bilig
WINTER 2026/ISSUE 116
89-125

Araştırma Makalesi / Research Article

Comparison of Turkish and Kazakh Banks Using Multi-Criteria Decision-Making Methods and Analysis with Artificial Neural Networks*

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Abstract

The financial statement data of banks and the economic analyses generated using these data play a crucial role in assessing the performance rankings of banks amid intensifying competitive conditions. This study aims to evaluate the economic performance of banks listed in the Borsa Istanbul (BIST) 50 index and five banks listed on the Kazakhstan Stock Exchange for the period 2013–2023, employing Multi-Criteria Decision-Making (MCDM) methods such as Standard Deviation (SD) and Combinative Distance-based Assessment (CODAS). The significance levels of factors affecting ranking outcomes were determined using the Weka program, and a financial performance

* Date of Arrival: 08 October 2024 – Date of Acceptance: 25 April 2025 – Date of Online First: 28 May 2025
Citation: Köroğlu, Çağrı, Ali Büyükmert, Mehmet Anbarcı, and Eren Temel. "Comparison of Turkish and Kazakh Banks Using Multi-Criteria Decision-Making Methods and Analysis with Artificial Neural Networks." *bilig*, no. 116, 2026, pp. 89-125, https://doi.org/10.12995/bilig.8402.
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ranking forecast for 2024–2025 was conducted for a randomly selected bank.

Upon examining the rankings obtained from SD and CODAS methods, M&T Bank consistently ranked among the top banks across both countries throughout the study period. Additionally, an analysis based on artificial neural networks revealed that, within CODAS ranking evaluations, total liability data proved to be the most influential determinant in both Turkish and Kazakh banking sectors.

Keywords

Banking sector, multi-criteria decision-making, financial performance analysis, Kazakhstan, Turkic world, Türkiye, artificial neural networks.

Türkiye-Kazakistan Bankalarının Çok Kriterli Karar Verme Yöntemleriyle Karşılaştırılması ve Yapay Sinir Ağlarıyla Analizi*

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Öz

Bankaların mevcut mali tablo verileri ve bu verilerin kullanılması sonucunda oluşturulan finansal analizler, artan rekabet koşullarında bankaların performans derecesini belirlemek konusunda önem arz etmektedir. Bu çalışmanın amacı, Borsa İstanbul (BIST) 50 endeksinde işlem gören bankaların ve Kazakistan Borsasında yer alan 5 bankanın 2013-2023 yıllarındaki finansal performanslarının Çok Kriterli Karar Verme (ÇKKV) yöntemlerinden Standart Deviation (SD) ve Combinative Distance-based Assessment (CODAS) yöntemleri kullanarak değerlendirmesidir. Bu amaçla söz konusu sıralama sonuçlarına etki eden faktörlerin etki dereceleri Weka programı kullanılarak belirlenmiş ve rastgele seçilen bir bankanın 2024-2025 yılsonu finansal performans sıralama tahmini yapılmıştır.

SD ve CODAS yöntemlerinin uygulanması sonucunda elde edilen sıralamalara bakıldığında her iki ülke bankaları arasında M&T Bankın çalışmaya konu olan yıllarda genel olarak ilk sıralarda yer aldığı görülmüştür. Yapay sinir ağları yöntemine göre

* Geliş Tarihi: 08 Ekim 2024 – Kabul Tarihi: 25 Nisan 2025 – Erken Görünüm Tarihi: 28 Mayıs 2025
Atıf: Köroğlu, Çağrı, Ali Büyükmert, Mehmet Anbarcı, ve Eren Temel. "Comparison of Turkish and Kazakh Banks Using Multi-Criteria Decision-Making Methods and Analysis with Artificial Neural Networks." *bilig*, no. 116, 2026, ss. 89-125, https://doi.org/10.12995/bilig.8402.

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elde edilen sonuçlar değerlendirildiğinde CODAS değerlendirme sıralamalarında, her iki ülkede de toplam yükümlülük verilerinin daha etkili olduğu anlaşılmıştır.

Anahtar Kelimeler
Bankacılık sektörü, çok kriterli karar verme, finansal performans analizi, Kazakistan, Türk dünyası, Türkiye, yapay sinir ağları.

Introduction

Banks are among the most vital financial and economic institutions globally. They provide a secure platform for individuals to safeguard their savings while reinvesting these funds into the economy. Additionally, banks facilitate capital provision for businesses and investors, promoting economic growth (Mishkin). Through financial services such as credit allocation, banks enable entrepreneurs to launch new projects, assist companies in expanding their operations, and empower individuals to make significant investment decisions regarding real estate, land, and vehicles (Allen et al.).

Decision-making, in its broadest sense, refers to selecting and determining an option from among multiple alternatives (Keeney). In many instances, this selection process incorporates various criteria, thus leading to Multi-Criteria Decision Making (MCDM) problems. MCDM problems aim to establish criteria based on distinct perspectives, encompassing rules, measures, and standards that guide decision-making processes. Within both business and academia, MCDM represents one of the most widely applied decision methodologies. Enhancing transparency and logic in decision-making, it contributes to improved decision quality. The primary advantage of MCDM lies in its ability to address conflicting scenarios effectively (Zavadskas and Turskis 159-160; Çakır and Can 1280). Consequently, MCDM remains a predominant area within operations research and facilitates decision support by defining multiple conflicting quantitative and qualitative criteria. Ultimately, these methods serve to select, rank, or classify alternatives based on their relevance within varying priority-based criteria (Özbek 25).

Given the need to determine ranking impacts and make future predictions, advanced statistical methods are indispensable. However, traditional statistical approaches often prove insufficient under modern conditions. To overcome such limitations, artificial neural networks and machine learning techniques are used to provide more precise solutions and enable realistic forecasting. Artificial neural networks emulate human cognitive learning mechanisms, allowing computers to perform fundamental functions such as learning, memory retention, generalization, and data-driven pattern recognition (Yegnanarayana 15-16; Yang and Wang 1050). In banking, artificial neural networks enable performance evaluation based on historical data while facilitating strategic planning through accurate forecasting of financial outcomes (Aydın and Çavdar; Zorić; Lokanan).

The banking sector is widely recognized as the driving force behind economic development across all nations (Naghshpour and Davis; Nguyen). Particularly within emerging economies, a high level of financial performance among banks correlates directly with national economic progression (Allen et al.). Therefore, evaluating the financial performance of banks holds significant importance.

This study primarily focuses on the banking sector within the Turkic World. Given the constraints on publicly available financial data in many Turkic nations, this study is limited to Türkiye and Kazakhstan, where comparative sectoral data is accessible. Furthermore, both countries are classified as emerging economies, and despite certain structural differences, they exhibit similarities in their banking systems and sectoral dynamics. The relative financial proximity of banks operating within these two nations further supports their suitability for comparative analysis.

The data used in this study was obtained from the Banks Association of Türkiye (TBB), Public Disclosure Platform (KAP), and InvestingPro. The sample consists of ten banks, including five listed on the Borsa Istanbul (BIST) 50 index and five randomly selected banks from the Kazakhstan Stock Exchange.

The study is structured as follows: First, an overview of MCDM methodologies—including SD and CODAS—is provided alongside relevant explanations of the Naive Bayes Multinomial algorithm, artificial neural networks, and machine learning techniques. Subsequently, the financial performance rankings of selected banks from Türkiye and Kazakhstan are calculated, followed by an analysis of the impact levels of financial parameters influencing these rankings. Finally, an artificial neural network and machine learning model is employed to predict the future financial performance ranking of a randomly selected bank.

