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ARAŞTIRMA MAKALESİ / RESEARCH ARTICLE

ASSESSMENT OF CAPITAL COMPONENTS IN INTEGRATED REPORTING

ENTEGRE RAPORLAMADA SERMAYE ÖGELERİNİN DEĞERLENDİRİLMESİ

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Abstract

This study aims to assess the indicators representing capital components in the context of integrated reporting. Focusing on the banking sector, the sample includes six banks listed in the BIST Bank Index that published integrated reports. The evaluation encompasses the years 2020-2023. Twenty-nine quantitative, accessible, and comparable indicators based on the International Integrated Reporting Framework were identified to determine the capital components disclosed in the integrated reports. The Entropy Method was employed to ascertain weight values for these indicators, while the TOPSIS, GRA, MARCOS, and COPRAS methods were used for evaluation and ranking. The findings highlight natural capital as the capital element with the highest weight value, while manufactured capital holds the lowest weight value. Notably, Yapı ve Kredi Bank secured the first rank in 2020 and 2021, with Akbank leading in 2022 and 2023. Halkbank ranked sixth in 2020, 2022 and 2023, and Vakıflar Bank ranked sixth in 2021. Overall, the banks' performance during 2020-2023 is considered average, with the highest performance observed in 2022. In conclusion, the study indicates ongoing development in integrated reporting within the banking sector, with an increasing frequency of usage.

Keywords: Integrated Reporting, Capital Components, Banking Sector
Jel Classification: M10, M40, M41

Özet

Bu çalışmanın amacı entegre raporlama kapsamında sermaye ögelerini temsil eden göstergelerin değerlendirilmesidir. Bu amaç çerçevesinde bankacılık sektörü ele alınarak BİST Banka Endeksi'ne kayıtlı ve entegre rapor yayınlayan 6 banka çalışmanın örneklemini oluşturmaktadır. Bankaların 2020-2022 yıllarına

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ait entegre raporların açıklanan sermaye ögelerine ait göstergelerin belirlenmesinde Uluslararası Entegre Raporlama Çerçevesi esas alınarak nicel, ulaşılabilir ve karşılaştırılabilir 29 gösterge tespit edilmiştir. Bu göstergelerin ağırlık değerlerinin belirlenmesinde Entropi Yöntemi, göstergelerin değerlendirilmesi ve bankaların sıralanmasında TOPSIS, GRA, MARCOS ve COPRAS yöntemleri kullanılmıştır. Elde edilen bulgulara göre en yüksek önem ağırlık değerine sahip sermaye ögesi doğal sermaye, en düşük önem ağırlık değerine sahip sermaye ögesi ise üretilmiş sermaye olarak belirlenmiştir. Ayrıca 2020 ve 2021 yıllarında Yapı ve Kredi bankası 1. sırada, 2022 ve 2023 yıllarında Akbank 1. sırada yer almaktadır. 2020, 2022 ve 2023 yıllarında Halkbank 6. sırada, 2021 yılında Vakıflar bankası 6. sırada bulunmaktadır. 2020-2023 dönemi boyunca bankaların performansının ortalama düzeyde gerçekleştiği ve en yüksek performansın 2022 yılına ait olduğu görülmektedir. Sonuç olarak entegre raporlamanın bankacılık sektöründe gelişim sürecinin devam ettiği ve kullanım sıklığının arttığını söylemek mümkündür.
Anahtar Kelimeler: Entegre Raporlama, Sermaye Ögeleri, Bankacılık Sektörü
Jel Sınıflandırması: M10, M40, M41

1. Introduction

The changing landscape marked by climate change, global economic crises, natural disasters, and resource depletion has shifted the expectations of business stakeholders. Also, as technological progress continues rapidly and the importance of concepts such as digitalization, digital transformation, artificial intelligence and sustainability increases, intellectual capital, produced capital and natural capital concepts have come to the forefront and the financial performance of businesses has increased along with their non-financial performance.

Consequently, stakeholders, particularly investors, now emphasize non-financial information alongside financial data in their decision-making processes. This paradigm shift has elevated the significance of corporate reporting, evolving from traditional annual reports to encompass corporate social responsibility, sustainability, and ultimately, integrated reports. Businesses contribute to the decision-making process of users by sharing their performances in capital elements included in their integrated reports with relevant users.

Against this backdrop, the current study aims to assess indicators representing capital elements within the realm of integrated reporting, with a specific focus on the banking sector. The study narrows its scope to banks listed in the BIST Bank Index, analyzing integrated reports from the years 2020 to 2023. In the selection process of indicators, this study meticulously considered quantitative, accessible, and comparable indicators in alignment with the guidelines set forth by the International Integrated Reporting Framework. In this study, the common indicators of capital components employed within the scope of integrated reporting in the banking sector and the integrated reporting performance of banks are identified and presented for the consideration of the reader.

