Research Article

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Financial Performance Evaluating and Ranking Approach for Banks in Bist Sustainability Index Using Topsis and K-Means Clustering Method

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Abstract

The purpose of this study is to identify, analyze, and evaluate the differences between banks in the Borsa İstanbul (BIST) Sustainability Index and other banks based on their financial performance. This study employs an approach based on a technique for order of preference by similarity to an ideal solution to evaluate and rank 46 Turkish banks with an evaluation framework consisting of 11 financial ratios between 2015 and 2019. The entropy, equal weight, standard, and variance methods were adapted to determine the weights of the financial ratios. Ultimately, the closeness coefficients of the banks derived from the four different weighted TOPSIS methods assist in identifying the positions of banks within other banks using K-means clustering analysis. However, this analysis has two main drawbacks. One is to determine the value of k and the other is to select the initial centers. The Calinski-Harabsz Index (CHI) was used to determine the validity of k. To solve the initial center drawback, we ran the clustering algorithm for all combinations of initial centers from the dataset. CHI is again used to determine which cluster group, derived from a different initial center, is more accurate. Finally, we present the results obtained by using this process for a set of 46 banks.

Keywords: *Financial Ratios, Calinski-Habarski Method, K-Means Clustering, Sustainability Index, TOPSIS*

1. Introduction

The banking industry is a foundational element of a country's financial system and crucial for financial and economic progress. Banks are the most crucial and major institutions that perform financial intermediation services and consist of different types of institutions with complex structures and functions, such as pension funds and insurance companies. Banks measure their financial performance for various reasons, such as in the sector of position, by making a comparison between themselves and their benchmarks and determining whether the organization is successful for both themselves and their shareholders (Parker, 2000:63). In addition, banks need to evaluate their financial performance to improve their productivity and competitiveness, because they have a highly dynamic and competitive environment. Recent research has assessed performance evaluation as an important issue especially in developed countries (Brauers, Ginevičius & Podviezko, 2014; Buallay et al., 2020; Finger, Gavious & Manos, 2018; Kwon & Lee, 2015; Pinto et al., 2017; Rebai, Azaiez & Saidane, 2012; Reddy, 2015).

Analyzing financial ratios is the standard tool for assessing financial performance. (Adedeji, 2014; Alam, Raza & Akram, 2011; Bansal, 2014; Cinca, Molinero & Larraz, 2005; Habib, 2015; Kumbirai & Webb, 2010; Rashid, 2018; Rodriguez & Rodriguez, 2018; Tarawneh, 2006; Wang, Lu & Wang, 2013). The complexity of corporate operations has led to an increase in the use of various methodologies that combine many indicators to evaluate financial performance in a multidimensional manner (Ahsan, 2016; Avkiran, 2011; Baral, 2005; Campisi et al., 2019; Matthew & Esther, 2012; Nimalathasan, 2008; Pekkaya & Erol Demir, 2018; Rao & Ibrahim, 2017; Sarlin & Eklund, 2013; Singh & Singla, 2016; Yüksel et al., 2018). Currently, banks are aware that if they ignore different types of issues, such as ethical, environmental, economic, social, and good corporate governance practices, they will face the risk of losing their reputation and customers, which means that it is not enough for them to achieve financial success with only commercial service production and sales. Therefore, the concept of sustainability is frequently on the agendas of banks and investors (Öner Kaya, 2010:76).

Sustainability is often associated with corporate social responsibility and involves customers, the community, environmental resources, employees, and reputation (Heizer, Render & Munson, 2017:233). With the inclusion of social responsibility, an increasing number of banks have begun publishing sustainability reports. The main purpose of this report is to measure a bank's ecological footprint and show the link between its financial and non-financial performance. Buallay et al. (2020) aimed to examine the relationship between bank performance after a financial crisis and sustainability reporting in developed and developing countries. To achieve sustainable development In Turkey, BIST has constructed an index that measures the responsibilities of certain businesses in both the social and environmental areas.

It is of great significance to assess, rank, and determine the similarities/dissimilarities of banks based on their financial performance, which can provide great benefits for understanding their natural structure. Ranking alternatives with respect to many properties is a primary issue in the Multi-Criteria Decision Making (MCDM) process. In this process, alternatives stand for banks and properties are the criteria that can measure financial performance. MCDM approaches appraise financial and/or non-financial criteria for performance evaluation of banks (Chang, 2006; Dubey & Sangle, 2019; Ho & Wu, 2006; Fukuyama & Matousek, 2017; Hunjak & Jakovčević, 2001; Hussain & Hoque, 2002; Ic et al., 2020; Kumar, Malathy & Ganesh, 2010; Misra & Arrawatia, 2013; Shah, Wu & Korotkov, 2019; Shaverdi, Akbari & Fallah Tafti, 2011; Wu, Tzeng & Chen, 2009). MCDM techniques have also been used to evaluate and compare the financial performance of banks in Turkey (Bayrakdaroğlu & Ege, 2008; Çetin & Çetin, 2010; Doğan, 2013; Ertuğrul & Karakaşoğlu, 2009; Gökalp, 2015; Kabakcı & Sarı (2019); Kalıntaş & Özarı, 2019; Kandemir & Karataş, 2016; Keten & Çağlar, 2019; Önder, Taş & Hepşen, 2014; Özdemir, 2013; Seçme, Bayrakdaroğlu & Kahraman, 2009; Tüysüz & Yıldız, 2020). On the other hand, there are many different methods for measuring the efficiency and productivity of the banking system (Assaf, Matousek & Tsionas, 2013; Fang, Hasan & Marton, 2011; Tecles & Tabak, 2010).

