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EVALUATION OF RATIO ANALYSIS RESULTS WITH ENTROPY, CILOS AND IDOCRIW TECHNIQUES: AN APPLICATION IN BORSA ISTANBUL LIQUID BANK INDEX[1]

Entropy, CILOS ve IDOCRIW Teknikleri ile Oran Analizi Sonuçlarının Değerlendirilmesi: Borsa İstanbul Likit Banka Endeksinde Bir Uygulama

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ABSTRACT

This study investigates the relative importance of twelve financial ratios used to evaluate the performance of seven banks listed on the Borsa Istanbul Liquid Bank Index (XLBNK) over the 2015–2024 period. Employing three objective Multi Criteria Decision Making techniques Entropy, CILOS, and IDOCRIW the study determines, ranks, and compares annual criterion weights across six performance dimensions: asset quality, balance sheet structure, income-expense structure, profitability, liquidity, and capital adequacy. Findings indicate that the Loans Received/Total Assets ratio consistently dominates under both the Entropy and IDOCRIW techniques throughout the study period, reflecting pronounced inter-bank dispersion in external funding structures. The CILOS technique, by contrast, assigns greater importance to asset quality and profitability ratios, particularly during the COVID-19 pandemic. The weight distributions produced by the Entropy and IDOCRIW techniques are found to be broadly convergent, while the CILOS technique yields more balanced and systemically differentiated weightings. The IDOCRIW framework, integrating both components, is shown to provide a more comprehensive basis for objective criterion weighting in financial ratio analysis.

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ÖZ

Bu çalışma, 2015–2024 döneminde Borsa İstanbul Likit Bankalar Endeksi'nde (XLBNK) yer alan yedi bankanın performansını değerlendirmek için kullanılan on iki finansal oranın göreceli önemini incelemektedir. Entropi, CILOS ve IDOCRIW olmak üzere üç objektif Çok Kriterli Karar Verme tekniğini kullanan çalışma, varlık kalitesi, bilanço yapısı, gelir-gider yapısı, karlılık, likidite ve sermaye yeterliliği olmak üzere altı performans boyutunda yıllık kriter ağırlıklarını belirlemekte, sıralamakta ve karşılaştırmaktadır. Bulgular, çalışma dönemi boyunca hem Entropi hem de IDOCRIW tekniklerinde Alınan Krediler/Toplam Varlıklar oranının tutarlı bir şekilde baskın olduğunu göstermektedir; bu durum, dış finansman yapılarında bankalar arasında belirgin bir dağılım olduğunu yansıtmaktadır. Buna karşılık, CILOS tekniği, özellikle COVID-19 pandemisi sırasında varlık kalitesi ve kârlılık oranlarına daha fazla önem atfetmektedir. Entropi ve IDOCRIW teknikleriyle elde edilen ağırlık dağılımlarının genel olarak birbirine yakın olduğu görülürken, CILOS tekniği daha dengeli ve sistematik olarak farklılaşmış ağırlıklar vermektedir. Her iki bileşeni de entegre eden IDOCRIW çerçevesi, finansal oran analizinde objektif kriter ağırlıklandırması için daha kapsamlı bir temel sağladığı görülmektedir.

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[1] This study is an adapted English version of the Turkish paper entitled "Evaluation of Ratio Analysis Results Using the Entropy, CILOS, and IDOCRIW Techniques: An Application to the Borsa Istanbul Liquid Banks Index," which was presented in full-text form at the 25th Finance Symposium held in Burdur, Türkiye, on 19–22 October 2022.

1. INTRODUCTION

The sustainability and development of the banking system leads to stable and efficient economic performance in the country. The proper use of financial resources helps achieve a smooth financial flow across countries. Therefore, it becomes imperative to measure the financial performance of banks to ensure transparent operations and cash flow within the country and in other countries.

In the banking sector, financial performance analysis is a type of analysis that evaluates various aspects of an institution such as profitability, asset quality, capital adequacy and operational efficiency by examining financial indicators such as a bank's income, expenses, assets, capital and debt structure; it can also be regarded as an important tool for determining the bank's financial position, identifying its risks and making strategic decisions (Süzülmüş and Yakut, 2024).

As there are many factors influencing bank performance, measuring financial performance involves complex decision-making problems that encompass a large number of variables. Multi-Criteria Decision Making (MCDM) methods are used in the literature to solve such problems. Where the decision-making process involves two or more variables and two or more alternatives to be evaluated, this is defined as a MCDM problem, and there are numerous developed MCDM methods available to solve such problems (Özer and Saygın, 2022)

The use of multi-criteria decision-making techniques (MCDM) in the objective weighting of financial evaluation criteria is considered important by practitioners and researchers. In these techniques, the options being evaluated for performance are analyzed using a set of factors called criteria. In some multi-criteria decision-making techniques, the degree of importance of the effect that the criteria under analysis have on performance is taken into account. Therefore, the importance weight of the criteria is determined. To determine the weight of the criteria, there are techniques that refer to the opinions and experiences of experts in the field, depending on the subject of the study, as well as weighting techniques based on fully objective evaluations and, additionally, hybrid techniques. In this context, it is important to consider how the importance weightings assigned to evaluation criteria yield results in different objective weighting techniques and how these results should be used (Atukalp, 2020: 29).

This study aims to determine the relative importance weights of financial ratios used in the analysis of banks traded on the Borsa Istanbul (BIST) Liquid Bank Index (XLBNK) on performance using MCDM techniques. The index's start date is 4 November 2019. The basic rules of the XLBNK index are as follows (BIST, 2022);

- The shares included in the BIST Liquid Bank Index are selected from among the bank shares listed on the Star Market during the relevant Index Period.
- Shares must have been traded on BIST for at least 60 days as of the end of the Valuation Period to be included in the indices.
- For banks with multiple share classes traded in separate series, only the share with the highest average market value of shares actually in circulation is included in the index.
- As of the Valuation Period, all bank shares with an average market value of over 1,500 million Turkish Liras and a daily average trading volume of over 75 million TL are included in the index, and the number of shares included in the index must be at least 6. If there are 6 banks in the Star Market, all 6 banks in the Star Market are included in the index. If there are more than 6 banks in the Star Market but fewer than 6 banks meet the criteria, all those that meet the criteria are included in the index.

> The remaining portion is completed with shares found by reducing the Daily Average Trading Volume criterion by 5 million Turkish Liras. If the required number of shares is still not reached, the shares found by reducing the average market value criterion of shares in actual circulation by 150 million Turkish Liras are added to complete the index.

In this context, it is important to evaluate the results of the ratio analysis, as the companies traded on the XLBNK index consist of Türkiye's largest banks and assets, and therefore play a key role in maintaining and developing the banking system.

The XLBNK index was specifically selected as the research sample for several interconnected reasons. First, the index comprises banks that meet objectively defined thresholds for market capitalisation and daily trading volume as set by Borsa İstanbul, ensuring a homogeneous and structurally comparable sample. This eliminates the distortions that may arise when banks of vastly different scales are evaluated together, thereby enhancing the reliability of ratio-based comparisons. Second, the banks listed on the XLBNK collectively represent a substantial share of Türkiye's total banking assets and transaction volume, making findings derived from this sample generalisable to the broader sector. Third, as market-making institutions, these banks are of direct relevance to investors, financial analysts, and regulatory bodies such as the Bankacılık Düzenleme ve Denetleme Kurulu (BDDK) and the Türkiye Cumhuriyet Merkez Bankası (TCMB); objective weighting of their financial ratios therefore yields actionable intelligence for both investment and supervisory decision-making. Finally, a review of the existing literature reveals that, whilst studies employing MCDM techniques in the Turkish banking sector predominantly focus on all deposit banks or the broader BIST Banking Index (XBANK), no prior study has applied the Entropy, CILOS, and IDOCRIW techniques in combination specifically to the XLBNK. The selection of this index thus not only addresses a clearly identified gap in the empirical literature but also ensures that the sample is confined to the most liquid and market-active participants, producing a set of empirical outputs with high practical applicability.

The study analyzed the ratio analysis results of seven banks traded on the BIST XLBNK index using data from the 2015-2024 period. In order to compare periods prior to 2019, the index's starting year, the 2015–2024 period has been included in the study. The analysis was conducted under 12 sub-evaluation criteria grouped under the main headings of asset quality, balance sheet structure, income-expense structure, profitability, liquidity, and capital adequacy. The importance levels of the evaluation criteria were determined, ranked, and compared separately for 2015-2024 using entropy, CILOS (Criterion Impact Loss), and IDOCRIW (The Integrated Determination of Objective Criteria Weights) techniques.

To ensure an objective and reliable evaluation of financial performance, it is imperative to utilize objective weighting methods that are free from the subjective biases of decision-makers. In this study, three prominent objective MCDM techniques Entropy, CILOS, and IDOCRIW were selected to analyze the financial ratios of banks within the XLBNK. The selection of this specific combination is driven by distinct methodological and structural reasons. Firstly, the Entropy method, derived from information theory, assigns weights based on the degree of dispersion and uncertainty within the dataset. However, Entropy tends to overlook the structural interrelationships and correlations among criteria, focusing solely on absolute data volatility. To address this limitation, the CILOS is incorporated, which evaluates the relative impact of criteria on one another and measures the 'impact loss' generated when the weight of one criterion shifts. CILOS provides a robust framework for capturing systemic interactions and parametric relationships between financial ratios.