The Banking Systems of Türkiye and Kazakhstan

Banks, as institutions fundamentally grounded in the principle of trust, constitute the backbone of economic systems. They operate with the assurance of safeguarding the assets of consumers, investors, and individual savers, thereby securing deposits, loans, and other financial assets in marketplace (Sharma and Choubey 295). As essential pillars of modern economies, banks play a pivotal role in maintaining financial stability. Functioning as both a secure repository and an intermediary for individuals and businesses, banks hold a central position in the preservation and management of capital. Through services such as deposit collection, credit provision, and investment management, they have become key actors shaping economic activities on both national and global scales (Ofodile et al. 350).

Situated at the core of the financial system, the banking sector offers an extensive array of services to individuals and institutions alike. Beyond basic functions such as deposit acceptance and loan issuance, banks also facilitate access to capital markets, manage financial risks, and finance international trade, thereby engaging in increasingly sophisticated financial operations (Abilov 2). Fundamentally, banks fulfill a critical custodial function, safeguarding client funds while simultaneously generating income through the extension of credit. Empowered to mobilize deposits and extend loans, banks also provide a diverse range of financial services that underpin broader economic growth (Okur and Tütüncüoğlu 522).

The structure of the Turkish banking system is categorized according to operational scope, institutional characteristics, and regulatory frameworks. Based on operational scope, banks are classified into deposit banks, participation banks, and development and investment banks. In terms of institutional characteristics, a distinction is made between banks established domestically and branches of banks founded abroad. Regulatory classifications further distinguish between public and private banks (Yetiz 115). As a vital component of the Turkish economy, the banking system demonstrates a robust presence both domestically and internationally. Its regulation and oversight are primarily carried out by the Central Bank of the Republic of Türkiye (CBRT) and the Banking Regulation and Supervision Agency (BRSA).

In contrast, Kazakhstan's banking system is organized under a two-tier structure. The first tier is represented by the National Bank of Kazakhstan (NBK), which functions as the central bank and holds comprehensive supervisory authority over all banking institutions. The second tier consists of commercial banks. As of 1995, Kazakhstan's banking system encompassed

130 banks, many operating with insufficient regulatory oversight and elevated risk profiles. Subsequent reforms initiated by the NBK, including sectoral consolidation and privatization efforts, significantly strengthened the system, reducing the number of banks to 38 by 2002. Among these, two were public banks, nineteen were privately owned, and seventeen operated with foreign capital (Tanınmış Yücememiş 190). According to the most recent data provided by the Agency for Regulation and Development of the Financial Market (ARDFM), as of 2024, 22 banks are actively operating in Kazakhstan.

Given the increasingly competitive and dynamic nature of the global financial environment, the necessity for banks to conduct comprehensive financial performance analyses and formulate strategic plans based on forward-looking projections has become ever more critical. Accordingly, banks must rigorously assess both their current conditions and future prospects by employing various analytical methods, considering factors such as prevailing economic conditions, political developments, inflationary trends, and other macroeconomic indicators.

Standard Deviation (SD) Method

The SD method is an approach that calculates the weights of criteria based on their standard deviations. The fundamental principle of this method lies in the contrast intensity of the criteria (Diakoulaki et al. 764). When the criterion values across alternatives are relatively close to one another, the SD method assigns lower weights to these criteria, as their discriminative power is considered diminished in such cases. In the literature, the SD method has been widely applied across various problem-solving contexts. Specifically, it has proven to be an effective tool for determining criterion weights in fields such as material selection, site selection, evaluation of energy alternatives, company benchmarking, and economic benefit analyses in industrial economics (Şahin, 77). Furthermore, the method's flexibility and applicability across different disciplines have contributed to its widespread adoption among researchers.

The procedural steps of the SD method are outlined as follows (Diakoulaki et al. 766):

Step1: First, the decision matrix, as specified in Equation (1), is constructed.

$$D = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix} \quad \mathrm{i} = 1,2,\ldots,\mathrm{m};\ \mathrm{j} = 1,2,\ldots,\mathrm{n} \qquad (1)$$

Step 2: The decision matrix is normalized using the equations given below. Equality (2) is used for criteria showing benefit characteristics, and Equality (3) is used for criteria showing cost characteristics.

$$x_{ij}^{*} = \frac{x_{ij} - min(x_{ij})}{max(x_{ij}) - min(x_{ij})}; \quad \mathrm{i} = 1,2,\ldots,\mathrm{m};\ \mathrm{j} = 1,2,\ldots,\mathrm{n} \qquad (2)$$

$$x_{ij}^{*} = \frac{max(x_{ij}) - x_{ij}}{max(x_{ij}) - min(x_{ij})}; \quad \mathrm{i} = 1,2,\ldots,\mathrm{m};\ \mathrm{j} = 1,2,\ldots,\mathrm{n} \qquad (3)$$

Step 3: The standard deviation of each of the criteria was calculated by Equation (4).

$$\sigma_j \sqrt{\frac{\sum_{i=1}^{m} (x_{ij} - \overline{x_j})^2}{m}}, \quad \mathrm{j} = 1,2,\ldots,\mathrm{n} \qquad (4)$$

Step 4: Weights for each criterion are calculated by Equation (5).

$$w_j = \frac{\sigma_j}{\sum_{j=1}^{n} \sigma_j}, \quad \mathrm{j} = 1,2,\ldots,\mathrm{n} \qquad (5)$$

CODAS Method

The CODAS method, developed in 2016 by Keshavarz Ghorabaee, Zavadskas, Turskis, and Antucheviciene, is a MCDM technique employed to effectively determine the performance ranking of alternatives (Keshavarz Ghorabaee et al. 28–29). This method is derived from the integration of the Simple Additive Weighting (SAW) and Weighted Product Method (WPM) ranking techniques, thereby combining the strengths of both approaches.

In the CODAS method, the performance score of an alternative is calculated using its Euclidean and Taxicab (also referred to as Manhattan or Hamming) distances from the negative ideal solution. While the primary distance metric utilized is the Euclidean distance, when the Euclidean distances of two alternatives are found to be very close, the Taxicab distance is employed to distinguish between them. A threshold parameter, determined by the decision-maker, is used to define how close the Euclidean distance must be for the Taxicab distance to be considered.

During the evaluation process, alternatives are compared pairwise, and both distance measures are simultaneously used in the calculation of performance scores. As a result of these comparisons, the alternative that is far from the negative ideal solution is deemed superior (i.e., preferable). The use of two different distance metrics in the CODAS method enhances the precision of the results (Ecer 290–291).

The procedural steps of the CODAS method are summarized as follows (Keshavarz Ghorabaee et al. 29–30; Şahin 115–116; Ijadi Maghsoodi et al. 1197–1198):

Step 1: Creation of the decision matrix X. The decision matrix is shown in Equation (6).