Moreover, each bank's position within the other banks is associated with a rank based on its financial performance. The K-means clustering algorithm has been used to identify similar banks and accurately determine their positions. In recent years, K-means has been widely used in various applications (Chévez et al., 2017; Fang et al., 2017; Govender & Sivakumar, 2020; Shamrat et. al., 2020). However, this analysis had two major drawbacks. One of the drawbacks is the determination of the value of k and the other is the selection of initial centers. Generally, the number of clusters (k values) is determined by experience and knowledge. In this study, the Calinski Harabsz Index (CHI) is used to determine the validity of k. To solve the initial center problem, we ran the clustering algorithm for all combinations of initial centers within the dataset. This procedure minimizes the problem of a random selection of initial clustering centers. Briefly, CHI is used to solve the initial center problem and determine the value of k. This index is generally used to determine the value of k. Because the logic behind this idea is the same, we decided to use this index to determine which cluster group was accurate.

The remaining parts of this study are organized as follows. Section 2 describes the research methodology and explains the main aim of the study regarding the proposed approach. In addition, this section highlights the use of this approach in similar cases. The application, along with the dataset and results, is presented in section 3 to illustrate the viability of the proposed approach. The final section provides conclusions and describes directions for future research.

2. Research Methodology

To determine the position of banks among other banks based on their financial performance, one method is to rank the banks and perceive the issue as a part of MCDM. The other method is to detect similar and dissimilar banks concerning their financial performance and perceive the issue as a part of clustering analysis. The third and advanced method is to distinguish between these two methods. Some studies have used advanced methods (Chu et al., 2021; Sun & Yu, 2021). The evaluation procedure of the latest technique we constructed for our study consists of seven main steps mentioned below.

Step 1: Determine the evaluation criteria (financial ratios are considered the most significant and accurate performance measures for banks' financial performance evaluation).

Step 2: Calculate the financial ratios of banks to analyze their financial performance.

Step 3: Calculate the weights of the financial ratios using various techniques (entropy, equal weight, standard, and variance).

Step 4: Conduct the TOPSIS method with different types of weight calculations to score and rank banks' financial performance.

Step 5: Cluster banks based on the scores calculated from the different TOPSIS methods using the K-means clustering algorithm for k=1, 2, 3, 4, and 5.

Step 6: For each value of k, run the K-means algorithm for all initial centers that can be obtained from the database and determine the significant cluster using CHI.

Step 7: Examine the significant cluster analysis results and determine the distribution of banks (explore whether banks that belong to the same cluster belong to the sustainability index).

The following sections provide detailed descriptions of each step.

2.1 Financial Ratios

Every industry has specific working and financial conditions regardless of whether it is small or large. Therefore, establishing benchmarks to compare these ratios is arduous. The size of a company within the same industry leads to the examination of different types of financial ratios (Frecknall-Hughes et al.; 2007). In this case, it is also insignificant to compare the same financial ratios for companies of different sizes. For instance, changes in exchange rates will impact the ratios over the years (Faello, 2015; Frecknall-Hughes et al.; 2007). As the main aim of this study is to evaluate and rank banks based on their financial ratios, the first step is to determine which financial ratios should be chosen. Different financial ratios can be used to assess a bank's financial or economic performance from different univariate perspectives (Edirisinghe & Zhang, 2007). These ratios can be classified in terms of their data sources, such as the balance sheet ratio (liquidity, capital adequacy, quality of assets, and balance sheet structure), the profit and loss account ratio, and inter-statement ratios (profitability, revenue expense structure, and operating rate). The financial performance criteria determined in the first step of the model are listed in Table 1.

Table 1: Evaluation criteria

Classification	Ratio Definition	Target
Capital adequacy	Capital Adequacy Ratio ($\boldsymbol{C_1}$)	Max
Balance sheet structure	Credits Obtained/Total Assets ($\boldsymbol{C_2}$)	Min
Quality of assets	Total Credit/Total Assets($\boldsymbol{C_3}$)	Max
	Frozen Receivables/Total Credit ($\boldsymbol{C_4}$)	Min
Liquidity	Liquid Assets/Total Assets ($\boldsymbol{C_5}$)	Max
	Liquid Assets/Deposit and Non-deposit Resources ($\boldsymbol{C_6}$)	Max
Profitability	Net Profit (Loss) for the Period/ Paid in Capital($\boldsymbol{C_7}$)	Max
	Pre-tax Profit/Total Assets($\boldsymbol{C_8}$)	Max
Revenue expense structure	Net Interest Income After Special Provisions/ Operating Gross Profit ($\boldsymbol{C_9}$)	Max
	Interest Revenue/Total Assets ($\boldsymbol{C_{10}}$)	Max
Operating rate	Net Operating Profit (Loss)/Total Assets ($\boldsymbol{C_{11}}$)	Max

2.2 Calculations of Importance Level (weight) of Each Criterion

Because the decision to determine the weight will greatly affect the results and findings of any method, we employ four different types of weight calculations, namely equal weight (EW), standard deviation (SD), variance, and entropy. All these methods are known as objective weighting methods, which means that they are derived from the information gathered from each criterion using a mathematical function to compute the weights without the interference of the decision maker (Odu, 2019). The EW method requires negligible information about criteria priorities and negligible input from decision-makers (Roszkowska, 2013). In this method, an equal importance level was assumed for each criterion.