Finally, the IDOCRIW serves as the methodological backbone of this research by mathematically integrating the information entropy from Entropy and the impact loss matrix from CILOS. Relying on a single objective method in financial analysis may lead to overlooking multi-dimensional data dynamics. The IDOCRIW technique synthesizes the strengths of both components, yielding more balanced, consistent, and comprehensive criteria weights that accurately reflect the intrinsic characteristics of the banking dataset. A review of the existing literature reveals that most studies evaluating the performance of the Turkish banking sector employ subjective methods based on expert opinions (such as AHP, ANP, or Delphi) or rely isolatedly on the Entropy method. Therefore, applying the hybrid IDOCRIW technique which bridges the gap between data dispersion and criteria interaction to the BIST Liquid Bank Index introduces methodological diversity and fills a significant gap in the empirical literature.

The next section of the study provides summaries of studies in the literature regarding the analysis techniques used. The third section explains the methodology used to carry out the study, including the techniques employed and the data set used for the application. The fourth section presents evaluations of the application outputs of the analysis, and the fifth section provides an overall evaluation of the study.

2. LITERATURE REVİEW

When studies examining the financial performance of the banking sector in the literature are evaluated from a critical perspective, it becomes apparent that these studies cluster according to specific methodological approaches, weighting preferences, time-period constraints and ownership structures. The existing literature on MCDM in banking can be problematised under three main headings in terms of its methodological and empirical dynamics:

The first group of studies in the literature relied on subjective methods such as AHP and Fuzzy AHP based on expert opinions or survey results to determine the importance levels of financial ratios or performance criteria. For example, Amile et al. (2013) weighted financial and non-financial criteria using Fuzzy AHP and ranked banks using TOPSIS, arguing that profitability was the most important criterion at the financial level. Similarly, Rezaei and Ketabi (2016) examined Iranian private banks using a Fuzzy AHP model, focusing on equity and portfolio criteria; whilst Guru and Mahalik (2021) analysed 26 banks in India using an integration of AHP and TOPSIS, placing the State Bank of India in first place.

However, in a dynamic sector such as banking which is exposed to macroeconomic shocks, liquidity fluctuations and sudden regulatory changes weightings based on human judgement carry a structural risk. Experts' subjective perceptions can mask the intrinsic signals and actual financial vulnerabilities rationally revealed by the data set, particularly during periods of crisis or uncertainty.

In order to overcome expert bias and subjectivity, there has been a growing trend in the literature towards fully mathematically based, objective weighting methods. Upon examining studies conducted in this regard, it is observed that the Entropy (or Fuzzy/Grey Entropy) method is overwhelmingly used as the weighting tool, either on its own or in combination with various ranking algorithms (TOPSIS, WASPAS, COPRAS, ARAS, CRADIS, MARCOS).

Among the studies in this group, Akbulut (2020) examined the 10 largest deposit-taking banks in Türkiye using the Grey Entropy, PSI and ARAS methods, and argued that the age of the bank is the most important criterion for performance. Coşkun et al. (2021) and Gezen (2021) preferred Entropy and WASPAS techniques; whilst Unvan and Ergenç (2022) opted for Fuzzy-Entropy and Fuzzy-COPRAS methods. This trend has continued in recent literature; Demirci (2023) analysed the CAMELS criteria using Entropy and MARCOS, whilst Ertuğrul and Çanakçıoğlu (2026) analysed the BIST Banking Index using Entropy and TOPSIS; Babacan et al. (2026) examined the effects of the pandemic using Entropy, COPRAS and PROMETHEE; and Çanakçıoğlu and Küçükönder (2026) analysed nine deposit-taking banks using the Entropy and CRADIS methods.

However, this extensive body of literature suffers from a methodological one-dimensionality. The entropy method measures the importance of a financial ratio solely by examining the absolute data distribution (information uncertainty/variance) among alternatives. This approach completely disregards the linear/structural interactions and correlations between financial ratios, as well as the systemic impact that a deterioration in one ratio would have on others. The fact that advanced techniques such as CILOS, which measures the loss of inter-criterion effects, or IDOCRIW (Keleş and Özdağoğlu, 2021), which comprehensively addresses objective criterion weights, remain extremely limited (or are not used at all) in the banking performance literature results in the multidimensional structure of the ratios not being fully reflected.

Another significant limitation in financial performance analyses is the selection of static time periods. A review of the literature reveals that macroeconomic shocks and crises can abruptly alter performance dynamics. For example, Keleş and Özdağoğlu (2021) examined the 2013–2020 period on an annual basis using the IDOCRIW and MULTIMOOSRAL techniques and declared 2013 to be the most successful period and 2020 the least successful. Yılmaz and Civelek (2025), on the other hand, examined the Kyrgyz banking sector within the context of global crises using the LOPCOW-RAFSI integration; they determined that the most critical criterion was the non-performing loan ratio and that the worst performance occurred again in 2020 (the pandemic year).

To measure the sectoral shocks of the COVID-19 pandemic, Armağan et al. (2021) employed the SECA technique; meanwhile, Nguyen et al. (2022) demonstrated, by combining the CRITIC, DEMATEL and TOPSIS methods for the Vietnamese banking sector, that the pandemic had a radically transformative impact on asset quality, liquidity and growth rates. This situation necessitates the use of hybrid objective models, which can more accurately measure the dynamic shifts and sensitivity in financial ratio priorities during crisis periods.

The empirical findings of existing studies show considerable variation and inconsistencies depending on the period under review, the country, and the ownership structures of the banks (public, private, foreign). In the Turkish sample, Uludağ and Ece (2018), in their analysis using the TOPSIS method based on 49 criteria, identified Ziraat Bank as the leader among public banks. Kablan and Erdoğan (2021), examining the period 1980–2018 using the COPRAS method, noted that foreign banks were more successful between 1980 and 2010, whilst public banks were more successful between 2010 and 2018. Similarly, in their studies, Gezen (2021) and Demirci (2023) reported that public banks outperformed private and foreign banks during specific sub-periods. Kadooğlu Aydın et al. (2023), using the Multi-MOORA method, and Süzülmüş and Yakut (2024), using the CRITIC, PROMETHEE and EDAS methods, found that Ziraat Bank achieved the highest performance in their analyses. Paksoy and Küçüker (2024), on the other hand, analysed the BIST XBANK index using the TOPSIS method and noted that Vakıfbank stood out in 2021, whilst Yapı Kredi did so in 2022–2023.

However, there are also studies in the literature that have reached the opposite conclusion. Whilst Çilek (2022) demonstrated that privately-owned banks were the most efficient group during the 2019–2021 period using SV and CoCoSo techniques; Şener and Şenol (2025), in their study using Grey Relational Analysis, argued that private banks (Garanti and Akbank) had the highest performance, whilst public banks (Halkbank, Vakıfbank, Ziraat) had the lowest. On the international stage, Gupta et al. (2021) analysed the Indian market using CRITIC and TOPSIS, Wanke et al. (2022) examined ASEAN countries using SWARA and TOPSIS, whilst Sama et al. (2022) analysed Indian private banks (led by HDFC Bank) using CRITIC, TOPSIS and GIA techniques, demonstrating that local and global dynamics give rise to different ratio priorities.

Upon reviewing the national and international MCDM literature, as summarised in detail above, no empirical study was found that evaluated the ratio analysis results of banks traded on XLBNK, the most active participants in the market, using a combination of Entropy, CILOS, and IDOCRIW techniques, and compared the objective weighting levels of financial ratios.In this regard, the key contributions of this study to the literature and the specific gaps it fills are as follows:

- Whilst the Entropy method, used in isolation in the overwhelming majority of the literature, fails to capture correlations between ratios, CILOS may overlook the absolute variance of the data. This study has overcome the limitation of "one-dimensional objective weighting" in the literature by mathematically integrating the weaknesses of both methods under the IDOCRIW technique. The weights of the ratios have been filtered through an integrated filter that simultaneously measures both the interbank distribution of data (Entropy) and the systemic impact of the ratios on one another (CILOS).
- The period under review, 2015–2024, coincides with the structural disruption caused by the COVID-19 pandemic. Unlike static analyses, this study dynamically highlights shifts in the prioritisation of financial ratios during the pre-crisis (2019), crisis (2020–2022) and post-crisis (2023–2024) periods.
- Studies in the banking literature generally lump all banks together without taking into account their scale or liquidity structure. This study, however, focuses directly on the XLBNK index, which comprises the most liquid and market-making players on the Istanbul Stock Exchange. In this respect, it has not only tested ratio interactions within a more homogeneous sample but has also established its unique place in the literature by producing a set of highly reliable empirical outputs that can be directly simulated in decision-making processes for investors and regulatory authorities (BDDK, TCMB).

3. METHOD

The study analyzed the results of the ratio analysis of banks traded on the BIST Liquid Bank Index using Entropy, CILOS, and IDOCRIW techniques determined and compared the objective importance weight levels of financial ratios. All seven banks traded on the BIST Liquid Bank Index were selected as the sample. In the study, the ratio analysis results for 2015-2024 were first weighted using the Entropy technique, then weighted using the CILOS technique, and finally weighted using the IDOCRIW technique, which combines the results of these two techniques. The Entropy, CILOS, and IDOCRIW techniques were applied using Microsoft Excel 2016. The data used in the analysis was obtained from the Türkiye Bankalar Birliği (TBB) website (TBB, 2022). The banks traded on the BIST Liquid Bank Index included in the sample and their symbols are presented in Table 1 (Kamu Aydınlatma Platformu, 2022).

Table 1. Banks Traded on the BIST Liquid Bank Index Included in the Sample

Code	Banks
B_1	Türkiye Halk Bankası A.Ş.
B_2	Türkiye Vakıflar Bankası T.A.O.
B_3	Akbank T.A.Ş.
B_4	Türkiye İş Bankası A.Ş.
B_5	Yapı ve Kredi Bankası A.Ş.
B_6	Türkiye Garanti Bankası A.Ş.
B_7	Türkiye Sınai Kalkınma Bankası A.Ş.

Note: Türkiye Sınai Kalkınma Bankası A.Ş. was removed from the BIST Liquid Banks Index in 2024 (KAP, 2026).