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix} \quad \mathrm{i} = 1,2,\ldots,\mathrm{m};\ \mathrm{j} = 1,2,\ldots,\mathrm{n} \tag{6}$$

Step 2: Obtaining the standardized decision matrix. The criteria showing maximum features are shown in Equality (7), and the criteria showing minimum features are shown in Equality (8).

$$x_{ij}^{*} = \frac{x_{ij}}{\max\limits_{i}(X_{ij})}; \quad \mathrm{i} = 1,2,\ldots,\mathrm{m};\ \mathrm{j} = 1,2,\ldots,\mathrm{n} \tag{7}$$

$$x_{ij}^{*} = \frac{\min\limits_{i}(X_{ij})}{X_{ij}}; \quad \mathrm{i} = 1,2,\ldots,\mathrm{m};\ \mathrm{j} = 1,2,\ldots,\mathrm{n} \tag{8}$$

Step 3: Obtaining the weighted standardized matrix. This matrix is found by multiplying the standardized matrix elements by the weights. This situation is shown in Equation (9).

$$r_{ij} = x_{ij}^{*} \times w_j; \quad \mathrm{i} = 1,2,\ldots,\mathrm{m};\ \mathrm{j} = 1,2,\ldots,\mathrm{n} \tag{9}$$

Step 4: Determine the negative ideal solution. The negative ideal solution values are as shown in Equality (10) and Equality (11). In this context, the smallest value in each column of the weighted decision matrix is selected.

$$ns = \left[ns_j\right]_{1\times m} \tag{10}$$

$$ns_j = min_i r_{ij} \tag{11}$$

Step 5: Calculating Euclidean and Taxicab distances. These two distance measures are used to determine the distances of alternatives from the negative ideal solution. The Euclidean distance formula is given in Equation (12) and the Taxicab distance formula is given in Equation (13).

$$E_i = \sqrt{\sum_{j=1}^{m}\left(r_{ij} - n_{sj}\right)^2} \tag{12}$$

$$T_i = \sqrt{\sum_{j=1}^{m}\left|r_{ij} - n_{sj}\right|} \tag{13}$$

Step 6: Creating the relative valuation matrix. Equality (15) is used to create the relative valuation matrix given in Equality (14).

$$R_a[h_{ik}]_{n\times m} \tag{14}$$

$$h_{ik} = (E_i - E_k) + \left(\psi(E_i - E_k) \times (T_i - T_k)\right) \tag{15}$$

ψ in Equation (15) is a threshold function to distinguish the equality of Euclidean distances of two alternatives. It is defined by Equation (16).

$$\psi(x) = \begin{cases} 1\ if\ |x| \geq \tau \\ 0\ if\ |x| \leq \tau \end{cases} \tag{16}$$

In Equation (15), ψ represents the threshold parameter determined by the decision-maker, and it is recommended that its value be set between 0.01 and 0.05. If the difference between the Euclidean distances of two alternatives is less than τ, the comparison between these alternatives is conducted using their Taxicab distances. In the literature, a threshold value of **τ = 0.02** is commonly accepted.

Step7: Calculation of the performance scores of alternatives. The performance score for each alternative is computed using Equation (17).

$$H_i = \sum_{k}^{n} h_{ik} \tag{17}$$

Artificial Neural Networks and Machine Learning

In recent years, there have been remarkable advancements in the fields of technology and computing worldwide. Among these developments, artificial intelligence (AI) has undoubtedly emerged as one of the most significant. AI is a fascinating technology capable of autonomously learning, demonstrating intelligence, and making decisions in a manner like human beings. It has found widespread applications across various fields, including medicine, engineering, marketing, and many others (Kaveh).

Artificial Neural Networks (ANNs) emulate the human brain by constructing extensive networks of artificial neurons, thereby developing computational and learning algorithms to model and predict complex phenomena that are otherwise difficult to understand. Through this process, ANNs create a behavioral model known as "experience" (Montesinos López et al.). An ANN typically consists of an input layer, one or more hidden layers, and an output layer. The nodes within these layers are referred to as neurons, and each neuron is interconnected with others. Initially, random values are assigned to these connections, and computations are performed using a sigmoid function. This process is repeated iteratively until the difference between the actual output and the predicted output reaches a minimum level of error process known as machine learning. Depending on the complexity of the data and the relationships among neurons, the number of hidden layers may be increased (Grekousis; Di Franco and Santurro).

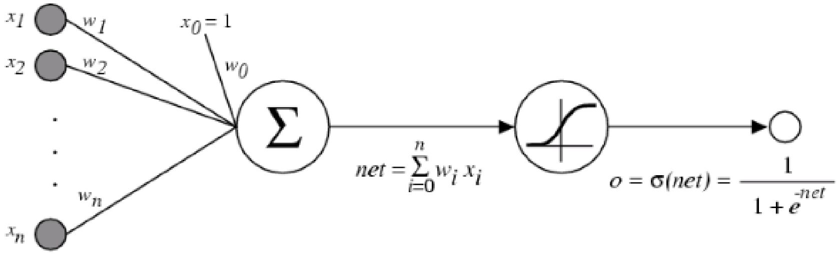

Figure 1. Sigmoid unit in neural networks

Sigmoid function: $\frac{1}{1 + e^{-x}}$

There are certain package programs that can be used to implement artificial neural networks and machine learning applications. One of these is the Weka package program. Weka is a popular machine learning software package program written in Java, developed at the University of Waikato in New Zealand (Arora and Suman).

Naive Bayes Algorithm

The Naive Bayes algorithm is a conditional probability-based approach that is widely used for data classification due to its simplicity and ease of implementation. It is among the most utilized data mining algorithms for classification tasks (Chen et al.).

The Naive Bayes classifier is based on Bayes' theorem, which is expressed as:

$$P(c/x) = \frac{P(x/c)P(c)}{P(x)}$$

where:

P(c/x); represents the posterior probability (conditional probability) of class c given predictor x,

P(x/c); is the likelihood, the probability of predictor x given class c,

P(c); denotes the prior probability of class c,

P(x); is the prior probability of predictor x.

Under the Naive Bayes assumption of feature independence, the posterior probability can be rewritten as:

$P(c/x) = P(x_1/c) \bullet P(x_2/c) \bullet \ldots\ldots\ldots P(x_n/c) \bullet P(c)$

Where $x_1, x_2, \ldots, x_n$ represent the features or attributes of the input data.

Findings

In this study, an analysis was conducted based on the financial data of five banks from Turkey and five banks from Kazakhstan, selected due to their significant roles in the banking sector of the Turkic world and their listing on their respective national stock exchanges. The financial data covering the years 2013–2023 were retrieved from the InvestingPro platform. These data sets constitute the evaluation criteria for the study. In the process of determining the criteria, previous studies in the literature (Beheshtinia and Omidi; Marjanović and Popović; Karadağ Ak et al.; Köroğlu and Anbarcı; Abdel-Basset et al.), along with the financial statement items disclosed by the banks themselves, were carefully considered. Moreover, official financial sources such as the Banks Association of Turkey (TBB), the Public Disclosure Platform (KAP), and the InvestingPro platform were utilized to ensure the accuracy and reliability of the data.

The application phase of the study was carried out in three main stages:

Stage 1: Financial Performance Ranking via MCDM Methods

In the first stage, the financial performance of the 10 selected banks was ranked using MCDM methods. The criteria included key financial indicators such as total liabilities, total assets, equity, total deposits, and net profit. The SD method was employed to objectively determine the weights of the criteria, while the CODAS method was applied to perform the final ranking of the banks based on these weighted criteria.

Stage 2: Feature Impact Analysis Using Naive Bayes Multinomial Classification

In the second stage, the performance indicators used in the SD and CODAS methods were subjected to analysis using the Weka data mining software. By applying the Naive Bayes Multinomial classification algorithm, the influence levels of each financial criterion on the final ranking outcomes were determined. This analysis provided insights into which financial parameters had the most significant impact on the performance scores, allowing for a deeper understanding of the key financial drivers within the banking sectors of Turkey and Kazakhstan.

Stage 3: Predictive Ranking via Artificial Neural Networks and Machine Learning

In the third and final stage, predictive analysis was conducted using ANNs and machine learning techniques. One randomly selected bank from the sample was subjected to a predictive modeling process to estimate its financial performance ranking for the end of 2024 and 2025. This model utilized historical financial data as inputs to forecast future rankings, providing a dynamic assessment of potential performance trends.

The banks included in the scope of the study are presented in Table 1.