The SD method was proposed by Wang and Zhang (2003) to deal with multiple attribute decision-making (MADM) problems with numerical information.

SD method determines the weights of each criterion w_j:

$$w_j = \frac{\sigma_j}{\sum_{k=1}^{m} \sigma_k}, \text{ for j=1,2,...,m.} \quad (1)$$

The variance method determines the weights of each criterion w_j:

$$w_j = \frac{\sigma_j^2}{\sum_{k=1}^{m} \sigma_k^2}, \text{ for j=1,2,...,m.} \quad (2)$$

The entropy weight was applied to calculate the weight of the financial ratios that are used as criteria to measure financial performance (Shannon, 1948).

$$r_{ij} = \frac{d_{ij}}{\sum_{i=1}^{m} d_{ij}}, \text{ for i=1,2,...,m and j=1,2,...,n.} \quad (3)$$

$$e_j = \frac{-1}{ln\ (m)} \sum_{i=1}^{m} r_{ij} ln\ (r_{ij}), \text{ for i=1, 2, ..., m and j=1, 2, ..., n.} \quad (4)$$

$$w_j = \frac{1-e_j}{\sum_{j=1}^{n}(1-e_j)}, \text{ for j=1,2,...,n.} \quad (5)$$

where r_{ij} denotes the ratio of d_{ij} in evaluation indicator j, e_j denotes the entropy value of the evaluation indicator, and j and w_j denotes the weight of indicator j.

2.3 TOPSIS Method

Owing to its simplicity and an unlimited range of criteria and performance attributes, the TOPSIS method, which was introduced by Hwang and Yoon (1981), has become a major MADM technique compared with other techniques such as AHP and ELECTRE (Bayyurt, 2013; Govindan, Khodaverdi & Jafarian, 2013, Özcan, Çelebi & Esnaf, 2011). The steps of the TOPSIS method are defined as follows:
Step 1: Calculation of The Decision Matrix

Decision matrix (DM) can be expressed as: $DM_{n\times m} = \begin{bmatrix} d_{11} & \cdots & d_{1m} \\ \vdots & \ddots & \vdots \\ d_{n1} & \cdots & d_{nm} \end{bmatrix}$,

where n is a set of alternatives (banks) and m is a set of criteria (number of financial ratios).

Step 2: Calculation of The Normalized Decision Matrix

The normalized decision matrix $NDM_{n\times m}$ is obtained from matrix DM with normalization process.

$$NDM_{n\times m} = \begin{bmatrix} z_{11} & \cdots & z_{1m} \\ \vdots & \ddots & \vdots \\ z_{n1} & \cdots & z_{nm} \end{bmatrix}, z_{ij} = \frac{d_{ij}}{\sqrt{\sum_{i=1}^{m} d_{ij}^2}} \quad (6)$$

where z_{ij} represents the normalized value of d_{ij}

Step 3: Determination of the Weighted Normalized Decision Matrix

The weighted normalized decision matrix $WNDM_{n\times m}$ is obtained from matrix NDM.

$$WNDM_{n\times m} = \begin{bmatrix} w_{11} & \cdots & w_{1m} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nm} \end{bmatrix}, \text{where } w_{ij} = w_j z_{ij} \quad (7)$$

Step 4: Determination of Positive and Negative Ideal Solution

Equations (8) and (9) can be used to determine the positive ideal vector (P^+) and negative ideal vector (P^-).

$$P^+ = (p_1^+, p_2^+, \dots, p_n^+) \text{ where } p_i^+ = \{max(w_{ij}), j \in J, min(w_{ij}), j \in J'\} \quad (8)$$

and $P^- = (p_1^-, p_1^-, \dots, p_n^-)$ where $p_i^- = \{min(w_{ij}), j \in J, max(w_{ij}), j \in J'\}$ (9)

Step 5: Calculation of the separation measures for each alternative

The separation from positive ideal alternative is:

$$S_i^+ = [\sum_{i=1}^{m}(p_i^+ - w_{ij})^2]^{1/2} \quad (10)$$

The separation from negative ideal is:

$$S_i^- = [\sum_{i=1}^{m}(p_i^- - w_{ij})^2]^{1/2} \quad (11)$$

Step 6: Calculation of relative closeness to the ideal solution:

$$C_i^* = \frac{S_i^-}{(S_i^+ + S_i^-)} \quad (12)$$

A larger C_i^* value indicates that alternative i is relatively good, whereas a smaller C_i^* value indicates that it is relatively poor.

However, the TOPSIS method has several drawbacks. One drawback is that it can cause a rank reversal. In this rank reversal phenomenon, the order of preference for alternatives changes when one or more alternatives are added or removed from the decision problem (García-Cascales & Lamata, 2012).

2.4 *K-Means Clustering Algorithm*

Clustering can be used to identify interesting patterns and distributions and yield possible insights into the underlying data (Halkidi, Batistakis & Vazirgiannis, 2001). It divides a given dataset into clusters such that the elements assigned to a particular cluster are similar or connected in a predefined sense (Schaeffer, 2007). One clustering method is the K-Means Clustering algorithm, which can group large amounts of data with relatively fast and efficient computation time (Khotimah, Irhamni & Sundarwati, 2016). The k-means algorithm is an iterative algorithm, which can be described by the following steps (Arora & Varshney, 2016; Dhanachandra, Manglem & Chanu, 2015):

Step 1: Determine the number of clusters

Step 2: Randomly choose k points as cluster (initial) centers

Step 3: Assign points to the closest cluster center.

Step 4: For each cluster, the new initial centers were determined.