Twelve ratios were used in the study. These ratios consist of groups of ratios for asset quality, balance sheet structure, income-expense structure, profitability, liquidity, and capital adequacy. The ratios and symbols used in the study are presented in Table 2.

Table 2. Financial Ratios Used in the Study

Ratio Group	Ratios	Code	Max/Min
Active Quality	Non-Performing Loans / Total Loans	AQ_1	Min
	Fixed Assets/Total Assets	AQ_2	Max
	Total Loans/Total Assets	AQ_3	Max
Balance Sheet Structure	Loans Received/Total Assets	BSS_1	Min
Revenue-Expense Structure	Interest Income/Interest Expenses	RES_1	Max
	Total Revenues/Total Expenses	RES_2	Max
Profitability	Average Return on Assets	PR_1	Max
	Average Return on Equity	PR_2	Max
Liquidity	Liquid Assets/Short-Term Liabilities	LQ_1	Max
	Liquid Assets/Total Assets	LQ_2	Max
Capital Adequacy	Equity/Total Assets	CA_1	Max
	Capital Adequacy Ratio	CA_2	Max

Non-Performing Loans / Total Loans: A high ratio indicates poor bank credit quality; therefore, a low ratio is preferred.

Fixed Assets/Total Assets: As this ratio, which is used to assess asset quality, provides information about the bank's physical infrastructure, a high figure is regarded as positive.

Total Loans/Total Assets: It reflects the bank's core business volume; as a high ratio indicates efficient use of assets, it is considered a positive indicator.

Loans Received/Total Assets: A high ratio indicates the bank's dependence on external funding; as an increase in this debt burden poses a risk, a low ratio is preferable.

Interest Income/Interest Expenses: A high ratio indicates that the bank is managing its interest margin effectively; this is beneficial.

Total Revenues/Total Expenses: A high score indicates high overall operational efficiency; it is a positive indicator.

Average Return on Assets: It indicates the extent to which assets generate profit; a high figure is preferable.

Average Return on Equity: It measures the return on equity; a high figure is desirable.

Liquid Assets/Short-Term Liabilities: It reflects the ability to meet short-term liabilities; a high ratio indicates strong liquidity.

Liquid Assets/Total Assets: It indicates what proportion of total assets is held in liquid form; a high ratio enhances financial flexibility.

Equity/Total Assets: It is an indicator of equity adequacy, and a high level reflects financial soundness.

Capital Adequacy Ratio: This ratio, which must be maintained above a minimum threshold under banking regulations, indicates financial resilience when it is high.

3.1. Entropy Technique

The entropy technique developed by Shannon is referred to in the literature as Shannon's Entropy technique (Shannon, 1948: 392-396). This technique considers the relative intensities of criterion importance in connection with the differentiation between data in order to evaluate the relative importance levels of criteria (Monghasemi et al., 2015: 3094). The entropy technique provides reliable results as an objective technique in situations where the results of non-objective techniques may be misleading due to the subjective or incomplete assessments of decision-makers. The objectivity of the technique can be considered its main advantage, but difficulties in accessing data can be considered a disadvantage (Şahin, 2021: 1598). The entropy technique consists of five stages (Şahin, 2021: 37-38; Petrov, 2022: 7-8; Chen et al., 2022: 5-6).

Step 1: The decision string is prepared as shown in Equation (1).

$$D = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \qquad i = 1, 2, \dots, m; j = 1, 2, \dots, n \tag{1}$$

Here,

m: the number of decision options,

n: the number of criteria defining each decision option,

x_{ij}: the value of decision option i according to criterion *j*.

Step 2: The decision string is normalized. Values related to criteria with different units are normalized and converted into a standard format. Normalization is performed using Equation (2).

$$x_{ij}^{*} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \qquad i = 1, 2, \dots, m; j = 1, 2, \dots, n \tag{2}$$

Here, x_{ij}^{*} represents the normalized form of the value of the decision option i according to the constraint *j*.

Step 3: The entropy values of the criteria are calculated. The entropy value (e_j) of each evaluation criterion is calculated using Equation (3).

$$e_j = -(\ln m)^{-1} \sum_{i=1}^{m} x_{ij}^{*} \ln(x_{ij}^{*}) \qquad j = 1, 2, \dots, n \tag{3}$$

Step 4: Differentiation levels are calculated. The differentiation levels (d_j) of the evaluation criteria are calculated using Equation (4).

$$d_j = 1 - e_j \qquad j = 1, 2, \dots, n \tag{4}$$

Step 5: The importance levels of the evaluation criteria are calculated. The importance weight of each evaluation criterion is calculated using Equation (5).

$$W_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \qquad j = 1, 2, \dots, n \tag{5}$$

The application steps of the entropy technique are shown in Figure 1.

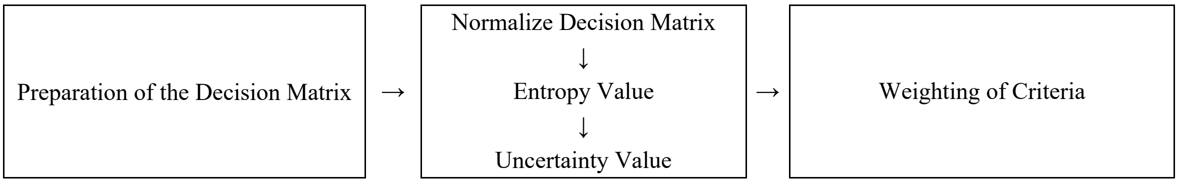

Figure 1. Application Steps of the Entropy Technique

3.2. CILOS Technique

The CILOS (Criterion Impact Loss) technique, referred to as the Criterion Impact Loss technique, measures the impact loss of each criterion when one of the criteria used is optimal, in other words, the maximum or minimum value (Mirkin, 1974: 256; Zavadskas and Podvezko, 2016: 269). CILOS, an objective new technique for criterion impact loss, is used to determine the relative impact loss incurred by a decision option when another criterion is chosen as the optimum (Sel, 2020: 38-39). The CILOS technique consists of six stages (Podvezko et al., 2017: 499-500; Pala, 2022: 168-170).

Step 1: The decision sequence of the CILOS technique is the same as the decision sequence expressed in the Entropy technique and is created using Equation (1).

Step 2: In order to apply the CILOS technique, it is first necessary to ensure that all criteria used in the analysis are at their maximum value. To this end, criteria at their minimum value are converted to their maximum value using Equation (6).

$$r_{ij} = \frac{min\ r_{ij}}{r_{ij}} \tag{6}$$

In Equation (6), provided that the values in the relevant column are not equal to 0, the minimum column value is divided by each column value and converted to the maximum property. This operation is not necessary for criteria with maximum properties.

Step 3: Normalization calculation is performed. Normalization is performed using Equation (7) to convert the value of each criterion to a standard state.

$$x_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{7}$$

During the normalization process, the value of each criterion's column element is divided by the value of the criterion's column total.

Step 4: The A matrix is constructed. The maximum value in each column is placed on the diagonals, and the A matrix is constructed using Equation (8).

$$h=j \rightarrow r_{hj} = max_i\ n_{ij} \tag{8}$$

The value corresponding to the diagonal, along with the row it is located in, should be moved to the square A array as is.

Step 5: The P sequence, which expresses the relative loss values of the evaluation criteria, is created. The $P = \left\| p_{kj} \right\|$ sequence is prepared using Equation (9).

$$p_{kj}=\frac{x_j - r_{kj}}{x_j} \tag{9}$$

In the P series, p_{kj} represents the relative loss value of the jth criterion when the kth criterion is selected as the optimal criterion.

Step 6: Criterion weight values are calculated. The weight vector $q=(q_1, q_2, \dots, q_m)$ to be assigned to the criteria is given by the sequence formula shown in Equation (10).

$$Fq^T=0 \tag{10}$$

The *F* sequence shown in Equation (10) is specified in Equation (11).

$$F = \begin{bmatrix} -\sum_{i=1}^{n} p_{k1} & p_{12} & \cdots & p_{1n} \\ p_{21} & -\sum_{i=1}^{n} p_{k2} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & -\sum_{i=1}^{n} p_{kn} \end{bmatrix} \tag{11}$$

The homogeneous equation solution is formed using Equation (10) and Equation (11). These are solutions that satisfy the condition shown in Equation (12), where the weights of the criteria are *q*.

$$\sum_{i=1}^{m} q_i=1 \tag{12}$$

The application steps of the CILOS technique are shown in Figure 2.

Decision Matrix	→	Conversion of Cost-Oriented Criteria to Benefit-Oriented Criteria ↓ Data Normalization ↓ Determining the Maximum Values in Columns ↓ Preparing the Square A Sequence ↓ Preparation of the P Series ↓ Preparation of the F Series	→	Determining the Final Weightings of the Criteria

Figure 2. Application Steps of the CILOS Technique

3.3. IDOCRIW Technique

The IDOCRIW technique (The Integrated Determination of Objective Criteria Weights) is defined as the determination of hybrid objective criteria weights and was introduced to the literature by Zavadskas and Podzenko (2016). In their study, Zavadskas and Podzenko (2016) combined the Entropy and CILOS techniques to propose the IDOCRIW technique.

The IDOCRIW technique is the first technique that integrates two different techniques in criterion weighting, thereby increasing the reliability and accuracy of the technique (Demir, 2020: 54). In their work, Zavadskas and Podzenko (2016) integrated the most useful features of the Entropy technique and the CILOS technique to create a new technique. The IDOCRIW technique consists of four stages (Zavadskas and Podzenko, 2016: 273-274).

Step 1: The decision string is determined. The decision string determination step is identical to the first step of the Entropy technique and the CILOS technique and is prepared using Equation (1).

Step 2: Entropy weights are determined. The application steps described in the entropy technique section are performed.