2. Conceptual Framework

Integrated report stands as the pinnacle of corporate reporting, serving as a comprehensive tool that amalgamates both financial and non-financial information. It functions to convey how an organization generates, protects, and consumes value across short, medium, and long-term horizons within the context of the external environment (IIRC, 2021:10). The International Integrated Reporting Council, established in 2010, guides organizations in preparing integrated reports (Aras and Sarıoğlu, 2015:16). The Council published the International Integrated Reporting Framework in 2013. The Council's International Integrated Reporting Framework, published in 2013 and finalized in 2021, serves to establish guidelines and content elements for integrated reporting and explain the fundamental concepts that support them (IIRC, 2021:10). Central to the framework are the capital elements—values utilized by organizations in product or service production—divided into six sub-dimensions: financial, manufactured, intellectual, human, social and relational, and natural capital (IIRC, 2021:19).

The landscape of integrated reporting in Turkey took root in 2011 when the Corporate Governance Association of Turkey (CGAT) and the Sustainable Development Association (SDA) jointly established a working group. Building on this initiative, the Turkish Industry and Business Association (TIBA) formed a working group titled "New Era in Corporate Reporting: Integrated Reporting" in 2015. This laid the foundation for further progress in integrated reporting practices. In 2016, responding to the need for a coordinated effort, the "Integrated Reporting Network Turkey (ERTA)" was founded to encourage companies to present their non-financial information in tandem with financial data, fostering an integrated approach. The momentum continued, and as of 2021, ERTA has persisted in its mission under the name "Integrated Reporting Association Turkey" (ERTA, 2024).

3. Literature

Below are summaries of several studies found in the literature on integrated reporting, with explanations provided regarding their purpose, methodology, and findings:

In 2015, researcher Melloni utilized the multiple regression analysis method to evaluate the quality of intellectual capital disclosures in integrated reporting by analyzing data from the capital elements in reports published on the IIRC website through content analysis. Melloni found that the majority of intellectual capital disclosures in integrated reports focused on relational capital. Additionally, the correlation between intellectual capital disclosures and performance, firm size, and tangible fixed assets was highlighted. Dumitru and Jinga (2015) utilized the content analysis method to study the integrated reporting practices of Takeda Pharmaceutical, a company based in Japan, for the years 2006-2015. Through a case study approach, they determined that the company's integrated reporting practices aligned with the principles of the International Integrated Reporting Framework. Ercan and Kestane (2017) conducted a content analysis to compare integrated reports prepared in Turkey with the principles outlined in the integrated reporting framework. Their analysis revealed differences in the value creation process even among enterprises in the same sector. They concluded that integrated reporting is still in the developmental stage in Turkey and called for standardization of the practice. Pistoni et al. (2018) assessed the quality of integrated reporting by analyzing integrated reports published in 2013-2014. They developed integrated reporting scores and found that the overall quality of integrated reports was low, indicating a need for improvement in the content of integrated reporting. Smit et al. (2018) examined the integrated reports of seven South African banks, assessing the implementation of the integrated reporting framework and concluding that these banks generally adhere to the framework's principles. Aras and Mutlu Yıldırım (2019) used content analysis to identify indicators for multiple capital elements in the integrated reports of BIST Sustainability Index banks from 2014 to 2017, revealing accessible and prominent indicators in the literature. Santis et al. (2018) analysed of intellectual capital disclosures in the integrated reports of financial services firms, exploring the elements of intellectual capital and its relationship with the value creation process. Through content analysis of 135 integrated reports from 2014 to 2016, the study revealed that a majority of the analyzed companies took a superficial approach, offering limited information about intellectual capital. Despite their awareness of its importance, these firms provided low-level information about the relationship between intellectual capital and the value-creation process. In a separate study, Şimşek and Terim (2020) used content analysis to assess the compliance of integrated reports from five Turkish organizations in 2016 with the International Integrated Reporting Framework's content elements. After calculating scores for meeting integrated report content requirements, they concluded that the integrated reports of these organizations largely align with the content elements outlined in the reporting framework. To propose a multi-capital-based model for assessing integrated corporate performance, Mutlu Yıldırım (2020) analyzed data from deposit banks listed in the BIST Sustainability Index for the years 2014-2017. Besides the capital elements outlined in the integrated reporting framework, the study incorporated governance capital, with criteria for these elements determined through content analysis. Performance evaluation employed Entropy-based TOPSIS and Gray Relational Analysis methods, revealing that intellectual capital held the highest weight in the proposed model based on the obtained performance scores. In a related study, Aras and Mutlu Yıldırım (2021) identified capital elements from the International Integrated Reporting Framework in the banking sector, evaluating bank data from 2014-2017 using the Entropy Method to assign weights to these elements. The results indicated that intellectual capital had the highest weighted importance. Furthermore, Gökoğlu and Tutkavul (2022) utilized the content analysis method to compare integrated reporting capital elements and criteria for these elements in the integrated reports of private and public capital banks operating in the finance sector in 2019. The findings indicate that private capital banks have higher integrated reporting scores compared to public capital banks. In a study by Tuğay and Temel (2022), the integrated reports of cement sector enterprises listed on Borsa Istanbul for 2018 and 2019 were analyzed using the content analysis method. The CRITIC method was then employed to determine the significance levels of indicators, and enterprise performances were assessed through the MAIRCA method. The study identified the most and least important criteria for enterprises and identified the highest and lowest-performing ones. Additionally, Uslu (2023) aimed to assess the compliance of the integrated report of Borsa Istanbul Group for 2021 with the International Integrated Reporting Framework, utilizing the content analysis method, and concluded that the integrated report of Borsa Istanbul Group aligns with the framework. Ahmed et al. (2023) explored the connection between corporate complexity and the disclosure of capital elements in integrated reports of European companies. Using the content analysis method, data were collected from 81 companies adopting the integrated reporting framework during the period 2014-2020. The study revealed a significant and positive relationship between disclosures of multiple capital elements and industrial complexity, whereas an insignificant and positive relationship was identified regarding geographical complexity.

