence from normal distribution assumptions and suitability for rank-based data rather than absolute values. The results revealed a negative correlation coefficient of -0.2364 between the two rank series. However, this correlation was found to be statistically insignificant at any conventional level of significance ($p = 0.4841$).

This suggests that there is no systematic alignment between İşbank's financial performance and its non-financial performance in relation to sustainability. In other words, years in which the bank achieved strong financial outcomes did not necessarily coincide with high non-financial performance, and likewise. This lack of parallelism indicates that financial and sustainability performances at İşbank are managed independently and have not been fully integrated-a result with critical implications for the strategic alignment of financial and ESG priorities.

4. Sensitivity and Comparative Analyses

To verify the robustness and reliability of the proposed hybrid model, a two-stage sensitivity analysis was employed in this section. The first stage involved assessing the impact of variations in criterion weights on the ranking of alternatives. The second stage investigated the rank reversal phenomenon by systematically removing the worst-performing alternative from the assessment set, examining how this exclusion would affect the final rankings.

4.1 Ranking Stability Based on Weight Sensitivity

The decision-making literature includes various analytical approaches for assessing the sensitivity of rankings to changes in criterion weights. In this paper, we adopted the approach proposed by Božanić *et al.,* [47] to test weight sensitivity. According to this methodology, the weight values of the most pivotal financial and non-financial performance indicators (FI5 and SI6) were decreased by 2% in each of 50 different scenarios. The decreased weight was then equally redistributed among the remaining indicators, resulting in a new set of adjusted criterion weights. These revised weights were then implemented in the ROV procedure to ascertain if there were any significant changes in the ranking of alternative years. The ranking results obtained from the sensitivity analysis for financial and non-financial performance indicators are given in Figures 2 and 3, respectively.

Examining both figures reveals that only minor ranking shifts were observed for a few years, while the positions of the best- and worst-performing periods remained largely unchanged. This outcome suggests that the proposed hybrid methodology is highly stable, with its ranking results being relatively insensitive to parameter fluctuations.