Step 3: CILOS weights are determined. The application steps described in the CILOS technique section are performed.

Step 4: Final weights are determined. IDOCRIW criterion weights (ω_j) are calculated using Equation (13), where entropy criterion weights are w_j and CILOS criterion weights are q_j.

$$(\omega_j) = \frac{w_j.q_j}{\sum_{i=1}^{n} w_j.q_j} \tag{13}$$

The application steps of the IDOCRIW technique are shown in Figure 3.

Step 1		Step 2		Step 3		Step 4
Preparing the Decision Matrix	→	Determining Entropy Weights ↓ Normalization of the Decision Tree ↓ Calculation of Entropy Levels ↓ Determination of Deviation Rates from Grades ↓ Determining Importance Weights	→	Determination of CILOS Weights ↓ Conversion of Cost-Oriented Criteria ↓ Normalization of Transformed Series ↓ Preparing the Square String ↓ Preparing the Relative Loss of Effect Scale ↓ Calculation of the Weight System Sequence ↓ Solution of Linear Equation System ↓ Determining Importance Weights	→	Determination of IDOCRIW Entropy Weights ↓ Combining Entropy and CILOS Weights ↓ Determination of Final Importance Weights

Figure 3. Application Steps of the IDOCRIW Technique

4. FINDINGS

This section explains the findings and evaluations reached as a result of analyses conducted using the Entropy technique, CILOS technique, and IDOCRIW technique. The analysis covers two main periods, including the 2015-2024 period and year-end data. For illustrative purposes, this section provides a comprehensive analysis of the 2019 data and only shows the analysis results for the 2020 data.

4.1. Application of Entropy Technique

The decision set for the 2019 year-end data of the 12 financial ratios selected as evaluation criteria, involving 7 banks, in the BIST Liquid Bank Index included in the study was prepared using Equation (1) and presented in Table 3. The criteria 'AQ_1' and 'BSS_1' were evaluated in terms of cost and were preferred to be minimum. The other evaluation criteria were considered benefit-oriented and were thought to be required to be maximum.

Table 3. 2019 Start Decision Sequence

Criterion Direction	**Min**	**Max**	**Max**	**Min**	**Max**	**Max**	**Max**	**Max**	**Max**	**Max**	**Max**	**Max**
Criteria	**AQ_1**	**AQ_2**	**AQ_3**	**BSS_1**	**RES_1**	**RES_2**	**PR_1**	**PR_2**	**LQ_1**	**LQ_2**	**CA_1**	**CA_2**
B_1	5.1	3.1	67.7	2.4	129.4	124.1	0.4	5.6	13.5	8.4	7.0	14.3
B_2	5.9	2.6	69.6	9.8	144.8	144.8	0.7	9.1	18.6	10.1	7.9	16.6
B_3	7.3	3.7	56.5	8.7	183.6	172.5	1.6	11.0	24.1	12.9	15.1	21.0
B_4	6.5	6.3	61.8	8.6	185.7	158.1	1.4	11.2	24.3	14.1	12.6	17.9
B_5	7.6	3.7	62.1	9.8	170.6	162.0	1.0	9.0	35.2	19.2	10.6	17.8
B_6	6.9	4.1	64.2	6.4	192.1	185.0	1.6	12.3	27.3	16.3	13.7	19.6
B_7	3.5	3.6	74.5	62.7	246.0	205.9	1.7	13.5	65.1	3.4	13.5	17.8

The initial decision sequence was normalised using Equation (2) and is presented in Table 4

Table 4. 2019 Normalised Decision Set

Criteria	**AQ_1**	**AQ_2**	**AQ_3**	**BSS_1**	**RES_1**	**RES_2**	**PR_1**	**PR_2**	**LQ_1**	**LQ_2**	**CA_1**	**CA_2**
B_1	0.120	0.116	0.148	0.022	0.103	0.108	0.049	0.078	0.065	0.099	0.088	0.115
B_2	0.138	0.094	0.153	0.090	0.116	0.126	0.088	0.127	0.089	0.120	0.098	0.133
B_3	0.170	0.135	0.124	0.080	0.147	0.150	0.186	0.154	0.116	0.153	0.188	0.168
B_4	0.152	0.233	0.135	0.079	0.148	0.137	0.162	0.156	0.117	0.167	0.156	0.143
B_5	0.177	0.136	0.136	0.091	0.136	0.141	0.116	0.125	0.169	0.228	0.132	0.143
B_6	0.161	0.150	0.141	0.059	0.153	0.161	0.194	0.171	0.131	0.194	0.171	0.157
B_7	0.082	0.134	0.163	0.578	0.196	0.179	0.206	0.188	0.313	0.040	0.168	0.142

The entropy values (e_j) were calculated using Equation (3) and are presented in Table 5.

Table 5. 2019 Entropy Values (e_j)

Criteria	**AQ_1**	**AQ_2**	**AQ_3**	**BSS_1**	**RES_1**	**RES_2**	**PR_1**	**PR_2**	**LQ_1**	**LQ_2**	**CA_1**	**CA_2**
B_1	-0.25	-0.25	-0.28	-0.08	-0.23	-0.24	-0.15	-0.20	-0.18	-0.23	-0.21	-0.25
B_2	-0.27	-0.22	-0.29	-0.22	-0.25	-0.26	-0.21	-0.26	-0.22	-0.25	-0.23	-0.27
B_3	-0.30	-0.27	-0.26	-0.20	-0.28	-0.28	-0.31	-0.29	-0.25	-0.29	-0.31	-0.30
B_4	-0.29	-0.34	-0.27	-0.20	-0.28	-0.27	-0.29	-0.29	-0.25	-0.30	-0.29	-0.28
B_5	-0.31	-0.27	-0.27	-0.22	-0.27	-0.28	-0.25	-0.26	-0.30	-0.34	-0.27	-0.28
B_6	-0.29	-0.29	-0.28	-0.17	-0.29	-0.29	-0.32	-0.30	-0.27	-0.32	-0.30	-0.29
B_7	-0.21	-0.27	-0.30	-0.32	-0.32	-0.31	-0.33	-0.31	-0.36	-0.13	-0.30	-0.28
Total	-1.92	-1.91	-1.94	-1.41	-1.93	-1.93	-1.86	-1.92	-1.82	-1.85	-1.91	-1.94
(e_j)	0.987	0.981	0.998	0.723	0.990	0.994	0.957	0.985	0.937	0.952	0.983	0.997

Using Equation (4), the uncertainty values (d_j) for each (e_j) value were calculated and are presented in Table 6.

Table 6. 2019 The uncertainty value (d_j) of the value (e_j)

Criteria	AQ_1	AQ_2	AQ_3	BSS_1	RES_1	RES_2	PR_1	PR_2	LQ_1	LQ_2	CA_1	CA_2
(d_j)	0.013	0.019	0.002	0.277	0.010	0.006	0.043	0.015	0.063	0.048	0.017	0.003

The importance weight of each criterion was calculated using Equation (5) and is presented in Table 7. The criterion with the highest weight value is considered the best criterion.

Table 7. 2015-2024 Criterion Weight Values (w_j)

Criteria	AQ_1	AQ_2	AQ_3	BSS_1	RES_1	RES_2	PR_1	PR_2	LQ_1	LQ_2	CA_1	CA_2
2015	0.136	0.085	0.001	0.412	0.008	0.015	0.042	0.022	0.260	0.013	0.005	0.001
2016	0.117	0.062	0.001	0.297	0.005	0.005	0.016	0.006	0.472	0.012	0.006	0.002
2017	0.120	0.044	0.002	0.312	0.008	0.007	0.016	0.006	0.457	0.014	0.011	0.003
2018	0.026	0.032	0.002	0.285	0.011	0.009	0.025	0.009	0.549	0.037	0.012	0.003
2019	0,025	0,037	0,004	0,538	0,018	0,011	0,084	0,030	0,122	0,093	0,032	0,006
2020	0.019	0.057	0.003	0.522	0.015	0.015	0.044	0.011	0.246	0.036	0.029	0.005
2021	0.010	0.049	0.004	0.370	0.016	0.023	0.092	0.052	0.319	0.036	0.022	0.006
2022	0.009	0.072	0.003	0.571	0.012	0.014	0.086	0.029	0.140	0.022	0.031	0.013
2023	0.020	0.044	0.005	0.382	0.013	0.015	0.080	0.044	0.350	0.020	0.018	0.009
2024	0.013	0.066	0.007	0.516	0.023	0.017	0.157	0.062	0.037	0.045	0.044	0.013

As shown in Table 7, at the 2015 period, the criterion with the highest importance was BSS_1 (Loans Received/Total Assets) with a value of 0.412, while the criterion with the lowest importance weight was AQ_3 (Total Loans/Total Assets) with a value of 0.001. At the 2016 period, the criterion with the highest importance was LQ_1 (Liquid Assets/Short-Term Liabilities) with a value of 0.472, while the criterion with the lowest importance weight was AQ_3 (Total Loans/Total Assets) with a value of 0.001. At the 2017 period, the criterion with the highest importance was LQ_1 (Liquid Assets/Short-Term Liabilities) with a value of 0.457, while the criterion with the lowest importance weight was AQ_3 (Total Loans/Total Assets) with a value of 0.002. At the 2018 period, the criterion with the highest importance was LQ_1 (Liquid Assets/Short-Term Liabilities) with a value of 0.549, while the criterion with the lowest importance weight was AQ_3 (Total Loans/Total Assets) with a value of 0.002. At the 2019 period, the criterion with the highest importance was BSS_1 (Loans Received/Total Assets) with a value of 0.538, while the criterion with the lowest importance weight was AQ_3 (Total Loans/Total Assets) with a value of 0.04. At the 2020 period, the criterion with the highest importance rating was BSS_1 (Loans Received/Total Assets) with a value of 0.522. The criterion AQ_3 (Total Loans/Total Assets) had the lowest importance weighting this year with a value of 0.003. At the 2021 period, the criterion with the highest importance was BSS_1 (Loans Received/Total Assets) with a value of 0.370, while the criterion with the lowest importance weight was AQ_3 (Total Loans/Total Assets) with a value of 0.003. At the 2022 period, the criterion with the highest importance was BSS_1 (Loans Received/Total Assets) with a value of 0.571, while the criterion with the lowest importance weight was AQ_3 (Total Loans/Total Assets) with a value of 0.003. At the 2023 period, the criterion with the highest importance was BSS_1 (Loans Received/Total Assets) with a value of 0.382, while the criterion with the lowest importance weight was AQ_3 (Total Loans/Total Assets) with a value of 0.005. At the 2024 period, the criterion with the highest importance was BSS_1 (Loans Received/Total Assets) with a value of 0.516, while the criterion with the lowest importance weight was AQ_3 (Total Loans/Total Assets) with a value of 0.007.