Table 1
Banks Included in the Study

Country	Bank Name	Stock Code
Türkiye	Akbank T.A.Ş.	AKBNK
	Türkiye Garanti Bankası A.Ş.	GARAN
	Türkiye Halk Bankası A.Ş.	HALKB
	Türkiye İş Bankası A.Ş.	ISCTR
	Yapı ve Kredi Bankası A.Ş.	YKBNK
Kazakhstan	Bank TsentrKredit AO	CCBN
	M&T Bank	MTBKZ
	Halyk Bank	HSBK
	Bank of America	BACKZ
	Fortebank	ASBN

There are numerous financial ratios available for measuring financial performance. Upon reviewing previous studies related to the banking sector, a set of ideal financial ratios has been selected for the purposes of this study. In total, ten financial ratios have been determined as the evaluation criteria. These ten ratios were chosen because they best reflect a bank's capital adequacy, balance sheet structure, asset quality, liquidity, and profitability performance.

The criteria used in this study are presented in Table 2.

Table 2
Financial Ratios Used as Evaluation Criteria

Ratio Group	Financial Ratio (Description)	Code	Direction
Capital Adequacy	Total Liabilities / Total Assets	CA1	Max
	Equity / Total Assets	CA2	Max
Balance Sheet Structure	Total Deposits / Total Assets	BSS1	Max
	Financial Assets / Total Assets	BSS2	Max
Asset Quality	Net Loans / Total Assets	AQ1	Max
	Total Deposits / Net Loans	AQ2	Min
Liquidity	Cash and Cash Equivalents / Total Assets	L1	Max
	Cash and Cash Equivalents / Short-Term Liabilities	L2	Max
Profitability	Return on Assets (ROA)	P1	Max
	Return on Equity (ROE)	P2	Max

Banks generate income by lending out the funds they collect from depositors. The difference between the deposit interest rates and the loan interest rates—referred to as the interest margin—constitutes the primary source of profit for banks. The criterion "Total Deposits / Total Assets (BSS1)" has been selected based on several studies in the literature (Parmaksız and Özdemir; Süzülmüş and Yakut; İbrahimov).

Since banks rely less on external borrowing to finance their loans, they incur lower interest expenses, making this approach more favorable. The criterion "Total Deposits / Net Loans (AQ2)" reflects this consideration and is therefore directionally defined as 'min' to indicate that a lower value is preferable for reducing interest expenses.

In the implementation phase of the study, the year 2022 was selected as a representative example for applying the MCDM methods. A consolidated ranking across all years is provided in the final section. Table 3 presents the financial performance results based on the financial data for the year 2022.

Table 3
Financial Performance Ratios for 2022

2022	Ratio Group	Capital Adequacy		Balance Sheet Structure		Asset Quality		Liquidity		Profitability	
	Ratios	CA1	CA2	BSS1	BSS2	AQ1	AQ2	L1	L2	P1	P2
	Direction	max	max	max	max	max	min	max	max	max	max
Türkiye	AKBNK	0,8660	0,1340	0,6290	0,3474	0,5280	1,1912	0,0470	0,0658	0,0630	0,5230
	GARAN	0,8833	0,1170	0,6971	0,2777	0,5749	1,2124	0,1456	0,1853	0,0540	0,5010
	HALKB	0,9360	0,0640	0,7576	0,2172	0,5712	1,3263	0,0593	0,0655	0,0020	0,0430
	ISCTR	0,8780	0,1220	0,5553	0,3009	0,5086	1,0919	0,0728	0,1011	0,0490	0,4510
	YKBNK	0,8930	0,1070	0,5957	0,2483	0,5267	1,1310	0,1377	0,2024	0,0540	0,5560
Kazakhstan	CCBN	0,9370	0,0630	0,7750	0,3275	0,4380	1,7506	0,2497	0,2850	0,0450	0,6840
	MTBKZ	0,8739	0,1261	0,8146	0,1393	0,6452	1,2625	0,0076	0,0088	0,0110	0,0920
	HSBK	0,8600	0,1400	0,7302	0,2205	0,5378	1,3579	0,1397	0,1818	0,0430	0,3180
	BACKZ	0,9105	0,0895	0,6326	0,3026	0,3386	1,8685	0,0730	0,0890	0,0090	0,1010
	ASBN	0,8770	0,1230	0,7252	0,1886	0,4207	1,7239	0,1097	0,1729	0,0380	0,3160

Based on the financial performance data presented in Table 3, the next stage involved the implementation of the first phase of the application, which included the use of MCDM methods.

Application of Multi-Criteria Decision-Making Methods

In this section, which involved the evaluation of a total of 10 banks, the weighting process was first carried out using the SD method. Subsequently, the banks were assessed using the CODAS method. Financial performance rankings were calculated using the financial data of the selected banks from 2013 to 2023, with the results ordered from best to least performing.

Weighting with the SD Method

Initially, using the financial performance ratios provided in Table 3, the maximum and minimum values for each criterion were determined based on Equations (2) and (3). Then, using these max and min values, the normalized decision matrix was constructed. The normalized decision matrix is presented in Table 4.

Table 4

Normalized Decision Matrix

	CA1	CA2	BSS1	BSS2	AQ1	AQ2	L1	L2	P1	P2
AKBNK	0,0779	0,9221	0,2839	1,0000	0,6178	0,1278	0,1629	0,2063	1,0000	0,7488
GARAN	0,3026	0,7013	0,5466	0,6651	0,7708	0,1552	0,5702	0,6390	0,8525	0,7145
HALKB	0,9870	0,0130	0,7799	0,3743	0,7585	0,3018	0,2139	0,2053	0,0000	0,0000
ISCTR	0,2338	0,7662	0,0000	0,7764	0,5543	0,0000	0,2693	0,3342	0,7705	0,6365
YKBNK	0,4286	0,5714	0,1557	0,5239	0,6135	0,0503	0,5374	0,7009	0,8525	0,8003
CCBN	1,0000	0,0000	0,8473	0,9040	0,3241	0,8482	1,0000	1,0000	0,7049	1,0000
MTBKZ	0,1801	0,8199	1,0000	0,0000	1,0000	0,2197	0,0000	0,0000	0,1475	0,0764
HSBK	0,0000	1,0000	0,6745	0,3901	0,6496	0,3425	0,5460	0,6263	0,6721	0,4290
BACKZ	0,6554	0,3446	0,2980	0,7848	0,0000	1,0000	0,2701	0,2901	0,1148	0,0905
ASBN	0,2208	0,7792	0,6552	0,2371	0,2678	0,8138	0,4217	0,5941	0,5902	0,4259
Standard deviation	0,3576	0,3578	0,3259	0,3167	0,2879	0,3639	0,2818	0,3005	0,3534	0,3454
Total	3,2910									

The standard deviation of each criterion was obtained using Equation (4). The sum of the obtained standard deviations was also taken. The weights of the criteria because of the SD method are given in Table 5.

Table 5

Weights of Criteria

	CA1	CA2	BSS1	BSS2	AQ1	AQ2	L1	L2	P1	P2
WJ	0,1087	0,1087	0,0990	0,0962	0,0875	0,1106	0,0856	0,0913	0,1074	0,1050

In Table 5, which was obtained by using Equation (5), the standard deviations of each criterion were found by dividing them by the sum of the standard deviations, and as a result, the weights of the criteria were found. These weights were used when evaluating with CODAS methods.

Evaluation of the CODAS Method

In this stage of the study, the financial performance ranking of the selected banks was determined using the CODAS method, considering the weights previously obtained from the SD method. The financial performance ratios presented in Table 3 form the decision matrix of the study. Based on Equations (7) and (8), the maximum and minimum values for each criterion were calculated. Considering these max and min values, Table 6 was constructed.