Step 5: Repeat Steps 2, 3, and 4 once the same points are allocated to each cluster.

In this study, the k-means clustering algorithm is applied to determine the number of accurate clusters that determine the natural structure of banks. In other words, we examine a significant number of Turkish bank splits.

2.5 *Calinski Harabsz Index*

A general problem in clustering analysis is determining the optimal number of clusters that fit the dataset. In other words, the process of estimating how well clustering recovers the natural groups present in a dataset is known as cluster validation (Halkidi, Batistakis & Vazirgiannis, 2001). There are many examples of internal validity indices (Baker& Hubert, 1975; Davies & Bouldin, 1979; Dunn, 1973; Rousseeuw, 1987). The CHI, which was proposed by Calinski and Harabasz in 1974, is calculated using (13).

$$CHI = \frac{B(k)/(k-1)}{W(k)/(n-k)} \tag{13}$$

where k is the corresponding number of clusters, B(k) is the intercluster divergence, W(k) is the intracluster divergence and n is the number of samples. A larger CHI value reflects a better data clustering result. CHI has been used in various studies (Kwon, Kang & Bae, 2014; León et al., 2017).

3. Application

The first two steps of the proposed approach involve the construction of a decision matrix. As the aim of this study is to analyze the financial performance of banks in Turkey, we first examine the classification of banks according to the Turkish Banking System. It is possible to classify banks in Turkey as central banks, deposit banks, foreign banks, development and investment banks, and participation banks, as shown in Figure 1. In this study, the Central Bank, Participation Banks, and the Bank of China were excluded.

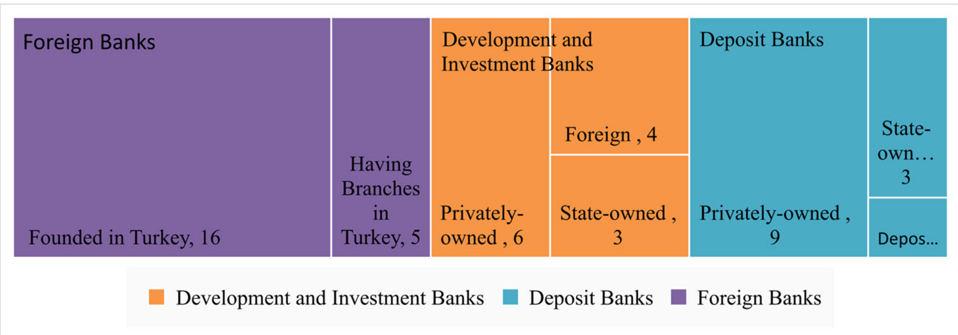


Figure 1: Classification of Banks in Turkey, 2020
Source: https://www.tbb.org.tr/en/modules/bankabilgileri/banka_Listesi.asp?tarih=10/10/2021

As there are several types of banks, they can be classified from different perspectives, such as whether they are listed on the sustainability index. The banks listed in the sustainability index during the study period are listed in Table 2.

Table 2: Banks listed in the sustainability index

Year	Banks
2015	Akbank, Garanti, Türkiye Vakıflar Bank, Yapı ve Kredi
2016	Akbank, Garanti, Türkiye Vakıflar Bank, Yapı ve Kredi, Türkiye İş Bank, Türkiye Sınai ve Kalkınma Bank
2017	Akbank, Garanti, Türkiye Vakıflar Bank, Yapı ve Kredi, Türkiye İş Bank, Türkiye Sınai ve Kalkınma Bank, Halk Bank
2018	Akbank, Garanti, Türkiye Vakıflar Bank, Yapı ve Kredi, Türkiye İş Bank, Türkiye Sınai ve Kalkınma Bank, Halk Bank
2019	Akbank, Garanti, Türkiye Vakıflar Bank, Yapı ve Kredi, Türkiye İş Bank, Türkiye Sınai ve Kalkınma Bank, Halk Bank, Şekerbank

Source: https://www.borsaistanbul.com/files/bist-sustainability-index-constituents-december-2020. Pdf

A decision matrix of 46 banks and 11 evaluation criteria was established, as illustrated in Table 3.

Table 3: Decision matrix, 2019

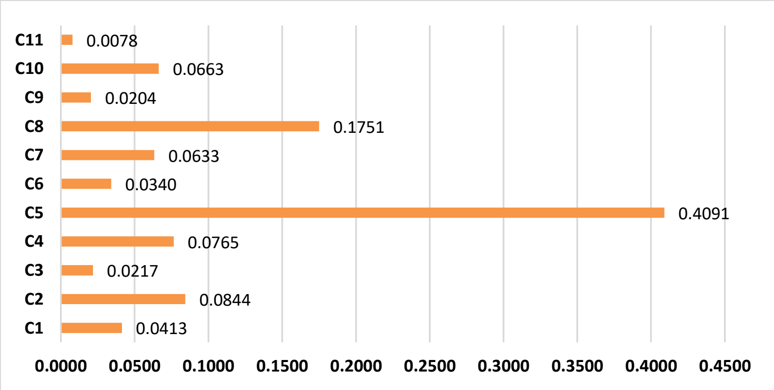
2019	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
B_1	17.02	5.31	68.95	2.83	10.43	8.83	1.18	101.42	79.50	1.18	10.10
B_2	14.33	2.41	67.65	5.15	9.99	8.37	0.43	137.62	45.66	0.43	10.22
B_3	16.61	9.79	69.64	5.93	12.22	10.10	0.86	112.09	25.68	0.86	10.03
B_4	197.47	0.00	0.00	...	38807.48	95.67	8.99	5.44	96.40	8.99	18.66
...	...	...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...	...	...
B_{43}	33.89	58.54	73.13	24.53	21.33	13.35	0.10	0.56	32.66	0.10	8.50
B_{44}	92.21	5.03	5.06	0.00	804.76	40.46	23.88	218.89	27.17	23.88	12.78
B_{45}	32.00	38.64	61.46	3.34	26.95	18.18	1.91	5.14	44.15	1.91	9.63
B_{46}	105.32	0.00	0.00	---	---	57.88	24.23	49.00	21.81	24.23	11.41

The normalized decision matrix is established using (6) and is illustrated in Table 4.