When the 2015-2024 weightings were evaluated collectively, the benchmarks BSS_1 (Loans Received/Total Assets) and LQ_1 (Liquid Assets/Short-Term Liabilities) were found to be the most important benchmarks. while the AQ_3 (Total Loans/Total Assets) criteria were the least important criteria.

4.2. Application of CILOS Technique

This section presents the application steps and results of the CILOS technique, one of the multi-criteria decision-making techniques. In the first step of applying this technique, the initial decision sequence shown in Table 3, which also constitutes the first step of the Entropy technique, was utilised. In the second step of the CILOS technique, since only benefit-oriented criteria are included, the 'AQ_1' and 'BSS_1' criteria were converted to benefit-oriented status using Equation (6) and are presented in Table 8.

Table 8. Conversion of Cost-Based Criteria to Benefit-Based Criteria in 2019

Criteria	AQ_1	AQ_2	AQ_3	BSS_1	RES_1	RES_2	PR_1	PR_2	LQ_1	LQ_2	CA_1	CA_2
B_1	0.684	3.147	67.654	1.000	129.381	124.072	0.412	5.620	13.541	8.367	7.045	14.332
B_2	0.595	2.551	69.641	0.246	144.785	144.805	0.747	9.131	18.551	10.099	7.874	16.614
B_3	0.483	3.653	56.542	0.277	183.600	172.529	1.575	11.034	24.061	12.896	15.085	20.973
B_4	0.540	6.313	61.796	0.280	185.662	158.127	1.372	11.175	24.275	14.141	12.578	17.865
B_5	0.464	3.684	62.056	0.245	170.605	162.027	0.979	8.979	35.221	19.250	10.629	17.814
B_6	0.512	4.071	64.212	0.375	192.109	185.018	1.641	12.262	27.300	16.342	13.745	19.567
B_7	1.000	3.631	74.512	0.038	246.005	205.856	1.748	13.511	65.128	3.352	13.493	17.792

Using Equation (7), the utility-based decision set was normalised and standardised, and is presented in Table 9.

Table 9. 2019 Normalised Decision Set

Criteria	AQ_1	AQ_2	AQ_3	BSS_1	RES_1	RES_2	PR_1	PR_2	LQ_1	LQ_2	CA_1	CA_2
B_1	0.160	0.116	0.148	0.406	0.103	0.108	0.049	0.078	0.065	0.099	0.088	0.115
B_2	0.139	0.094	0.153	0.100	0.116	0.126	0.088	0.127	0.089	0.120	0.098	0.133
B_3	0.113	0.135	0.124	0.112	0.147	0.150	0.186	0.154	0.116	0.153	0.188	0.168
B_4	0.126	0.233	0.135	0.114	0.148	0.137	0.162	0.156	0.117	0.167	0.156	0.143
B_5	0.108	0.136	0.136	0.100	0.136	0.141	0.116	0.125	0.169	0.228	0.132	0.143
B_6	0.120	0.150	0.141	0.152	0.153	0.161	0.194	0.171	0.131	0.194	0.171	0.157
B_7	0.234	0.134	0.163	0.016	0.196	0.179	0.206	0.188	0.313	0.040	0.168	0.142

Using Equation (8), the Square A sequence, created by sorting the rows containing the maximum value in each column, is presented in Table 10. When preparing the Square A sequence, the maximum value of the first column forms the first diagonal, the maximum value of the second column forms the second diagonal, and the maximum value of the third column forms the third diagonal, and so on. The other elements of the rows are transferred to the Square A sequence as they are.

Table 10. 2019 A-Criterion Square Array Values

Criteria	AQ_1	AQ_2	AQ_3	BSS_1	RES_1	RES_2	PR_1	PR_2	LQ_1	LQ_2	CA_1	CA_2
AQ_1	0.234	0.134	0.163	0.016	0.196	0.179	0.206	0.188	0.313	0.040	0.168	0.142
AQ_2	0.126	0.233	0.135	0.114	0.148	0.137	0.162	0.156	0.117	0.167	0.156	0.143
AQ_3	0.234	0.134	0.163	0.016	0.196	0.179	0.206	0.188	0.313	0.040	0.168	0.142
BSS_1	0.160	0.116	0.148	0.406	0.103	0.108	0.049	0.078	0.065	0.099	0.088	0.115
RES_1	0.234	0.134	0.163	0.016	0.196	0.179	0.206	0.188	0.313	0.040	0.168	0.142
RES_2	0.234	0.134	0.163	0.016	0.196	0.179	0.206	0.188	0.313	0.040	0.168	0.142
PR_1	0.234	0.134	0.163	0.016	0.196	0.179	0.206	0.188	0.313	0.040	0.168	0.142
PR_2	0.234	0.134	0.163	0.016	0.196	0.179	0.206	0.188	0.313	0.040	0.168	0.142
LQ_1	0.234	0.134	0.163	0.016	0.196	0.179	0.206	0.188	0.313	0.040	0.168	0.142
LQ_2	0.108	0.136	0.136	0.100	0.136	0.141	0.116	0.125	0.169	0.228	0.132	0.143
CA_1	0.113	0.135	0.124	0.112	0.147	0.150	0.186	0.154	0.116	0.153	0.188	0.168
CA_2	0.113	0.135	0.124	0.112	0.147	0.150	0.186	0.154	0.116	0.153	0.188	0.168

Using the data in Table 11, the relative loss sequence for the criteria was prepared using Equation (9) and is presented in Table 11.

Table 11. 2019 P-Criterion Relative Loss Sequence Values

Criteria	AQ_1	AQ_2	AQ_3	BSS_1	RES_1	RES_2	PR_1	PR_2	LQ_1	LQ_2	CA_1	CA_2
AQ_1	0.000	0.425	0.000	0.962	0.000	0.000	0.000	0.000	0.000	0.826	0.106	0.152
AQ_2	0.460	0.000	0.171	0.720	0.245	0.232	0.215	0.173	0.627	0.265	0.166	0.148
AQ_3	0.000	0.425	0.000	0.962	0.000	0.000	0.000	0.000	0.000	0.826	0.106	0.152
BSS_1	0.316	0.502	0.092	0.000	0.474	0.397	0.764	0.584	0.792	0.565	0.533	0.317
RES_1	0.000	0.425	0.000	0.962	0.000	0.000	0.000	0.000	0.000	0.826	0.106	0.152
RES_2	0.000	0.425	0.000	0.962	0.000	0.000	0.000	0.000	0.000	0.826	0.106	0.152
PR_1	0.000	0.425	0.000	0.962	0.000	0.000	0.000	0.000	0.000	0.826	0.106	0.152
PR_2	0.000	0.425	0.000	0.962	0.000	0.000	0.000	0.000	0.000	0.826	0.106	0.152
LQ_1	0.000	0.425	0.000	0.962	0.000	0.000	0.000	0.000	0.000	0.826	0.106	0.152
LQ_2	0.536	0.417	0.167	0.755	0.306	0.213	0.440	0.335	0.459	0.000	0.295	0.151
CA_1	0.517	0.421	0.241	0.723	0.254	0.162	0.099	0.183	0.631	0.330	0.000	0.000
CA_2	0.517	0.421	0.241	0.723	0.254	0.162	0.099	0.183	0.631	0.330	0.000	0.000

The F series given in Equation (11) has been calculated and prepared as shown in Table 12 below.

Table 12. 2019 F-Series Values

Criteria	AQ_1	AQ_2	AQ_3	BSS_1	RES_1	RES_2	PR_1	PR_2	LQ_1	LQ_2	CA_1	CA_2
AQ_1	-2.345	0.425	0.000	0.962	0.000	0.000	0.000	0.000	0.000	0.826	0.106	0.152
AQ_2	0.460	-4.734	0.171	0.720	0.245	0.232	0.215	0.173	0.627	0.265	0.166	0.148
AQ_3	0.000	0.425	-0.912	0.962	0.000	0.000	0.000	0.000	0.000	0.826	0.106	0.152
BSS_1	0.316	0.502	0.092	-9.652	0.474	0.397	0.764	0.584	0.792	0.565	0.533	0.317
RES_1	0.000	0.425	0.092	0.962	-1.533	0.000	0.000	0.000	0.000	0.826	0.106	0.152
RES_2	0.000	0.425	0.000	0.962	0.000	-1.166	0.000	0.000	0.000	0.826	0.106	0.152
PR_1	0.000	0.425	0.000	0.962	0.000	0.000	-1.617	0.000	0.000	0.826	0.106	0.152
PR_2	0.000	0.425	0.000	0.962	0.000	0.000	0.000	-1.459	0.000	0.826	0.106	0.152
LQ_1	0.000	0.425	0.000	0.962	0.000	0.000	0.000	0.000	-3.140	0.826	0.106	0.152
LQ_2	0.536	0.417	0.000	0.755	0.306	0.213	0.000	0.335	0.459	-7.272	0.295	0.151
CA_1	0.517	0.421	0.167	0.723	0.254	0.162	0.440	0.183	0.631	0.330	-1.734	0.000
CA_2	0.517	0.421	0.241	0.723	0.254	0.162	0.099	0.183	0.631	0.330	0.000	-1.677

The F series presented in Table 13 was used in the equation $Fq^T=0$ given in Equation (10), and the q importance levels were calculated by satisfying the condition in Equation (12). Table 13 presents the normalised q criterion weights analysed for 2015-2024 using the CILOS technique.