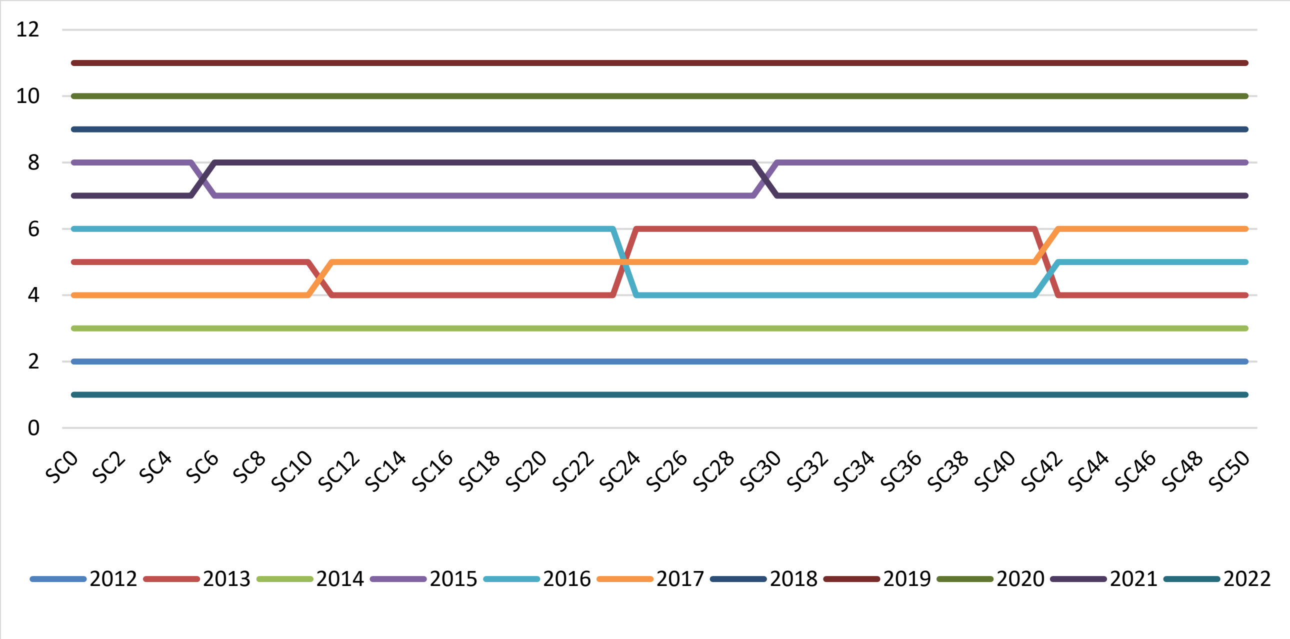

Fig. 2. Rankings Based on Adjusted Weights (For Financial Indicators)

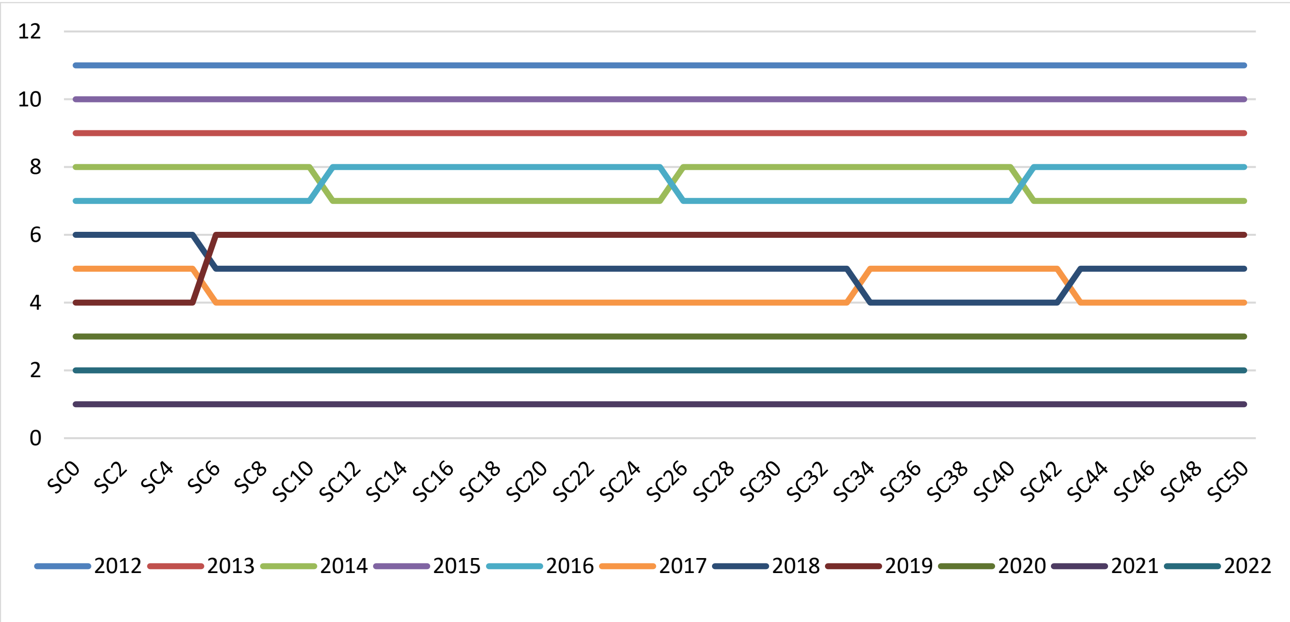

Fig.3. Rankings Based on Adjusted Weights (For Non-Financial Indicators)

4.2 Assessment of the Proposed Model's Robustness via Rank Reversal Analysis

The second part of the sensitivity analysis examined the rank reversal phenomenon to assess the stability of the suggested decision-making framework. Specifically, the alternative with the lowest performance was systematically eliminated from the analysis to determine the impact of its removal on the overall ranking structure [48]-[49]. Separate analyses were executed for financial and non-financial performance rankings across 11 distinct scenarios. The findings are demonstrated in Figures 4 and 5. Examining these figures reveals that eliminating the worst-performing alternative from the assessment had no effect on the final rankings. This outcome indicates that the suggested hybrid methodology demonstrates a high level of ranking stability, further demonstrating its effectiveness and dependability in performance assessment contexts.