The prevalent use of the content analysis method is evident in the researchers' approach to studying integrated reporting, the integrated reporting framework, and capital elements. In the present study, the purpose was to evaluate the financial and non-financial performances of banks by using Multiple Decision Making Methods based on the performance indicators regarding capital elements included in the integrated reports of banks as one of the important financial institutions. It is considered that the results will contribute to the literature on performance evaluation in the banking sector within the scope of integrated reporting.

4. Methodology

In this section, the research provides an overview of the sample, variables, and methodologies employed.

4.1. Purpose of the Research

This study aims to assess the indicators representing capital components in the context of integrated reporting. Focusing on the banking sector, the sample includes six banks listed in the BIST Bank Index that published integrated reports. The evaluation encompasses the years 2020-2023.

4.2. Scope and Limitations of the Research

The study focused on evaluating the performance of banks in the banking sector traded in the Borsa Istanbul Bank Index regarding capital elements within the scope of integrated reporting. In this context, the indicators of capital elements in the banks' integrated reports for 2020-2023 were analyzed and the financial and non-financial performances of the banks were evaluated. However, analyzing a small number of banks posed a limitation for the study because the indicators of capital elements included in the integrated reports of banks made integrated reporting vary for some banks, the reporting start dates were different and there were missing indicators in some reports.

4.2. Sampling of the Research

The sample of the study focuses on evaluating capital elements in integrated reporting, specifically targeting banks listed in the Borsa Istanbul Banking Index. This sector was chosen due to its higher prevalence of integrated reporting compared to others. Table 1 details information about the banks in the BIST Bank Index, including their respective codes, names, integrated report start dates, and current integrated report release dates.

Table 1: Banks in the BIST Bank Index

	Bank Code	Bank	Integrated Report Start Date	Current Integrated Report Release Date
1	AKBNK	AKBANK T.A.Ş.	2020	2023
2	ALBRK	ALBARAKA TÜRK PARTICIPATION A.Ş.	2022	2023
3	ICBCT	ICBC TURKEY BANK T.A.Ş.	-	-
4	SKBNK	ŞEKERBANK T.A.Ş.	2022	2023
5	GARAN	TÜRKIYE GARANTI BANK A.Ş.	2017	2023
6	HALK	HALK BANK A.Ş.	2020	2023
7	ISCTR	TÜRKİYE İŞ BANK A.Ş.	2018	2023
8	TSKB	TÜRKİYE SINAI KALKINMA BANK A.Ş.	2016	2023
9	VAKBN	TÜRKİYE VAKIFLAR BANK T.A.O.	2019	2023
10	YKBNK	YAPI AND KREDI BANK A.Ş.	2019	2023

Source: KAP, ERTA

Table 1 reveals that there are 10 banks in the BIST Bank Index as of 2024, with only one bank not publishing an integrated report. Also, although the reporting start dates of banks that publish reports vary, it was observed that two banks started publishing reports as of 2022. The reporting start dates vary among banks, and incomplete data was identified for one bank, resulting in a study sample of 6 banks. The research period spans 2020-2023 to ensure comparability and accurate inferences regarding the level of integrated reporting.