Table 13. 2015-2024 CILOS Criteria Weightings

Criteria	AQ_1	AQ_2	AQ_3	BSS_1	RES_1	RES_2	PR_1	PR_2	LQ_1	LQ_2	CA_1	CA_2
2015	0.014	0.025	0.332	0.026	0.059	0.037	0.027	0.034	0.016	0.068	0.192	0.168
2016	0.020	0.034	0.195	0.034	0.104	0.080	0.073	0.092	0.020	0.046	0.193	0.109
2017	0.021	0.033	0.109	0.036	0.095	0.072	0.102	0.142	0.021	0.037	0.211	0.121
2018	0.031	0.039	0.120	0.041	0.057	0.063	0.082	0.274	0.017	0.024	0.134	0.118
2019	0.055	0.050	0.140	0.044	0.092	0.110	0.079	0.088	0.041	0.037	0.135	0.130
2020	0.162	0.043	0.102	0.041	0.087	0.084	0.064	0.140	0.029	0.036	0.083	0.129
2021	0.184	0.040	0.079	0.049	0.069	0.057	0.076	0.116	0.025	0.035	0.099	0.172
2022	0.133	0.034	0.123	0.040	0.124	0.092	0.056	0.098	0.034	0.042	0.086	0.139
2023	0.095	0.058	0.105	0.051	0.074	0.075	0.067	0.135	0.032	0.074	0.125	0.109
2024	0.198	0.058	0.122	0.041	0.077	0.088	0.048	0.067	0.082	0.055	0.067	0.097

As shown in Table 13, at the 2015 period, the criterion with the highest importance was AQ_3 (Total Loans/Total Assets) with a value of 0.332, while the criterion with the lowest importance weight was AQ_1 (Non-Performing Loans / Total Loans) with a value of 0.014. At the 2016 period, the criterion with the highest importance was AQ_3 (Total Loans/Total Assets) with a value of 0.195, while the criterion with the lowest importance weight was AQ_1 (Non-Performing Loans / Total Loans) with a value of 0.020. At the 2017 period, the criterion with the highest importance was CA_1 (Equity/Total Assets) with a value of 0.211, while the criterion with the lowest importance weight was AQ_1 (Non-Performing Loans / Total Loans) with a value of 0.021. At the 2018 period, the criterion with the highest importance was PR_2 (Average Return on Equity) with a value of 0.274, while the criterion with the lowest importance weight was LQ_1 (Liquid Assets/Short-Term Liabilities) with a value of 0.017. At the 2019 period, the criterion with the highest importance was AQ_3 (Total Loans/Total Assets) with a value of 0.140, while the criterion with the lowest importance weight was LQ_2 (Liquid Assets/Total Assets) with a value of 0.037. At the 2020 period, the criterion with the highest importance rating was AQ_1 (Non-Performing Loans /Total Loans) with a value of 0.162. The criterion LQ_1 (Liquid Assets/Short-Term Liabilities) had the lowest importance weighting this year with a value of 0.029. At the 2021 period, the criterion with the highest importance was AQ_1 (Non-Performing Loans /Total Loans) with a value of 0.184, while the criterion with the lowest importance weight was LQ_1 (Liquid Assets/Short-Term Liabilities) with a value of 0.025. At the 2022 period, the criterion with the highest importance was CA_2 (Capital Adequacy Ratio) with a value of 0.139, while the criterion with the lowest importance weight was LQ_1 (Liquid Assets/Short-Term Liabilities) with a value of 0.034. At the 2023 period, the criterion with the highest importance was PR_2 (Average Return on Equity) with a value of 0.135, while the criterion with the lowest importance weight was LQ_1 (Liquid Assets/Short-Term Liabilities) with a value of 0.032. At the 2024 period, the criterion with the highest importance was AQ_1 (Non-Performing Loans /Total Loans) with a value of 0.198, while the criterion with the lowest importance weight was BSS_1 (Loans Received/Total Assets) with a value of 0.041.

When the weightings for the 2015–2024 period are assessed collectively: AQ_3 (Total Loans/Total Assets) in 2015, 2016 and 2019; CA_1 (Equity/Total Assets) in 2017; in 2018, PR_2 (Average Return on Equity); in 2020, 2021 and 2024, AQ_1 (Non-Performing Loans/Total Loans); in 2022, CA_2 (Capital Adequacy Ratio); in 2023, PR_2 (Average Return on Equity) were identified as the most significant indicators. In 2015, 2016 and 2017, AQ_1 (Non-Performing Loans / Total Loans); in 2018, 2020, 2021, 2022 and 2023, LQ_1 (Liquid Assets / Short-Term Liabilities); in 2019, LQ_2 (Liquid Assets/Total Assets); in 2024, the BSS_1 (Loans Received/Total Assets) criterion was found to be the least significant criterion.

4.3. Application of IDOCRIW Technique

In this section, IDOCRIW criterion weights were calculated using the criterion weights obtained as a result of applying the Entropy and CILOS techniques. Using the entropy and CILOS criterion weights presented in Table 7 and Table 13, the importance weights were calculated using the IDOCRIW technique via Equation (13) and are presented in Table 14.

Table 14. 2015-2024 IDOCRIW Criteria Importance Values

	AQ_1	AQ_2	AQ_3	BSS_1	RES_1	RES_2	PR_1	PR_2	LQ_1	LQ_2	CA_1	CA_2
2015	0.080	0.088	0.013	0.445	0.020	0.023	0.046	0.031	0.172	0.035	0.039	0.007
2016	0.081	0.073	0.008	0.350	0.018	0.014	0.041	0.020	0.331	0.019	0.038	0.006
2017	0.078	0.045	0.007	0.348	0.023	0.016	0.050	0.026	0.307	0.016	0.072	0.012
2018	0.025	0.039	0.007	0.367	0.020	0.017	0.064	0.076	0.296	0.028	0.051	0.009
2019	0.026	0.035	0.009	0.443	0.032	0.023	0.126	0.049	0.094	0.066	0.083	0.015

2020	0.069	0.053	0.006	0.472	0.029	0.027	0.062	0.035	0.156	0.028	0.052	0.013
2021	0.036	0.039	0.007	0.363	0.022	0.026	0.139	0.121	0.158	0.025	0.042	0.021
2022	0.026	0.052	0.007	0.484	0.031	0.027	0.101	0.059	0.100	0.019	0.056	0.037
2023	0.036	0.047	0.009	0.363	0.017	0.021	0.099	0.112	0.209	0.027	0.043	0.018
2024	0.049	0.072	0.016	0.400	0.034	0.027	0.141	0.078	0.057	0.047	0.056	0.023

As shown in Table 14, at the 2015 period, the criterion with the highest importance was BSS_1 (Loans Received/Total Assets) with a value of 0.445, while the criterion with the lowest importance weight was CA_2 (Capital Adequacy Ratio) with a value of 0.007. At the 2016 period, the criterion with the highest importance was BSS_1 (Loans Received/Total Assets) with a value of 0.350, while the criterion with the lowest importance weight was CA_2 (Capital Adequacy Ratio) with a value of 0.006. At the 2017 period, the criterion with the highest importance was BSS_1 (Loans Received/Total Assets) with a value of 0.348, while the criterion with the lowest importance weight was AQ_3 (Total Loans/Total Assets) with a value of 0.007. At the 2018 period, the criterion with the highest importance was BSS_1 (Loans Received/Total Assets) with a value of 0.367, while the criterion with the lowest importance weight was AQ_3 (Total Loans/Total Assets) with a value of 0.007. At the 2019 period, the criterion with the highest importance was BSS_1 (Loans Received/Total Assets) with a value of 0.443, while the criterion with the lowest importance weight was AQ_3 (Total Loans/Total Assets) with a value of 0.009. At the 2020 period, the criterion with the highest importance rating was BSS_1 (Loans Received/Total Assets) with a value of 0.472. The criterion AQ_3 (Total Loans/Total Assets) had the lowest importance weighting this year with a value of 0.006. At the 2021 period, the criterion with the highest importance was BSS_1 (Loans Received/Total Assets) with a value of 0.363, while the criterion with the lowest importance weight was AQ_3 (Total Loans/Total Assets) with a value of 0.007. At the 2022 period, the criterion with the highest importance was BSS_1 (Loans Received/Total Assets) with a value of 0.484, while the criterion with the lowest importance weight was AQ_3 (Total Loans/Total Assets) with a value of 0.007. At the 2023 period, the criterion with the highest importance was BSS_1 (Loans Received/Total Assets) with a value of 0.363, while the criterion with the lowest importance weight was AQ_3 (Total Loans/Total Assets) with a value of 0.009. At the 2024 period, the criterion with the highest importance was BSS_1 (Loans Received/Total Assets) with a value of 0.400, while the criterion with the lowest importance weight was AQ_3 (Total Loans/Total Assets) with a value of 0.016.

When the weightings for the 2015–2024 period are assessed collectively: BSS_1 (Loans Received/Total Assets) has been identified as the most significant indicator for all years. In 2015 and 2016, CA_2 (Capital Adequacy Ratio); and in 2017, 2018, 2019, 2020, 2021, 2022, 2023 and 2024, AQ_3 (Total Loans/Total Assets) was found to be the least significant criterion.