Table 4: Normalization decision matrix, 2019

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
B_1	0.0001	0.0002	0.0004	0.0007	0.0000	0.0001	0.0004	0.0000	0.0001	0.0004	0.0018
B_2	0.0001	0.0001	0.0004	0.0013	0.0000	0.0001	0.0002	0.0000	0.0000	0.0002	0.0018
B_3	0.0001	0.0003	0.0004	0.0015	0.0000	0.0001	0.0003	0.0000	0.0000	0.0003	0.0018
B_4	0.0017	0.0000	0.0000	0.0000	0.0000	0.0014	0.0033	0.0000	0.0001	0.0033	0.0034
...	...	...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...	...	...
B_{43}	0.0003	0.0017	0.0005	0.0062	0.0000	0.0002	0.0000	0.0000	0.0000	0.0000	0.0015
B_{44}	0.0008	0.0001	0.0000	0.0000	0.0000	0.0006	0.0087	0.0000	0.0000	0.0087	0.0023
B_{45}	0.0003	0.0011	0.0004	0.0008	0.0000	0.0003	0.0007	0.0000	0.0000	0.0007	0.0017
B_{46}	0.0009	0.0000	0.0000	0.0000	0.0000	0.0008	0.0088	0.0000	0.0000	0.0089	0.0021

To calculate the weighted normalization matrix, the weights of the 11 criteria were calculated using four different types of weight calculations, as explained in Section 2.2. Future researchers may use more types of weight calculation methods to bring about desirable criteria, such as the Critic and Swara methods. Graph 1 illustrates the entropy weights of the 11 criteria for the year 2019.



Graph 1: Weight Distribution of Entropy Method, 2019

As shown in Graph 1, according to the entropy method, the most important financial ratio is C_5, followed by C_8. Table 5 illustrates the weights of all financial ratios based on the variance, standard deviation, entropy, and equal-weight methods.

Table 5: Importance level of financial ratio between 2015 and 2019 based on 4 types of weight methods

Year	Weight Methods	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
2015	Variance	0.0639	0.0125	0.0177	0.0032	0.6963	0.0168	0.0002	0.1753	0.0136	0.0002	0.0002
	St. Deviation	0.1207	0.0534	0.0635	0.0271	0.3982	0.0618	0.0064	0.1998	0.0556	0.0064	0.0071
	Equal	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909
	Entropy	0.1122	0.1118	0.0340	0.2364	0.1741	0.0447	0.0304	0.1969	0.0112	0.0333	0.0151
2016	Variance	0.0065	0.0021	0.0032	0.0008	0.9383	0.0029	0.0000	0.0425	0.0036	0.0000	0.0000
	St. Deviation	0.0531	0.0300	0.0372	0.0190	0.6385	0.0353	0.0040	0.1360	0.0393	0.0040	0.0036
	Equal	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909
	Entropy	0.0754	0.0892	0.0304	0.2372	0.2680	0.0355	0.0380	0.1604	0.0153	0.0395	0.0112
2017	Variance	0.0000	0.0000	0.0000	0.0000	0.9995	0.0000	0.0000	0.0004	0.0000	0.0000	0.0000
	St. Deviation	0.0053	0.0032	0.0037	0.0023	0.9581	0.0036	0.0006	0.0184	0.0038	0.0006	0.0005
	Equal	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909
	Entropy	0.0472	0.0676	0.0185	0.1750	0.4127	0.0264	0.0578	0.1178	0.0079	0.0593	0.0099
2018	Variance	0.0001	0.0000	0.0000	0.0000	0.9982	0.0000	0.0000	0.0016	0.0001	0.0000	0.0000
	St. Deviation	0.0066	0.0037	0.0042	0.0038	0.9287	0.0042	0.0014	0.0370	0.0082	0.0014	0.0007
	Equal	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909
	Entropy	0.0443	0.0676	0.0185	0.1516	0.3702	0.0338	0.0832	0.1302	0.0045	0.0862	0.0099
2019	Variance	0.0000	0.0000	0.0000	0.0000	0.9961	0.0000	0.0000	0.0031	0.0007	0.0000	0.0000
	St. Deviation	0.0056	0.0034	0.0040	0.0012	0.9053	0.0038	0.0010	0.0503	0.0237	0.0010	0.0006
	Equal	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909	0.0909
	Entropy	0.0413	0.0844	0.0217	0.0765	0.4091	0.0340	0.0633	0.1751	0.0204	0.0663	0.0078

Using the importance level illustrated in Graph 1 and Table 5, the entropy-weighted normalization decision matrix is calculated.