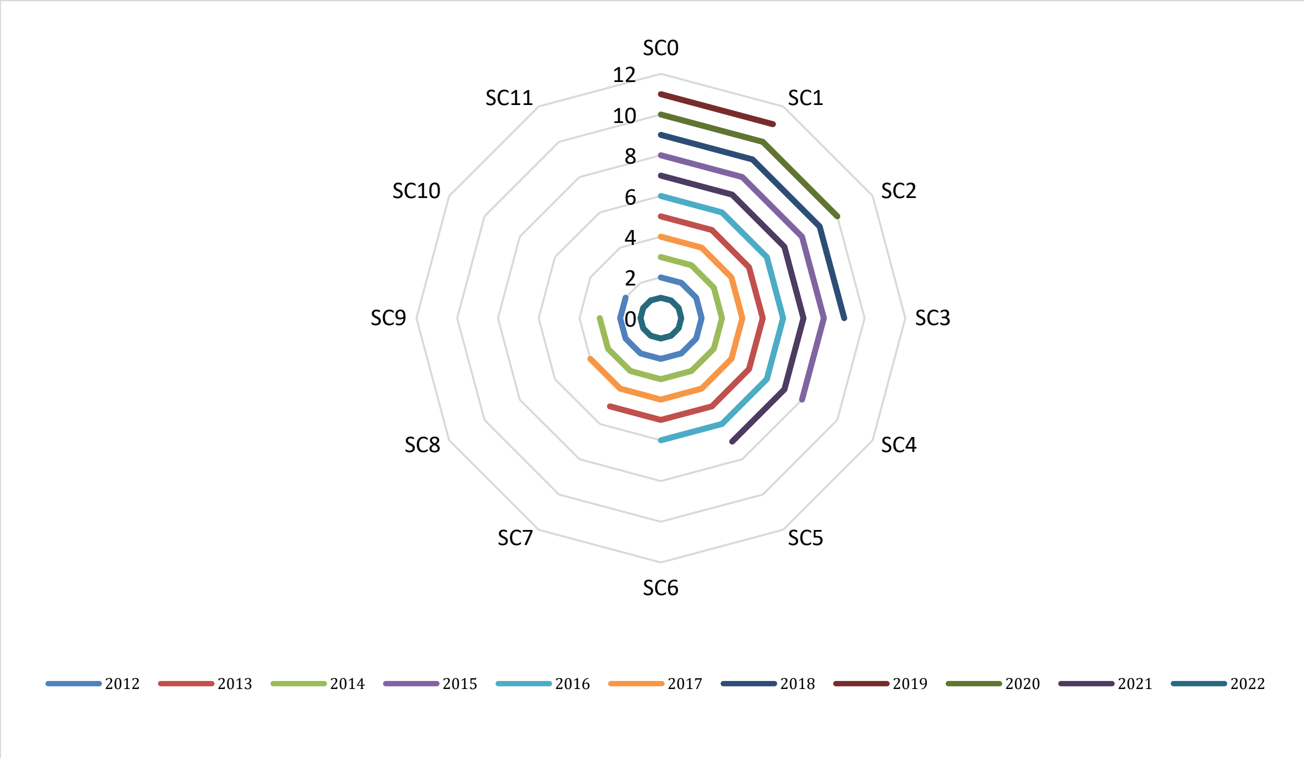

Fig. 4. Impact of Rank Reversal on Final Rankings (For Financial Indicators)