Table 15 presents the rankings of the Entropy (E), CILOS (C) and IDOCRIW (I) criterion importance values for 2015-2024.

Table 15. 2015-2024 Entropy, CILOS and IDOCRIW Criteria Rankings

	2015			**2016**			**2017**			**2018**			**2019**			**2020**			**2021**			**2022**			**2023**			**2024**		
	E	**C**	**I**	**E**	**C**	**I**	**E**	**C**	**I**	**E**	**C**	**I**	**E**	**C**	**I**	**E**	**C**	**I**	**E**	**C**	**I**	**E**	**C**	**I**	**E**	**C**	**I**	**E**	**C**	**I**
AQ_1	3	12	4	3	12	3	3	12	3	5	10	8	8	8	9	7	***1***	3	10	***1***	7	11	2	10	6	5	7	10	***1***	7
AQ_2	4	10	3	4	9	4	4	10	6	4	9	6	5	9	7	3	9	5	5	10	6	4	11	6	5	10	5	3	9	4
AQ_3	12	***1***	11	12	***1***	11	12	4	12	12	3	12	12	***1***	12	12	4	12	12	5	12	12	4	12	12	4	12	12	2	12
BSS_1	***1***	9	***1***	2	9	***1***	2	9	***1***	2	8	***1***	***1***	10	***1***	***1***	10	***1***	***1***	9	***1***	***1***	10	***1***	***1***	11	***1***	***1***	12	***1***
RES_1	9	5	10	9	4	9	8	6	8	8	7	9	9	5	8	8	5	8	9	7	10	10	3	8	10	7	11	8	6	9
RES_2	7	6	9	10	6	10	9	7	9	10	6	10	10	4	10	9	6	10	7	8	8	8	6	9	9	6	9	9	4	10

PR_1	5	8	5	5	7	5	5	5	5	6	5	4	4	7	2	4	8	4	3	6	3	3	8	2	3	9	4	2	11	2
PR_2	6	7	8	7	5	7	10	2	7	9	***1***	3	7	6	6	10	2	7	4	3	4	6	5	4	4	***1***	3	4	7	3
LQ_1	2	11	2	***1***	11	2	***1***	11	2	***1***	12	2	2	11	3	2	12	2	2	12	2	2	12	3	2	12	2	7	5	5
LQ_2	8	4	7	6	8	8	6	8	9	3	11	7	3	12	5	5	11	9	6	11	9	7	9	11	7	7	8	5	10	8
CA_1	10	2	6	8	2	6	7	***1***	4	7	2	5	6	2	4	6	7	6	8	4	5	5	7	5	8	2	6	6	7	6
CA_2	11	3	12	11	3	12	11	3	11	11	4	11	11	3	11	11	3	11	11	2	11	9	***1***	7	11	3	10	11	3	11

According to Table 15, in 2015, the criterion ranked first according to the Entropy and IDOCRIW techniques was the BSS_1 (Loans Received/Total Assets) criterion, while the criterion ranked first according to the CILOS technique was the AQ_3 (Total Loans/Total Assets) criterion. In 2015, the criterion AQ_3 (Total Loans/Total Assets) ranked last according to the Entropy, CA_2 (Capital Adequacy Ratio) IDOCRIW techniques, while the criterion AQ_1 (Non-Performing Loans / Total Loans) ranked last according to the CILOS technique. In 2016, according to the Entropy method, the criterion ranked first was LQ_1 (Liquid Assets/Short-Term Liabilities), whilst according to the IDOCRIW methods it was BSS1 (Loans Received/Total Assets); according to the CILOS method, the criterion ranked first was AQ_3 (Total Loans/Total Assets). In 2016, the AQ_3 criterion (Total Loans/Total Assets) ranked lowest according to the Entropy method, whilst the CA_2 (Capital Adequacy Ratio) ranked lowest according to IDOCRIW technique; meanwhile, the AQ_1 criterion (Non-performing Loans/Total Loans) ranked lowest according to the CILOS technique. In 2017, according to the Entropy method, the criterion ranked first was LQ_1 (Liquid Assets/Short-Term Liabilities), whilst according to the IDOCRIW methods it was BSS1 (Loans Received/Total Assets); according to the CILOS method, the criterion ranked first was CA_1 (Equity/Total Assets). In 2017, the criterion AQ_3 (Total Loans/Total Assets) ranked last according to the Entropy and IDOCRIW techniques, while the criterion AQ_1 (Non-performing Loans/Total Loans) ranked last according to the CILOS technique. In 2018, according to the Entropy method, the criterion ranked first was LQ_1 (Liquid Assets/Short-Term Liabilities), whilst according to the IDOCRIW methods it was BSS1 (Loans Received/Total Assets); according to the CILOS method, the criterion ranked first was PR_2 (Average Return on Equity). In 2018, the criterion AQ_3 (Total Loans/Total Assets) ranked last according to the Entropy and IDOCRIW techniques, while the criterion LQ_1 (Liquid Assets/Short-Term Liabilities) ranked last according to the CILOS technique. In 2019, the criterion ranked first according to the Entropy and IDOCRIW techniques was the BSS_1 (Loans Received/Total Assets) criterion, while the criterion ranked first according to the CILOS technique was the AQ_3 (Total Loans/Total Assets) criterion. In 2019, the criterion AQ_3 (Total Loans/Total Assets) ranked last according to the Entropy and IDOCRIW techniques, while the criterion LQ_2 (Liquid Assets/Total Assets) ranked last according to the CILOS technique. In 2020, the criterion ranked first according to the Entropy and IDOCRIW techniques was the BSS_1 (Loans Received/Total Assets) criterion, while the criterion ranked first according to the CILOS technique was the AQ_1 (Non-Performing Loans/Total Loans) criterion. In 2020, the criterion AQ_3 (Total Loans/Total Assets) ranked last according to the Entropy and IDOCRIW techniques, while the criterion LQ_1 (Liquid Assets/Short-Term Liabilities) ranked last according to the CILOS technique. In 2021, the criterion ranked first according to the Entropy and IDOCRIW techniques was the BSS_1 (Loans Received/Total Assets) criterion, while the criterion ranked first according to the CILOS technique was the AQ_1 (Non-Performing Loans/Total Loans) criterion. In 2021, the criterion AQ_3 (Total Loans/Total Assets) ranked last according to the Entropy and IDOCRIW techniques, while the criterion LQ_1 (Liquid Assets/Short-Term Liabilities) ranked last according to the CILOS technique. In 2022, the criterion ranked first according to the Entropy and IDOCRIW techniques was the BSS_1 (Loans Received/Total Assets) criterion, while the criterion ranked first according to the CILOS technique was the CA_2 (Capital Adequacy Ratio) criterion. In 2022, the criterion AQ_3 (Total Loans/Total Assets) ranked last according to the Entropy and

IDOCRIW techniques, while the criterion LQ_1 (Liquid Assets/Short-Term Liabilities) ranked last according to the CILOS technique. In 2023, the criterion ranked first according to the Entropy and IDOCRIW techniques was the BSS_1 (Loans Received/Total Assets) criterion, while the criterion ranked first according to the CILOS technique was the PR_2 (Average Return on Equity) criterion. In 2023, the criterion AQ_3 (Total Loans/Total Assets) ranked last according to the Entropy and IDOCRIW techniques, while the criterion LQ_1 (Liquid Assets/Short-Term Liabilities) ranked last according to the CILOS technique. In 2024, the criterion ranked first according to the Entropy and IDOCRIW techniques was the BSS_1 (Loans Received/Total Assets) criterion, while the criterion ranked first according to the CILOS technique was the AQ_1 (Non-Performing Loans /Total Loans) criterion. In 2024, the criterion AQ_3 (Total Loans/Total Assets) ranked last according to the Entropy and IDOCRIW techniques, while the criterion BSS_1 (Loans Received/Total Assets) ranked last according to the CILOS technique.

An examination of the findings reveals that the BSS_1 (Loans Received/Total Assets) ratio consistently exhibits the highest weight under both the Entropy and IDOCRIW techniques throughout the analyzed period. However, this result should not be interpreted directly as this ratio being the most vital indicator of banking performance per se. In decision theory, the Entropy-based approach determines weights strictly based on the degree of data dispersion, contrast intensity, and informational variance among the alternatives (banks). In the context of the Turkish banking sector, there is a structural divergence in funding mechanisms between investment/development banks (TSKB) and traditional commercial/state banks within the index. Since investment banks are prohibited from accepting deposits, they rely heavily on foreign and domestic loans received for institutional funding, creating a massive statistical variance compared to commercial banks. Consequently, this high data dispersion triggers the mathematical structure of the Entropy method, yielding a dominant weight. This outcome serves as a methodological validation rather than a performance hierarchy, indicating that decision-makers must evaluate objective weights in conjunction with sectoral and structural realities.

5. CONCLUSION

This study examined the relative importance of twelve financial ratios employed in the analysis of the financial structures for seven banks listed on the BIST Liquid Bank Index (XLBNK) over the 2015–2024 period, employing three objective multi-criteria decision-making (MCDM) weighting techniques Entropy, CILOS, and IDOCRIW in an integrated and comparative framework. The evaluation criteria encompassed six performance dimensions: asset quality (non-performing loans/total loans, fixed assets/total assets, total loans/total assets), balance sheet structure (loans received/total assets), income-expense structure (interest income/interest expenses, total income/total expenses), profitability (average return on assets, average return on equity), liquidity (liquid assets/short-term liabilities, liquid assets/total assets), and capital adequacy (equity/total assets, capital adequacy ratio). The findings obtained go beyond being mere mathematical outputs; they offer important economic and financial insights that shed light on the structural transformation of the Turkish banking sector over the past decade, its funding strategies and its macroeconomic vulnerabilities.