Table 6
Normalized Decision Matrix

	CA1	**CA2**	**BSS1**	**BSS2**	**AQ1**	**AQ2**	**L1**	**L2**	**P1**	**P2**
	max	max	max	max	max	min	max	max	max	max
AKBNK	1,0820	1,0448	1,2952	1,0000	1,2220	0,9167	5,3120	4,3311	1,0000	1,3078
GARAN	1,0608	1,1966	1,1687	1,2510	1,1223	0,9006	1,7145	1,5380	1,1667	1,3653
HALKB	1,0011	2,1875	1,0753	1,5996	1,1296	0,8233	4,2069	4,3497	31,5000	15,9070
ISCTR	1,0672	1,1475	1,4670	1,1546	1,2687	1,0000	3,4313	2,8181	1,2857	1,5166
YKBNK	1,0493	1,3084	1,3675	1,3990	1,2250	0,9655	1,8136	1,4081	1,1667	1,2302
CCBN	1,0000	2,2222	1,0511	1,0610	1,4732	0,6237	1,0000	1,0000	1,4000	1,0000
MTBKZ	1,0722	1,1100	1,0000	2,4942	1,0000	0,8649	32,9688	32,2883	5,7273	7,4348
HSBK	1,0895	1,0000	1,1156	1,5758	1,1998	0,8041	1,7864	1,5678	1,4651	2,1509
BACKZ	1,0291	1,5637	1,2878	1,1480	1,9058	0,5844	3,4221	3,2038	7,0000	6,7723
ASBN	1,0684	1,1382	1,1233	1,8417	1,5337	0,6334	2,2768	1,6482	1,6579	2,1646

While creating Table 6, the max and min values were multiplied by the decision matrix values in Table 3. The 9 criteria in the study are max and 1 criterion is min. The max-oriented criteria were multiplied by the max values and the min-oriented AQ2 criterion was multiplied by the min value. Then, the weighted decision matrix in Table 7 was calculated using Equality (9).

Table 7

Weighted Decision Matrix

	CA1	CA2	BSS1	BSS2	AQ1	AQ2	L1	L2	P1	P2
AKBNK	0,1176	0,1136	0,1283	0,0962	0,1069	0,1014	0,4548	0,3955	0,1074	0,1373
GARAN	0,1153	0,1301	0,1157	0,1204	0,0982	0,0996	0,1468	0,1404	0,1253	0,1433
HALKB	0,1088	0,2378	0,1065	0,1539	0,0988	0,0910	0,3602	0,3972	3,3830	1,6695
ISCTR	0,1160	0,1248	0,1453	0,1111	0,1110	0,1106	0,2938	0,2573	0,1381	0,1592
YKBNK	0,1140	0,1422	0,1354	0,1346	0,1072	0,1068	0,1553	0,1286	0,1253	0,1291
CCBN	0,1087	0,2416	0,1041	0,1021	0,1289	0,0690	0,0856	0,0913	0,1504	0,1050
MTBKZ	0,1165	0,1207	0,0990	0,2400	0,0875	0,0956	2,8226	2,9484	0,6151	0,7803
HSBK	0,1184	0,1087	0,1105	0,1516	0,1050	0,0889	0,1529	0,1432	0,1574	0,2258
BACKZ	0,1118	0,1700	0,1275	0,1105	0,1667	0,0646	0,2930	0,2926	0,7518	0,7108
ASBN	0,1161	0,1237	0,1112	0,1772	0,1342	0,0700	0,1949	0,1505	0,1781	0,2272

The weighted decision matrix in Table 7 was obtained by multiplying the weights obtained from the SD method with the normalized decision matrix values in Table 6. Euclidean and Taxicab distances were calculated using Equality (12) and Equality (13) and this situation is given in Table 8.

Table 8

Euclid and Taxicab Distances

	Ei	Ti
AKBNK	0,4822	0,8048
GARAN	0,1032	0,2810
HALKB	3,6562	5,6528
ISCTR	0,2830	0,6130
YKBNK	0,1152	0,3245
CCBN	0,1459	0,2325
MTBKZ	4,0484	6,9718
HSBK	0,1688	0,4083
BACKZ	0,9364	1,8453
ASBN	0,2112	0,5292

These two distance measures are used to determine the distance of banks from the negative ideal solution. Then, the relative evaluation matrix in Table 9 is created.

Table 9
Relative Evaluation Matrix

	CA1	CA2	BSS1	BSS2	AQ1	AQ2	L1	L2	P1	P2
AKBNK	0,0000	0,3830	-2,8662	0,2000	0,3706	0,3402	-3,1264	0,3159	-0,4447	0,2726
GARAN	-0,3751	0,0000	-3,1713	-0,1787	-0,0120	-0,0428	-3,4173	-0,0655	-0,8071	-0,1074
HALKB	3,4817	3,9347	0,0000	3,7131	3,9184	3,8908	-0,3819	3,8531	2,9269	3,7980
ISCTR	-0,1984	0,1810	-3,0331	0,0000	0,1689	0,1382	-3,2865	0,1147	-0,6373	0,0720
YKBNK	-0,3636	0,0120	-3,1637	-0,1669	0,0000	-0,0308	-3,4104	-0,0536	-0,7963	-0,0956
CCBN	-0,3325	0,0427	-3,1297	-0,1361	0,0307	0,0000	-3,3765	-0,0228	-0,7650	-0,0648
MTBKZ	4,0061	4,4732	0,4026	4,2443	4,4562	4,4285	0,0000	4,3889	3,4311	4,3317
HSBK	-0,3109	0,0658	-3,1215	-0,1137	0,0538	0,0230	-3,3703	0,0000	-0,7455	-0,0422
BACKZ	0,4636	0,8593	-2,5127	0,6695	0,8462	0,8160	-2,7930	0,7896	0,0000	0,7443
ASBN	-0,2696	0,1085	-3,0920	-0,0718	0,0964	0,0656	-3,3428	0,0424	-0,7062	0,0000

Table 9 was created with the help of Equality (14) and Equality (15). Equality (15) is used while creating the relative evaluation matrix given in Equality (14). As can be seen, Euclidean and Taxicab distances directly affect the obtaining of this matrix. Table 10 was calculated with the help of the formula in Equality (17), which is the last processing step of the CODAS method.

Table 10
Evaluation Scores and Ranking

	Hi	Ranking
AKBNK	-4,5551	4
GARAN	-8,1771	10
HALKB	29,1346	2
ISCTR	-6,4806	5
YKBNK	-8,0688	9
CCBN	-7,7539	8
MTBKZ	34,1627	1
HSBK	-7,5617	7
BACKZ	-0,1171	3
ASBN	-7,1694	6

As a result of applying all the process steps in the CODAS method, rankings for the year 2022 were obtained. The ranking results for the years 2013-2023, which are the subject of the study, are given in Table 11.

Table 11
Rankings for the Years 2013-2023

	AKBNK	GARAN	HALKB	ISCTR	YKBNK	CCBN	MTBKZ	HSBK	BACKZ	ASBN
2013	2	3	1	4	5	8	6	10	9	7
2014	5	7	1	4	6	2	8	9	3	10
2015	3	2	7	4	5	6	1	10	8	9
2016	4	2	6	5	7	9	1	10	8	3
2017	3	2	7	5	6	10	1	9	4	8
2018	4	7	6	2	3	8	1	9	5	10
2019	3	7	5	6	8	2	1	10	4	9
2020	5	8	2	7	6	4	1	10	3	9
2021	8	10	2	7	6	3	1	5	4	9
2022	4	10	4	5	9	8	1	7	3	6
2023	3	8	7	9	10	5	2	6	4	1

When the rankings obtained for all years in the study are examined in general, it is seen that MTBKZ bank showed the best average performance. It can be said that AKBNK, HALKB and BACKZ banks also showed good performance in general.