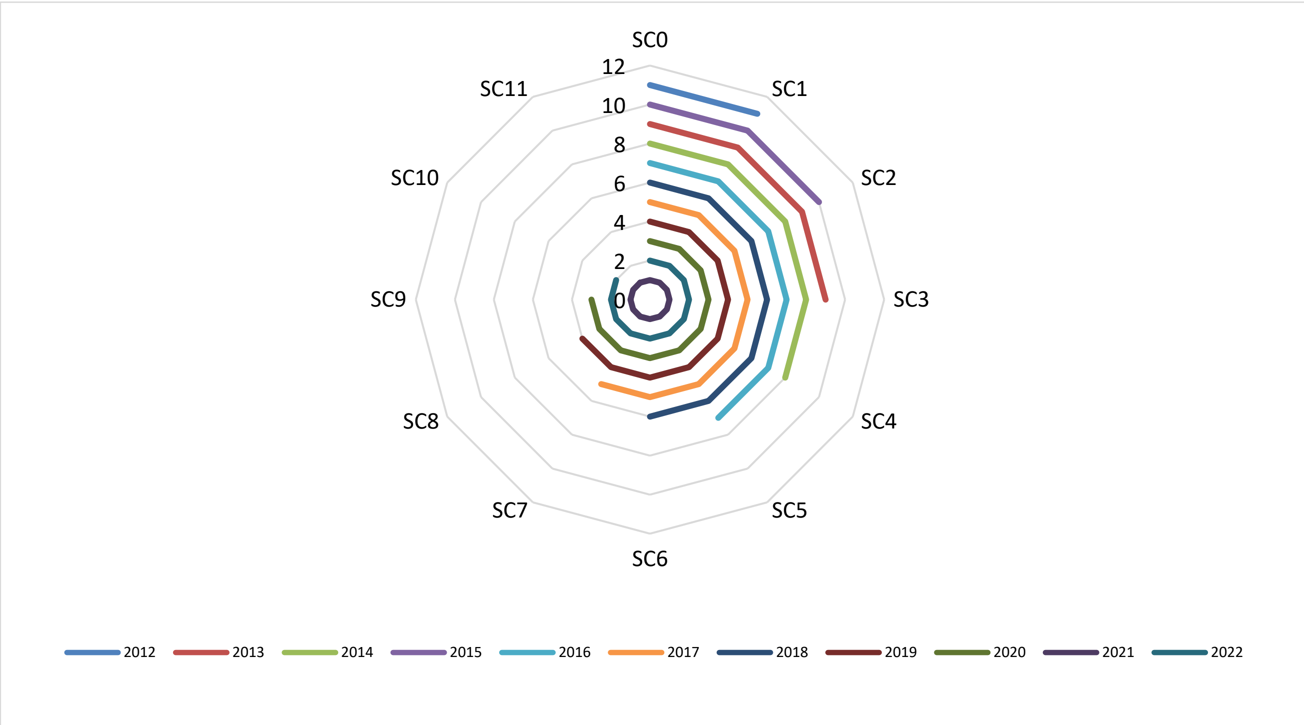

Fig. 5. Impact of Rank Reversal on Final Rankings (For Non-Financial Indicators)

5. Discussion and Policy Recommendations

The weighting analysis conducted via the MAXC procedure provides key insights into the structural dynamics underlying both the financial and non-financial performance profiles of Türkiye İş Bankası. From a financial perspective, the predominance of return on average assets and return on average equity as the highest-weighted indicators affirms the bank's strategic emphasis on profitability as a central driver of financial performance. These results are consistent with traditional financial theory, which positions ROA and ROE as core metrics of operational efficiency and shareholder value creation. The non-performing loans-to-total loans ratio, the third most influential financial indicator, reflects the institution's focus on asset quality and credit risk containment-both of which are critical in maintaining financial stability, especially in turbulent macroeconomic conditions. With respect to non-financial ESG criteria, the MAXC results underscore the substantial weight placed on community engagement, management quality, and human rights. This prioritization reflects growing institutional sensitivity to social and governance dimensions of sustainability performance, particularly in line with international ESG standards and stakeholder expectations. These insights are essential for bank management, regulatory bodies, and investors seeking to navigate the increasingly integrated landscape of financial soundness and sustainability.