The Entropy technique results reveal that the BSS1 (Loans Received/Total Assets) ratio emerged as the most important criterion in the majority of the years analysed (2015, 2019, 2020, 2021, 2022, 2023, and 2024), with importance weight values ranging from 0.297 to 0.571. The LQ_1 (Liquid Assets/Short-Term Liabilities) ratio, on the other hand, dominated in the 2016, 2017, and 2018 periods, recording values between 0.457 and 0.549. From a methodological standpoint, the Entropy technique assigns higher weights to criteria exhibiting greater dispersion across alternatives; accordingly, the consistently dominant position of BSS_1 reflects the pronounced structural heterogeneity of the XLBNK sample with respect to external borrowing. This heterogeneity is primarily attributable to the presence of Türkiye Sınai Kalkınma Bankası (B_7), a development and investment bank that finances its operations predominantly through long-term international borrowings rather than retail deposits, resulting in a BSS_1 value of 62.7 in 2019 compared to a range of 2.4–9.8 for the remaining six banks. The AQ_3 (Total Loans/Total Assets) ratio consistently recorded the lowest importance weight across all years (0.001–0.007), indicating that this ratio exhibits the least inter-bank variability within the sample and therefore contributes minimally to performance differentiation under the Entropy framework.

The CILOS technique, which evaluates the relative impact loss of each criterion when another is set to its optimal value, produced markedly different weightings from those of the Entropy method, thereby demonstrating the complementary nature of the two approaches. Under the CILOS framework, AQ_3 (Total Loans/Total Assets) ranked first in 2015, 2016, and 2019; CA_1 (Equity/Total Assets) in 2017; PR_2 (Average Return on Equity) in 2018 and 2023; AQ_1 (Non-Performing Loans/Total Loans) in 2020, 2021, and 2024; and CA_2 (Capital Adequacy Ratio) in 2022. The prominence of AQ_1 during the 2020–2021 period is particularly noteworthy, as this coincides with the acute phase of the COVID-19 pandemic, during which asset quality deterioration and non-performing loan pressures intensified across the Turkish banking sector. Similarly, the elevated importance of CA_1 and CA_2 in certain periods reflects the critical role of solvency buffers in maintaining regulatory compliance and investor confidence during episodes of macroeconomic stress. The CILOS technique also produces weight distributions that are considerably more balanced than those of the Entropy method ranging from 0.029 to 0.162 in 2020 compared to 0.003 to 0.522 indicating that, from a systemic inter criterion perspective, the financial ratios of XLBNK banks are more evenly consequential than the data dispersion analysis alone would suggest.

The IDOCRIW technique, which mathematically integrates the Entropy and CILOS weights, consistently identified BSS_1 (Loans Received/Total Assets) as the most important criterion across all ten years of the study period, with importance weight values ranging from 0.348 (2017) to 0.484 (2022). This finding underscores that, when both data dispersion and inter-criterion impact loss are considered simultaneously, the external funding structure of banks constitutes the single most differentiating financial ratio in terms of criterion importance weight within the XLBNK sample throughout the entire 2015–2024 period. The AQ_3 (Total Loans/Total Assets) ratio was identified as the least important criterion under IDOCRIW for 2017–2024, while CA_2 (Capital Adequacy Ratio) held this position in 2015 and 2016. The convergence between Entropy and IDOCRIW rankings in which BSS1 consistently ranks first under both techniques confirms that the dominant signal in this dataset is the structural dispersion in external borrowing rather than inter-criterion systemic interactions. The importance weight levels under the IDOCRIW technique ranged from 0.009 to 0.443 in 2019 and from 0.006 to 0.472 in 2020, reflecting an intermediate distributional profile between the highly dispersed Entropy weights and the more balanced CILOS weights.

A comparative assessment of the three techniques reveals both convergences and divergences that carry substantive analytical implications. The weight ranking results produced by the Entropy and IDOCRIW techniques are broadly similar across all ten years a finding attributable to the structural dominance of BSS1 dispersion in the dataset, which propagates from the Entropy component into the integrated IDOCRIW weights. However, the CILOS technique produces materially different rankings, particularly in the post-2019 period, where AQ_1 (Non-Performing Loans/Total Loans) rises to prominence as pandemic-related credit quality pressures intensify. This divergence is not a methodological inconsistency; rather, it reflects the distinct informational content of each technique. Entropy captures what is most variable; CILOS captures what is most systemically consequential; and IDOCRIW synthesises both signals. The implication for practitioners is that reliance on a single objective weighting method may provide an incomplete picture of financial ratio importance, and that the IDOCRIW framework offers a more comprehensive and robust basis for performance assessment.

The consistently dominant weight assigned to BSS_1 (Loans Received/Total Assets) under both the Entropy and IDOCRIW techniques across the 2015–2024 period carries significant analytical implications for financial ratio analysis results evaluation in the Turkish banking sector. From a financial perspective, the primacy of this ratio underscores the critical role of funding structure during a decade characterised by exchange rate volatility, tightening global liquidity conditions, and significant macroeconomic shocks including the 2018 currency crisis and the COVID-19 pandemic. The ratio's dominance suggests that how banks manage their external funding dependency constitutes the single most differentiating financial ratio in terms of criterion importance weight within the XLBNK sample, and should therefore be accorded particular attention by investors and regulatory authorities such as the BDDK and TCMB in their risk assessment frameworks.

The fact that the BSS_1 (Loans Received / Total Assets) consistently carried the highest weighting in both the Entropy and IDOCRIW methods throughout the analysis period highlights the Turkish banking sector's structure of dependence on external funding and syndicated loans as a form of financial asymmetry. The Entropy mechanisms assignment of a high weight to this ratio stems from the extreme divergence (contrast intensity) between the funding models of traditional deposit-taking banks and development/investment banks (such as TSKB) that lack the authority to take deposits. From an economic perspective, this situation confirms that the local deposit pool is insufficient to sustain the Turkish banking systems balance sheet growth and that banks are intrinsically dependent on global liquidity conditions (international syndication, securitisation and eurobond issuances). The dominant weight of BSS_1 serves as an economic indicator showing just how high banks external debt roll over risk and consequently their systemic risk sensitivity is during macroeconomic shocks or exchange rate fluctuations.

An Assessment of CILOS Results in Terms of the Relationship Between Financial Vulnerability and Profitability The CILOS method, which measures the loss of systemic impact of the criteria on one another rather than outliers in the data, highlights ratios such as AQ_1 (Non-Performing Loans/Total Loans) and PR_2 (Average Return on Equity) highlights the delicate balance between fragility and profitability in the banking sector. The high systemic impact of AQ_1 (asset quality) demonstrates that deteriorations in the loan portfolio (an increase in NPLs) are not merely a loss item, but the primary source of fragility that paralyses the bank's debt-repayment capacity and the efficiency of its resource allocation. The prominence of PR_2 (Average Return on Equity), meanwhile, indicates that, in an environment of high inflation and volatile interest rates, banks are obliged to safeguard equity profitability in order to prevent capital erosion and finance sustainable growth. The CILOS findings highlight the following fundamental economic reality: sustainable profitability (PR_2) in the Turkish banking sector is only possible through the disciplined management of asset quality (AQ_1) and the minimisation of vulnerabilities; maintaining one without the other triggers systemic risk.

The dynamic criterion weights derived from the research serve as strategic decision-support tools for the sector's various stakeholders: For policymakers, the high weighting of BSS_1 indicates that macroprudential measures (such as reserve requirements or syndicated lending limits) should be designed to reduce external debt dependence. Furthermore, CILOS's emphasis on AQ_1 can be used as an early warning signal to monitor asset quality during periods of economic slowdown. For investors wishing to make rational portfolio choices within the XLBNK index, this study offers the opportunity to subject banks to a multi-dimensional risk-return analysis based not only on their overall profitability but also on their external funding risks (BSS_1) and capital adequacy structures (CA_1, CA_2). For senior bank management, these weightings serve as a guide for capital allocation and strategic planning. Managers should identify the ratios highlighted by Entropy and CILOS (BSS_1, AQ_1, PR_2) as key performance indicators and, whilst optimising the external debt/deposit balance in asset-liability management, prioritise credit scoring models that safeguard asset quality.

This study makes several contributions to the existing literature. First, it addresses a methodological gap by demonstrating that the one-dimensional application of the Entropy method which dominates the existing MCDM banking literature in Türkiye—may overweight criteria that are structurally outlier-driven rather than genuinely important from an inter-criterion systemic perspective. Second, by covering the 2015–2024 period, the study captures the full arc of pre-crisis stability, the acute COVID-19 shock, and the post-pandemic normalisation phase, enabling a dynamic assessment of how financial ratio priorities shift under different macroeconomic regimes. Third, the exclusive focus on the XLBNK index comprising the most liquid and market-active banks on BIST ensures a structurally homogeneous sample while simultaneously generating findings of direct relevance to market participants and regulators. Future research could extend this framework by combining the IDOCRIW weighting technique with ranking methods such as TOPSIS, MARCOS, or CRADIS to produce a comprehensive performance ranking of XLBNK banks across the full study period, or by applying the methodology to other sectoral indices to assess the generalisability of the findings.

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EVALUATION OF RATIO ANALYSIS RESULTS WITH ENTROPY, CILOS AND IDOCRIW TECHNIQUES: AN APPLICATION IN BORSA ISTANBUL LIQUID BANK INDEX

Research and Publication Ethics Statement

The author declares that all ethical principles and rules were carefully observed during the collection, analysis, and reporting of the data. The author also accepts full responsibility for the use of all images, figures, photographs, and similar materials included in this study.

Author Contributions:

This study was prepared as a single-authored work.

Ethics Committee Approval:

The author declares that Ethics Committee Approval was not required for this study.