Application with Artificial Neural Networks

Top 10 Ranking

Akbank

The Naive Bayes Multinomial classification was applied. As a result of the classification, the accuracy rate of the data was calculated as 63.64%. According to this classification, Akbank is ranked within the top five 85% of the time, and within the bottom five 15% of the time. The error rate was determined to be 36%. When a Random Tree analysis was conducted, the accuracy rate increased to 81.82%. According to this analysis, the most influential factor on the ranking was the value of cash and cash equivalents. If the cash and cash equivalents were below 60.17B, the bank was classified within the top five; if the value was equal to or greater than 60.17B, then the ranking was influenced by the value of total liabilities. Specifically, if total liabilities were less than 1190.2B, the bank was placed in the bottom five, while values greater than 1190.2B resulted in placement within the top five. When evaluating the influence level of classes on the results for Akbank, entropy and probability values were analyzed using Shannon's Theory. Based on this analysis, the most significant data class for this bank was identified as cash and cash equivalents.

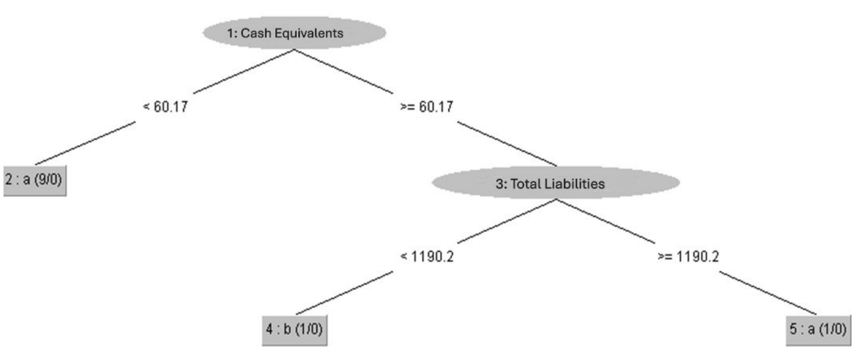

Figure 2. Classification result for Akbank

Garanti Bank

When the Naive Bayes Multinomial classification was applied, the accuracy rate 90.9%. According to this result, the probability of being ranked in the top five is 38%, while the likelihood of being in the bottom five is 68%. The error rate was determined to be 8.1%. When the Random Tree analysis was conducted, the accuracy rate was calculated as 72.73%. According to this analysis, if the total liabilities are equal to or greater than 333.5B, the bank is placed in the bottom five. If the total liabilities are less than 333.5B, then the analysis considers the value of net loans. If net loans are equal to or greater than 165.45B, the bank again ranks in the bottom five. However, if net loans are less than 165.5B, then the total assets data become influential. If total assets are equal to or greater than 231.3B, the bank remains in the bottom five; if less than 231.3B, it is placed in the top five. According to this analysis, for Garanti Bank to be ranked in the top five, the total liabilities must be below 333.5B, net loans must be below 165.5B, and total assets must also be less than 231.3B. When the influence levels of the classes on the results were evaluated using Shannon's Theory through entropy and probability analysis, the most significant data class for this bank was found to be total liabilities.

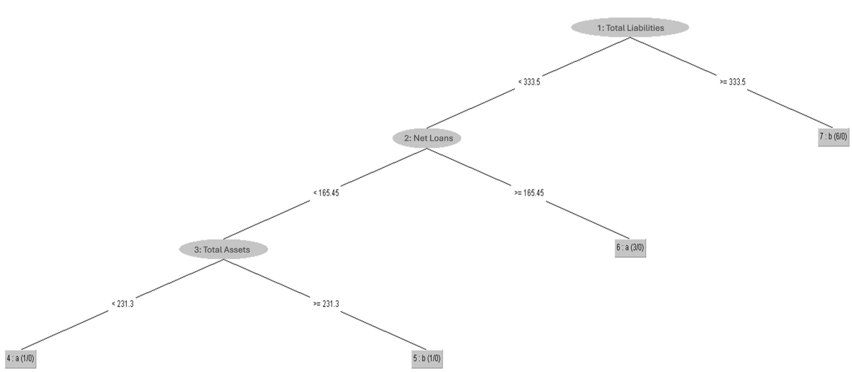

Figure 3. Classification result for Garanti Bank

Halk Bank

When the Naive Bayes Multinomial classification was applied, the accuracy rate was found to be 72.73%. Accordingly, the probability of ranking in the top five is 54%, while the probability of ranking in the bottom five is 46%. The error rate was calculated as 27%. When the Random Tree analysis was conducted, the accuracy rate was determined to be 81.82%. According to this analysis, if the total liabilities are less than 156.65B, the bank is ranked in the top five. If total liabilities are equal to or greater than 156.65B, the total deposit values become influential. If total deposits are less than 275.65B, the bank remains in the top five; if equal to or greater than 275.65B, the total liabilities again become the determining factor. If the total liabilities are less than 11250.3B, the bank is ranked in the top five; if equal to or greater than this value, it is placed in the bottom five. When the influence levels of the classes on the results were evaluated using Shannon's Theory through entropy and probability analysis, the most significant data class for this bank was identified as total liabilities.

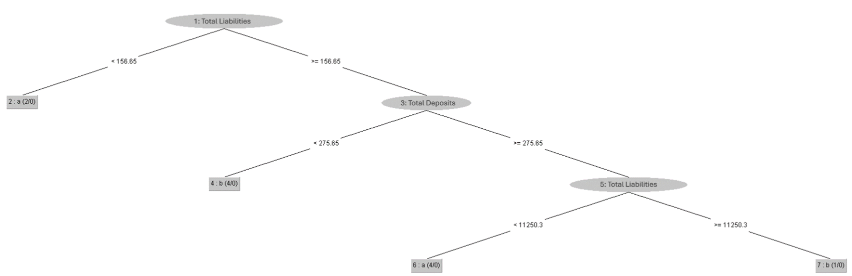

Figure 4. Classification result for Halk Bank

Türkiye İş Bank

When the Naive Bayes Multinomial classification was applied, the accuracy rate was found to be 90.91%. Accordingly, the probability of ranking in the top five is 62%, while the probability of ranking in the bottom five is 38%. The error rate was calculated as 9%. When the Random Tree analysis was conducted, the accuracy rate was determined to be 81.82%. According to this analysis, if the total assets are less than 532.5B, the bank is ranked in the top five. If the total assets are equal to or greater than 532.5B, the long-term liabilities become the determining factor. If the value of long-term liabilities is less than 268.1B, the bank is ranked in the bottom five; if it is equal to or greater than 268.1B, the bank is placed in the top five. When the influence levels of the classes on the results were evaluated using

Shannon's Theory through entropy and probability analysis, the most significant data class for this bank was identified as total assets.

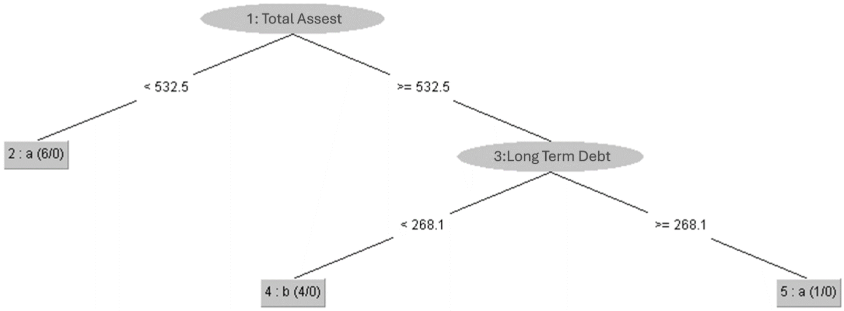

Figure 5. Classification result for Türkiye İş Bankası

Yapı Kredi Bank

When the Naive Bayes Multinomial classification was applied, the accuracy rate was found to be 72.73%. Accordingly, the probability of ranking in the top five is 31%, while the probability of being in the bottom five is 69%. The error rate was calculated as 27%. In the Random Tree analysis, the accuracy rate was found to be 63.64%. According to this analysis, if the total liabilities are equal to or greater than 352.2B, the bank is ranked in the bottom five; if less than 158.35B, it ranks in the top five. If total liabilities are between 158.35B and 352.2B, the total assets value becomes decisive. If the total assets are equal to or greater than 346.75B, the bank is placed in the top five; if less than 346.75B, the total equity value is considered. If total equity is equal to or greater than 24.6B, the bank is ranked in the bottom five. If it is less than 24.6B, the total liabilities again become the key determinant. If the total liabilities are less than 193.45B, the bank is placed in the bottom five; if equal to or greater than 193.45B, it ranks in the top five. According to the entropy and probability analysis performed using Shannon's Theory to evaluate the influence level of the classes, the most significant data class for this bank was identified as total liabilities.