The empirical findings obtained from the current case study provide valuable strategic insights into the strengths and weaknesses of the performance of Türkiye İş Bankası from financial and non-financial perspectives. The study's contributions go beyond academia, offering practical recommendations for professionals, decision-makers and various stakeholder groups. The key practical and managerial implications based on the findings are presented below. Practical Implications;

- ✓ Firstly, the research introduces a novel decision-making tool that can be utilized to assess bank performance across financial and non-financial dimensions.
- ✓ Bank managers and decision-making authorities can optimize resource allocation by focusing on the discrepancies observed between financial and ESG-based non-financial performance indicators to address gaps.
- ✓ Risk management departments within the bank can develop more proactive strategies by focusing on performance indicators that were found to be weak during specific time periods.
- ✓ Strategic planning teams can integrate the objectivity offered by the MAXC-based ROV methodology into institutional decision-making processes to periodically assess corporate performance.
- ✓ By identifying the most and lowest impact performance indicators, managers can priorities investment areas critical to improving performance, gaining a competitive advantage and ensuring sustainable operations.
- ✓ External investors and stakeholders can use the findings of this case assessment to evaluate the bank's temporal stability and adjust their investment decisions accordingly.
- ✓ Sustainability departments within the bank can analyses periods of low ESG performance to develop new objectives or improve existing initiatives in areas such as social responsibility and environmental sustainability.

Managerial implications:

- ✓ Integrate both financial and non-financial indicators into the performance assessment process to gain a more comprehensive understanding of corporate performance.

- ✓ Comparative assessment across financial and environmental, social and governance (ESG)-based dimensions establishes a basis for operational and sustainability-oriented initiatives, while offering stakeholders valuable insights into the effectiveness of the bank’s strategies.
- ✓ Non-financial ESG indicators, such as employee satisfaction and governance quality, should be incorporated into new policy development and training programmers due to their demonstrated impact on overall performance.
- ✓ Public disclosure of successes in non-financial performance areas can enhance the bank’s brand value and stakeholder perception when used strategically.
- ✓ In periods of low performance, detailed internal audits and control mechanisms can be initiated to implement corrective and developmental measures.
- ✓ The bank's decision-making bodies can adopt the proposed hybrid evaluation framework for continuous monitoring and data-driven decision-making processes.

6. Conclusions

In today's financial landscape, the success of the banking sector requires a multidimensional assessment that goes beyond traditional financial measures. Besides conventional financial stability, profitability and liquidity measures, non-financial indicators such as environmental sensitivity, social responsibility and corporate governance have become key factors in achieving a sustainable competitive advantage. Therefore, assessing the performance of banks requires an integrated framework combining rational analysis of financial data from balance sheets and income statements with a systematic assessment of their social contributions and governance practices. This multidimensional framework allows decision-makers to analyze historical performance and the institution’s future resilience and long-term sustainability. In this context, the current article presents an integrated framework for assessing the multidimensional performance of Türkiye İş Bankası, the largest privately owned commercial bank in the Turkish banking sector in terms of total assets. The proposed framework combines the MAXC objective weighting approach and the ROV alternative ranking approach. To validate the applicability of the framework, a real-time case study was performed. This case examined 9 financial and 10 non-financial ESG-based performance indicators for the period from 2012 to 2022. Another key goal of the research is to analyze the bank’s performance from financial and non-financial perspectives and to determine if a statistically significant relationship exists between these two dimensions.