Table 6: Entropy weighted normalization decision matrix, 2019

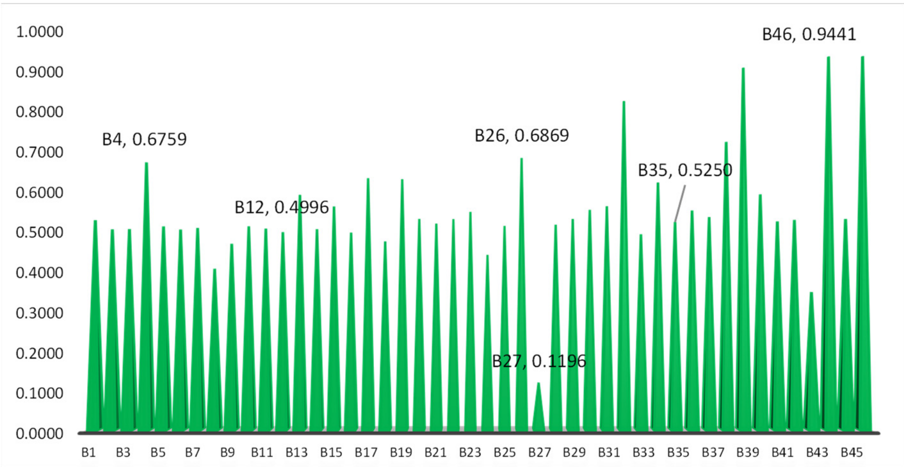
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
B_1	0.000006	0.000013	0.000009	0.000055	0.000000	0.000004	0.000027	0.000004	0.000002	0.000029	0.000014
B_2	0.000005	0.000006	0.000009	0.000100	0.000000	0.000004	0.000010	0.000005	0.000001	0.000010	0.000014
B_3	0.000006	0.000024	0.000010	0.000115	0.000000	0.000005	0.000020	0.000004	0.000000	0.000021	0.000014
B_4	0.000070	0.000000	0.000000	0.000000	0.000011	0.000047	0.000208	0.000000	0.000002	0.000218	0.000026
...	...	...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...	...	...
B_{43}	0.000012	0.000145	0.000010	0.000475	0.000000	0.000007	0.000002	0.000000	0.000001	0.000003	0.000012
B_{44}	0.000033	0.000012	0.000001	0.000000	0.000000	0.000020	0.000552	0.000008	0.000001	0.000580	0.000018
B_{45}	0.000011	0.000095	0.000008	0.000065	0.000000	0.000009	0.000044	0.000000	0.000001	0.000046	0.000014
B_{46}	0.000037	0.000000	0.000000	0.000000	0.000000	0.000029	0.000560	0.000002	0.000000	0.000588	0.000016

According to (8) and (9), one may determine how far away each viable option is from the positive and negative ideal. The relative degree of approximation was calculated using (12). The financial performance of the 46 banks ranked by their closeness coefficient (CC) values are listed in Table 7.

Table 7: Positive and negative ideal solution and closeness coefficient, 2019 entropy-based TOPSIS

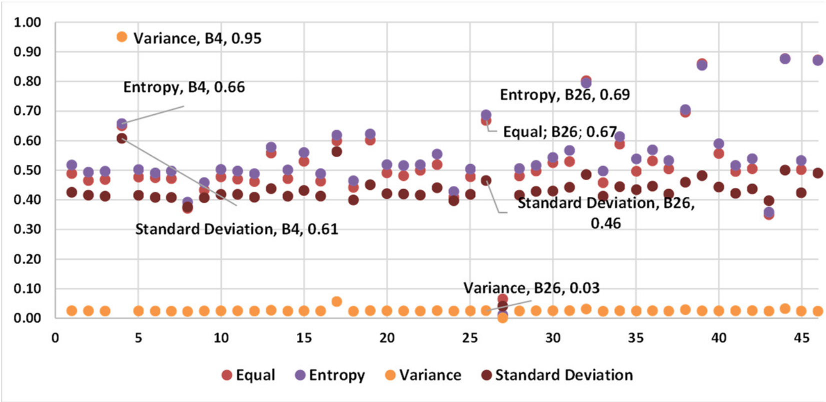
Bank	S_i^+	S_i^-	2019-Closeness Coefficient	Bank	S_i^+	S_i^-	2019-CC
B_1	0.0008	0.0009	0.5298	B_{43}	0.0010	0.0005	0.3482
B_2	0.0008	0.0008	0.5065	B_{44}	0.0001	0.0014	0.9433
B_3	0.0008	0.0008	0.5073	B_{45}	0.0008	0.0009	0.5328
B_4	0.0005	0.0011	0.6759	B_{46}	0.0001	0.0015	0.9441

Table 7 shows that the CC of bank B_{46} equals 0.9441, indicating that B_{44} has the best financial performance, whereas bank B_{27}'s CC equals 0.1196, indicating that B_{27} has the worst financial performance, as illustrated in Graph 2.



Graph 2: Entropy-based TOPSIS CC, 2019

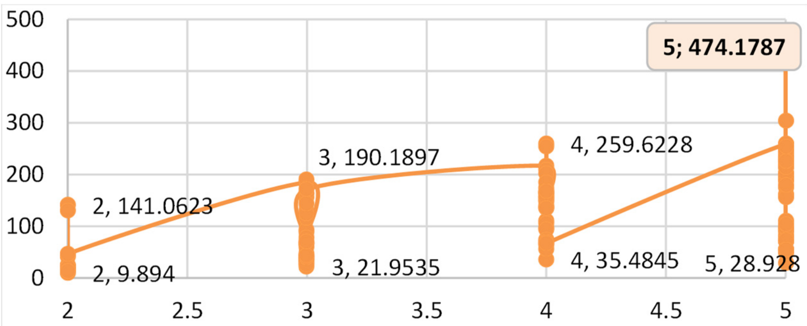
The weights of the financial ratios are determined using the equal weight, entropy, variance, and standard deviation methods. Therefore, the CC values were also calculated using the weights derived from these weight calculation methods. For each year, we have four different ranking findings based on different weights, as illustrated in Graph 3.