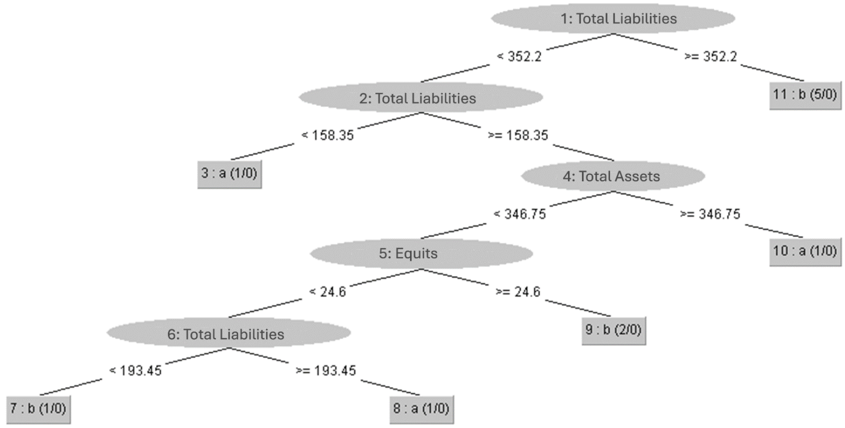

Figure 6. Classification result for Yapı Kredi Bank

BankTsentrKredit

When the Naive Bayes Multinomial classification was applied, the accuracy rate yielded as 63.64%. The model predicts, the probability of ranking in the top five is 46%, while the probability of being in the bottom five is 54%. The error rate was determined as 36%. In the Random Tree analysis, the accuracy rate was also found to be 63.64%. According to this analysis, if the net loans value is less than or equal to 828.5B, the bank is classified in the bottom five; if it is greater than 828.5B, the bank is placed in the top five. Based on the analysis of minimum entropy and probability values using Shannon's Theory to evaluate the influence level of the variables, the most significant data class for this bank was identified as net loans.

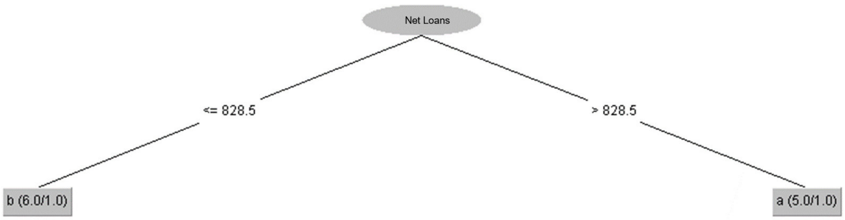

Figure 7. Classification result for Bank TsentrKredit

M&T Bank

When the Naive Bayes Multinomial classification was applied, the accuracy rate was calculated as 90.91%. Accordingly, there is a 77% probability of being ranked in the top five and a 23% probability of being in the bottom five. The error rate was determined to be 9%. In the Random Tree analysis, the accuracy rate was found to be 100%. According to this analysis, if the total liabilities value is less than or equal to 15,379.5B, the bank is classified in the bottom five; if it is greater than 15,379.5B, it is placed in the top five. Based on Shannon's Theory, which analyzes data classes in terms of minimum entropy and probability values, the most significant data class for this bank was identified as net loans.

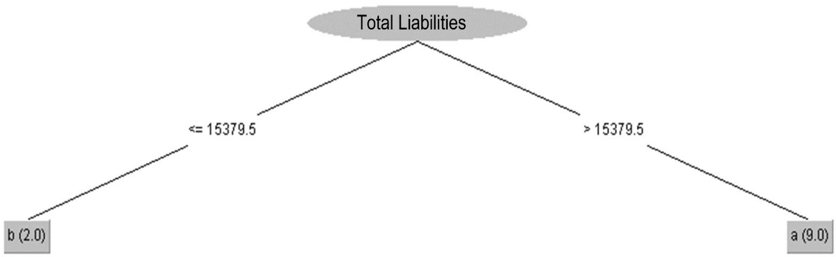

Figure 8. Classification result for M&T Bank

Halyk Bank

When the Naive Bayes Multinomial classification was applied, the accuracy rate was found to be 81.82%. Accordingly, there is a 15% probability of being ranked in the top five and an 85% probability of being in the bottom five. The error rate was calculated as 18%. In the Random Tree analysis, the accuracy rate was 90.91%. According to this analysis, if the total assets value is between 11,239.6B and 13,243.25B, the bank is ranked in the top five; if it exceeds 13,243.25B, it is placed in the bottom five. Based on the analysis of the data classes using Shannon's Theory in terms of minimum entropy and probability values, the most significant data class for this bank was identified as total assets.

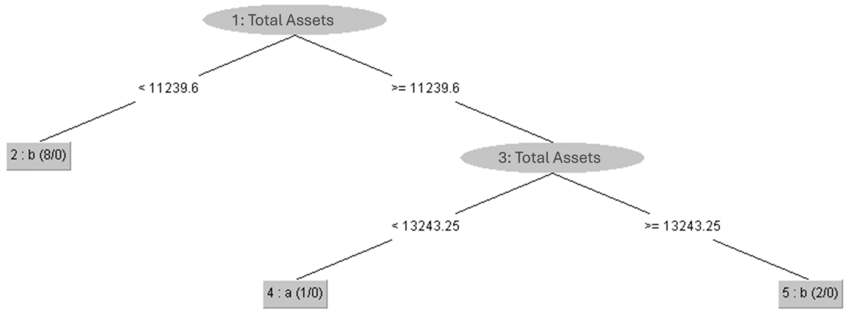

Figure 9. Classification result for Halyk Bank

Bank of America

When the Naive Bayes Multinomial classification was applied, the accuracy rate was found to be 90.91%. According to this, there is a 69% probability of being ranked in the top five and a 31% probability of being in the bottom five. The error rate was calculated as 9%. In the Random Tree analysis, the accuracy rate was 81.82%. According to this analysis, if the total liabilities value is greater than or equal to 655,622.8B, the bank is placed in the top five; if it is less than 655,622.8B, short-term liabilities become influential. If short-term liabilities are less than 1,618,950B, the bank is ranked in the top five; if they are equal to or greater than 1,618,950B, it is placed in the bottom five. Based on Shannon's Theory, which analyzes the data classes in terms of minimum entropy and probability values, the most significant data class for this bank was identified as total liabilities.