In the first stage of the two-phase assessment, the objective weight of the selected financial and non-financial performance indicators was determined by applying the MAXC procedure. The results obtained through the MAXC procedure indicate that the three most significant financial performance criteria for the 2012–2022 period were return on average assets, return on average equity and the ratio of non-performing loans to total loans. In contrast, the credit-to-asset ratio, the deposit-to-asset ratio and the price-volume ratio were identified as the financial performance criteria with the lowest impact on bank performance. Regarding non-financial ESG-based indicators, the analysis indicated that community, management, and human rights were the most impactful criteria. In comparison, innovation, corporate social responsibility and the workforce were given the lowest weights, indicating a comparatively limited effect on the bank’s non-financial performance. Overall, this balanced assessment of financial and non-financial ESG-based performance criteria provided an objective and comprehensive overview of the bank's performance within a multidimensional framework.

In the second part of the assessment, the performance scores and corresponding rankings for each year were calculated for Türkiye İş Bankası with the ROV procedure, based on the criterion weights derived from the MAXC methodology. The findings of the ROV procedure show that the bank's financial and non-financial performance exhibited significant fluctuations over the 2012–2022 period. In terms of financial performance, the bank's best-performing years were 2022, 2012 and 2014, and its lowest-performing years were 2019, 2020 and 2018. In contrast, the highest performance levels with respect to non-financial ESG-based indicators were observed in 2021, 2022, and 2020. Following this dual assessment, Spearman's rank correlation analysis was performed to investigate the existence of a statistically significant relationship between financial and non-financial performance rankings. The outcome revealed a negative correlation between the two rank series; however, this correlation was not statistically significant at any conventional level. This finding means that the bank’s financial success in certain years did not necessarily translate into high performance in non-financial areas. In other words, performance components appear to be shaped independently of each other. Consequently, performance assessments in the banking sector that rely solely on financial measures may fail to provide a comprehensive view. Therefore, it is essential to incorporate non-financial indicators, particularly those related to environmental, social and governance (ESG) dimensions, into performance assessment frameworks to ensure a more holistic and accurate understanding of institutional effectiveness.

The final part of the current case analysis verified the robustness and consistency of the suggested decision-making approach. The first stage of the two-phase sensitivity and comparative analysis examined the potential impact of changes in criterion weights on financial and non-financial performance rankings. The second stage examined the effect of rank reversal-specifically, the exclusion of the lowest-performing alternative-on the final rankings. The sensitivity analysis results showed that changes to the importance weights of performance indicators or the elimination of the worst-performing alternative did not significantly alter the final rankings. These results demonstrate that the proposed hybrid decision-making model produces consistent, stable and reliable outcomes.

This study has several methodological and structural limitations despite its contributions. Firstly, the performance assessment was based only on a chosen set of financial and ESG-related non-financial indicators, which limits the scope of the evaluation. Although the chosen criteria are grounded in literature and stakeholder relevance, alternative indicators may yield different insights. Secondly, as the analysis focused solely on Türkiye İş Bankası, the results may not be applicable to the wider Turkish banking sector. Although the case study focuses exclusively on Türkiye İş Bankası, the proposed hybrid framework is designed to be methodologically flexible and scalable. Future applications of MCDM models and fuzzy sets, such as, LMAW, DNMA [50], Parsimonious Best Worst Method [51], Fuzzy Simple Weight Calculation [52] and Intuitionistic Fuzzy Z-Numbers [53] may extend the model to include cross-sectional assessments involving multiple banks within or across national banking systems. This would facilitate comparative benchmarking and allow for institutional heterogeneity to be examined under a unified analytical lens. Furthermore, the dataset covering the evaluation period is limited to the years 2012–2022. This means that the potential effects of economic fluctuations and regulatory changes may not have been fully reflected due to temporal constraints. Additionally, while decision-making procedures provide decision-makers with a systematic and analytical framework, selecting a particular model reflects the researcher's methodological preferences and may indirectly influence the results. Future empirical research could enhance the generalizability and applicability of the findings by incorporating alternative decision-making approaches and utilizing broader datasets. Furthermore, these assessments could be expanded by integrating methodologies based on grey system theory and fuzzy logic clustering frameworks, which could provide additional insights into traditional decision-making models.

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Data Availability Statement

"The dataset employed in this work was derived from the Refinitiv Eikon database".

Conflicts of Interest

"The author/s declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper"

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