Graph 3: The CCs determined by different methods, 2019

The CC of bank B_4 equals 0.95 with variance weight calculation method, 0.66 with entropy, 0.61 with standard deviation, and 0.09 with equal.

Because the k-means algorithm is sensitive to the initial centers, we applied the algorithm to all possible initial centers from inside the data set for k=2, 3, 4, and 5. For any value of k, we examine different cluster set groups and CHI is used to determine which group is more accurate. In addition, the optimal number of clusters was determined by CHI. The cluster number *k* and the corresponding index values for 2019 are shown in Graph 4.



Graph 4: CHI of cluster groups for k=2, 3, 4, and 5, 2019.

We applied the same process for the other years and the CHI values for each cluster group are illustrated in the Appendix.

Table 8 illustrates the findings of the K-means clustering method with the highest CHI index value between 2015 and 2019. All banks included in the sustainability index belong to the same cluster except for 2015. B_4 alone formed separate clusters for 2017, 2018, and 2019. However, in 2016 and 2015, B_4 belonged to a cluster with other banks.

Table 8: K-Means clustering result with highest CHI: 2019-2015

	Cluster	Banks	# Banks	Sustainability Index
2019	1	$B_1, B_2, B_3, B_5, B_6, B_7, B_8, B_9, B_{10}, B_{11}, B_{12}, B_{14}, B_{15}, B_{16}, B_{18}, B_{20}, B_{21}$ $B_{22}, B_{23}, B_{24}, B_{25}, B_{28}, B_{29}, B_{30}, B_{31}, B_{33}, B_{35}, B_{36}, B_{37}, B_{41}, B_{42}, B_{45}$	32	Included (8)
	2	$\boldsymbol{B_4}$	1	Not included
	3	$B_{13}, B_{17}, B_{19}, B_{26}, B_{34}, B_{38}, B_{40}$	7	Not included
	4	B_{27}, B_{43}	2	Not included
	5	$B_{32}, B_{39}\ B_{44}, B_{46}$	4	Not included
2018	1	$B_1, B_2, B_3, B_5, B_6, B_7, B_8, B_9, B_{10}, B_{11}, B_{12}, B_{13}, B_{14}, B_{15}, B_{16}, B_{18}, B_{20}, B_{21}$ $B_{22}, B_{23}, B_{24}, B_{25}, B_{28}, B_{31}, B_{33}, B_{35}, B_{36}, B_{37}, B_{40}, B_{41}, B_{42}, B_{45}$	32	Included (7)
	2	$\boldsymbol{B_4}$	**1**	**Not included**
	3	$B_{17}, B_{19}, B_{26}, B_{30}, B_{32}, B_{34}, B_{38}$	7	Not included
	4	B_{27}, B_{29}, B_{43}	3	Not included
	5	B_{39}, B_{44}, B_{46}	3	Not included
2017	1	$B_1, B_2, B_3, B_5, B_6, B_7, B_8, B_9, B_{10}, B_{11}, B_{12}, B_{13}, B_{14}, B_{15}, B_{16}, B_{18}, B_{19}, B_{20}, B_{21}$ $B_{22}, B_{23}, B_{24}, B_{25}, B_{27}, B_{28}, B_{31}, B_{33}, B_{35}, B_{36}, B_{37}, B_{40}, B_{42}, B_{43}, B_{45}$	34	Included (7)
	2	$\boldsymbol{B_4}$	1	Not included
	3	$B_{17}, B_{26}, B_{30}, B_{32}, B_{34}, B_{38}, B_{41}$	7	Not included
	4	B_{29}	1	Not included
	5	B_{39}, B_{44}, B_{46}	3	Not included
2016	1	$B_1, \boldsymbol{B_4}, B_{13}, \boldsymbol{B_{17}}, B_{19}, \boldsymbol{B_{26}}, B_{30}, B_{34}, B_{40}, B_{41}, B_{45}$	**11**	Not included
	2	$B_2, B_3, B_5, B_6, B_7, B_8, B_9, B_{10}, B_{11}, B_{12}, B_{14}, B_{15}, B_{16}, B_{18}, B_{21}$ $B_{22}, B_{23}, B_{24}, B_{25}, B_{27}, B_{28}, B_{31}, B_{33}, B_{35}, B_{36}, B_{37}, B_{42}, B_{43}$	28	Included (6)
	3	B_{20}, B_{29}, B_{44}	3	Not included
	4	B_{32}	1	Not included
	5	B_{38}, B_{39}, B_{46}	3	Not included
2015	1	$B_1, B_2, B_3, B_5, B_6, B_{11}, B_{15}, B_{19}, B_{28}, B_{31}, B_{36}, B_{37}, B_{39}, B_{42}$	14	Included (3) Not included (11)
	2	$\boldsymbol{B_4}, \boldsymbol{B_{17}}, \boldsymbol{B_{26}}, B_{32}$	**4**	Not included
	3	$B_7, B_8, B_9, B_{10}, \boldsymbol{B_{12}}, B_{13}, B_{14}, B_{16}, B_{18}, B_{20}, B_{21}, B_{22}, B_{23}, B_{24}, B_{25}, B_{27}, B_{35}$	17	Included (1) Not included (16)
	4	B_{29}, B_{33}, B_{43}	3	Not included
	5	$B_{30}, B_{34}, B_{38}, B_{40}, B_{41}, B_{44}\ B_{45}, B_{46}$	8	Not included