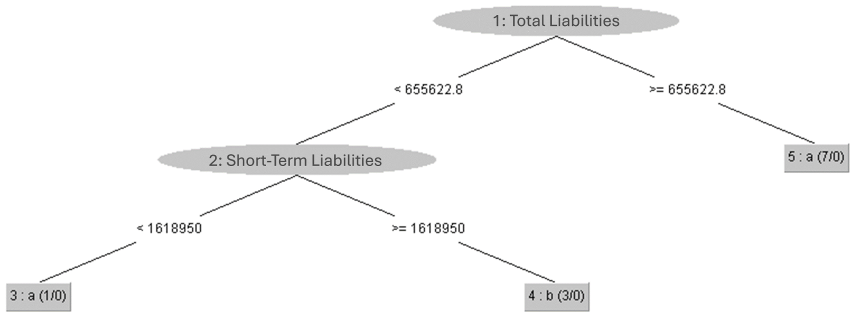

Figure 10. Classification result for Bank of America

Fortebank

When the Naive Bayes Multinomial classification was applied, the accuracy rate was found to be 63.64%. According to this, there is a 23% probability of being ranked in the top five and a 77% probability of being in the bottom five. The error rate was calculated as 36%. In the Random Tree analysis, the accuracy rate was determined to be 81.82%. According to this analysis, if the total liabilities value is greater than or equal to 2,634.5B, the bank is ranked in the top five; if it is less than 2,634.5B, return on assets becomes the influential variable. If the return on assets is greater than or equal to 0.01, the bank is placed in the bottom five; if it is less than 0.01, total liabilities become influential again. If total liabilities are greater than or equal to 969.7B, the bank is ranked in the top five; if lower, in the bottom five. Based on Shannon's Theory, which analyzes data classes in terms of minimum entropy and probability values, the most significant data class for this bank was identified as total liabilities.

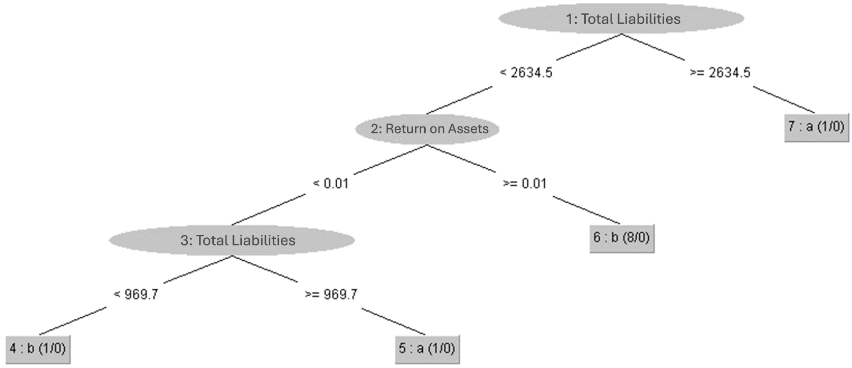

Figure 11. Classification result for Fortebank

Forecast for Akbank for the Next Two Years

The numerical values of Akbank's rankings based on the CODAS evaluation were used to generate artificial neural networks using the *Functions/ Multilayer Perceptron* algorithm in the Weka software. Due to the relatively limited dataset, three hidden layers with configurations of 10, 15, and 10 neurons were constructed to reduce errors caused by insufficient data volume. A machine learning process with 20,000 iterations was applied to the created neural network, resulting in a model with a remarkably low error rate of 0.00019.

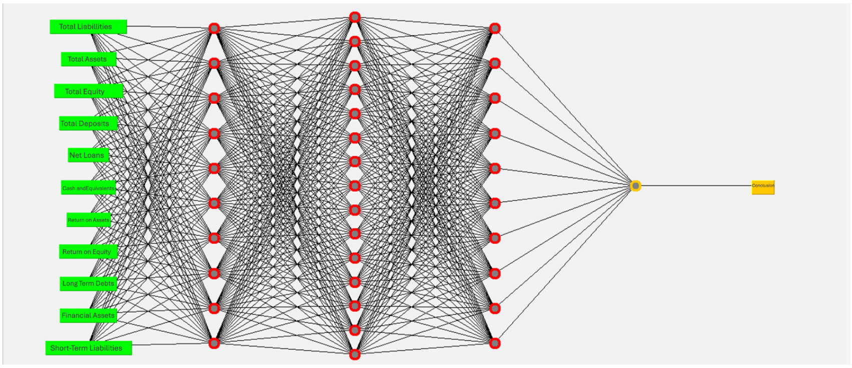

Figure 12. Forecast made for Akbank

The resulting artificial neural network model demonstrated a prediction accuracy of 99.98%, indicating a highly reliable forecasting capability. It was also determined that 87.6% of the data used in the neural network model were statistically significant. This model has been recorded as a reference framework. Subsequently, using the numerical values of Akbank's CODAS-based ranking, a two-year forecast was carried out through this reference model. Based on the findings obtained within this framework, Akbank is projected to rank 4th by the end of 2024 and 1st by the end of 2025.

Results and Recommendations

In this study, the banking sectors of Turkey and Kazakhstan were compared and analyzed using MCDM methods-specifically SD and CODAS-and artificial neural networks. The banking sector plays a critical role in the economic development processes of both countries, and the efficient performance of banks is a key element in ensuring national financial stability. In this context, the use of SD and CODAS methods enables a more comprehensive analysis by considering a wide range of variables and criteria in the evaluation and comparison of banks.

MCDM techniques allow for the evaluation of banks' financial performance, customer services, risk management practices, and technological advancements under various criteria. The MCDM methods employed in this study demonstrated how these criteria influence the financial performance of banks in both countries. Additionally, the analysis conducted through artificial neural networks provided a robust tool for forecasting bank performance and identifying potential areas for future improvement.

Based on the implementation of the SD and CODAS methods in alignment with the study's criteria, Akbank emerged as the top-performing financial institution in Turkey, while MTBKZ ranked highest among Kazakhstani banks. Conversely, HSBK exhibited the weakest performance among all banks analyzed. While banks must consider numerous factors in improving their financial performance, integrating evaluations performed through MCDM methods into this process can offer a valuable alternative perspective.

In this study, financial data for Akbank from 2013 to 2023 was utilized to construct and train an artificial neural network via machine learning.

Using this model, the financial performance rankings of Akbank for 2024 and 2025 were predicted with approximately 99% accuracy. According to the model, Akbank is forecasted to rank 4th by the end of 2024 and 1st by the end of 2025. Furthermore, the findings indicate that within CODAS evaluations, total liabilities were the most influential variable across both countries. Other significant indicators included total assets, net loans, and cash equivalents.

Ultimately, while the banking systems of Turkey and Kazakhstan demonstrate both similarities and differences, it is evident that Turkey's more advanced financial infrastructure and diversified banking sector provide a notable advantage in terms of performance. Nevertheless, the rapid growth and innovative initiatives observed in Kazakhstani banks highlight emerging opportunities within a regional context.

In order for banks to more effectively assess their current standing, integrating environmental variables (such as financial literacy levels and demographic factors) into the artificial neural network analysis could enable institutions to better understand the determinants of their ranking and take more targeted, efficient measures for future improvements.

This study holds the potential to contribute valuable insights to both the academic literature and the financial sector through the application of MCDM and neural network techniques within the banking industry-an area of fundamental importance to national economic development. Furthermore, by addressing a gap in the literature where these two methodologies have rarely been employed in tandem, this research offers a novel perspective to the field.

Nevertheless, as with any research, certain limitations must be acknowledged. In studies involving artificial neural networks, an inverse relationship between data quantity and error rates is evident. Due to the relatively limited number of annual observations in this study, the performance rankings were simplified into two nominal categories-top 5 and bottom 5 performers-to mitigate high error rates. This approach helped reduce the average error rate to approximately 21.5%. Future studies utilizing quarterly rather than annual evaluation data could further minimize errors by increasing the number of meaningful observations.

The analyses conducted via Weka used the same dataset as that employed in CODAS evaluations. A review of the results indicates variability in the factors affecting banks' rankings, which can be attributed to the limited sample size. For such analyses, the inclusion of regional variables and diverse data categories in addition to quarterly data could yield more robust and insightful results.

Contribution Rate Statement

The authors' contribution rates in this study are equal.

Conflict of Interest Statement

There is no conflict of interest with any institution or person within the scope of this study. There is no conflict of interest between the authors.

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