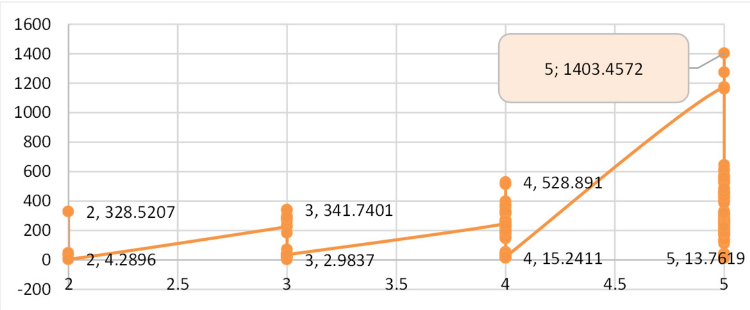
4. Conclusions, Limitations, and Future Directions

Accurate bank classification allows banks to establish specific financial targets. Both banks and investors benefit from the improvement of the classification algorithm. Using the fifth step of the proposed approach, we explore the number of clusters in which Turkish banks split. One can examine clusters with crucial different ratios or other structural features and determine some labels for these clusters in order. In this study, it was determined that in the long-run Turkish banks were divided into five different clusters instead of being divided into two separate groups namely, the only option is good or bad. The findings are robust because we minimize the initial center drawback of the k-means algorithm by running it for all combinations of initial centers from the dataset and for the different number of clusters simultaneously.

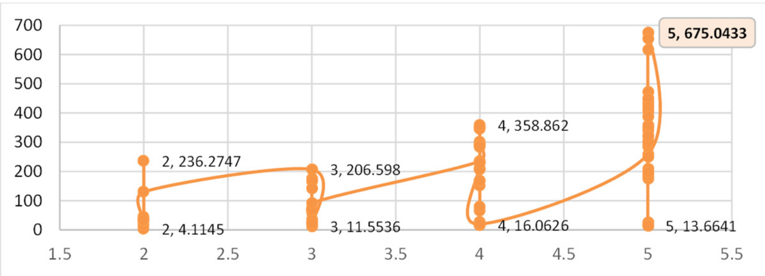
All banks included in the Sustainability Index belong to the same cluster, except for 2015. In 2015, B_{12}, which is included in the Sustainability Index, belonged to a cluster with banks that are not included in the index. This means that its financial performance is not similar to that of banks included in the Sustainability Index. In other words, this study sheds light on banks listed in the Sustainability Index with the same financial performance level. However, in other years, the banks included in the Sustainability Index are in the same cluster. In other words, being included in the Sustainability Index means that these banks have similar features unrelated to finance. However, their belonging to the same cluster indicates that they also have similar financial performance. For future research, one can use the proposed approach with other features (not financial ratios) of banks, companies, and countries and examine findings that are similar to financial performance. For future research, one can use the proposed approach with other features (not financial ratios) of banks, companies, and countries and examine findings with similar financial performance.

The present study was subject to the selection of the cluster validation method and initial centers. We minimized the initial center drawback by running an algorithm for all combinations of initial centers from inside the dataset, which is the key strength of this study. However, we do not know the existence of the initial centers from outside the dataset which results in many accurate clusters. For future researchers, one can figure out this drawback can be addressed.

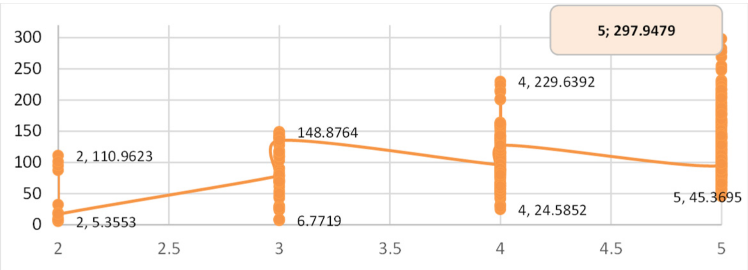
Appendix A



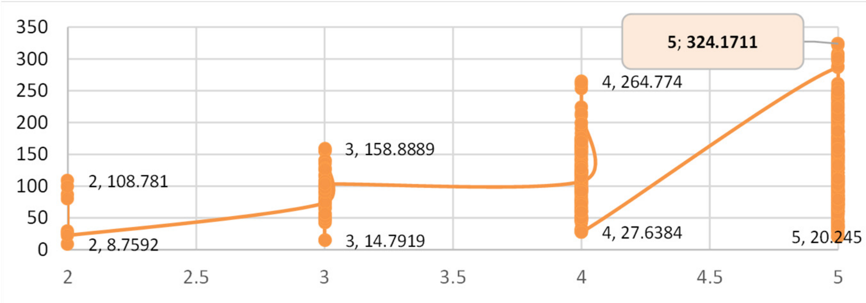
Graph A.1. CHI of cluster groups for k=2, 3, 4, and 5, 2018



Graph A.2 CHI of cluster groups for k=2, 3, 4, and 5, 2017



Graph A.3. CHI of cluster groups for k=2, 3, 4, and 5, 2016



Graph A.4 CHI of cluster groups for k=2, 3, 4, and 5, 2015

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