4.3. Variables of the Research

To determine the indicators of multiple capital components in integrated reporting, the study relies on the capital elements outlined in the International Integrated Reporting Framework. Following the approach in the study by Aras and Mutlu Yıldırım (2019), indicators for financial, manufactured, intellectual, social and relational, human, and natural capital elements were derived through the content analysis method. Common indicators published by the banks in the study were then identified, resulting in a set of 29 indicators across six capital elements. The detailed indicator set is presented in Table 2.

Table 2: Indicators for Multiple Capital Elements

FINANCIAL CAPITAL		
Indicator Code	**Indicators**	**Indicator type**
FC1	Capital Adequacy Ratio	Benefit
FC2	Return on Average Assets	Benefit
FC3	Return on Average Equity	Benefit
FC4	Net Profit/Loss for the Period	Benefit
FC5	Interest Income/Interest Expense	Benefit
FC6	Asset Size	Benefit
FC7	Total Loans and Receivables/Total Deposits	Cost

FC8	Nonperforming Loans (Net)/Cost of Total Loans and Receivables	Cost
FC9	Liquid Assets/Short Term Liabilities	Benefit
	MANUFACTURED CAPITAL	
Indicator Code	**Indicators**	**Indicator type**
MC1	Tangible Assets (Net)/Asset Size	Benefit
MC2	Number of Branches/Asset Size	Benefit
MC3	Number of ATMs / Asset Size	Benefit
	INTELLECTUAL CAPITAL	
Indicator Code	**Indicators**	**Indicator type**
IC1	Intangible Assets (Net)/Assets Size	Benefit
IC2	Number of Customers Actively Using Digital Banking Channels/Total Number of Customers	Benefit
	HUMAN CAPITAL	
Indicator Code	**Indicators**	**Indicator type**
HC1	Ratio of Female Employees	Benefit
HC2	Average Hours of Training/Total Employees	Benefit
HC3	Personnel Expenses/Other Operating Expenses	Benefit
HC4	Personnel Expenses/Total Employees	Benefit
HC5	Total Number of Employees	Benefit
HC6	Ratio of Female Employees Returning to Work Post Maternity Leave	Benefit
	SOCIAL and RELATIONAL CAPITAL	
Indicator Code	**Indicators**	**Indicator type**
SRC1	Total Number of Customers	Benefit
SRC2	Consumer Loans/Total Loans and Receivables	Benefit
SRC3	Expenditure on Advertising/Total Assets	Benefit
	NATURAL CAPITAL	
Indicator Code	**Indicators**	**Indicator type**
NC1	Total Energy Consumption/ Total Employees	Cost
NC2	Total Water Consumption/ Total Employees	Cost
NC3	Total Electricity Consumption/ Total Number of Employees	Cost
NC4	Total Greenhouse Gas Emissions (Scope 1 + Scope 2)/ Total Employees	Cost
NC5	Amount of Recycled Waste/Total Employee	Benefit
NC6	Paper Consumption/ Total Employee	Cost

Source: Aras and Mutlu Yıldırım (2019)

4.4. Methods

MCDM methods were applied to assess the indicators of capital components in the integrated reports of banks as part of the research. Initially, the weight values for 29 indicators (criteria) were computed using the Entropy Method. Subsequently, banks (alternatives) were ranked using TOPSIS, GRA, MARCOS, and COPRAS methods. The selection of these methods was based on a combination of their frequent usage in previous studies and the introduction of new methodologies. In this context, the TOPSIS method was preferred because it is understandable and easily applicable, provides ease of calculation, allows reliable ranking (Gómez-López et al., 2009: 1506) and was used frequently in previous studies. The Gray Relational Analysis Method was preferred because it is used in solving complex problems where there is a small number of data (Kuo et al., 2008:81). The MARCOS method was preferred because it is a flexible method and allows many alternatives to be evaluated together (Ecer, 2020: 338). The COPRAS method was preferred because its calculation time is short and understandable, it provides ease of use and is transparent (Mulliner et al., 2013: 274). In addition, to validate the applicability of the methods used in the study instead of each other, the Spearman Rank Correlation test was conducted instead of pairwise comparisons. Detailed explanations of the methods utilized are provided below.

Entropy Method

This method serves as a neutral weighting approach for determining criteria weights. It involves calculating the entropy value based on the index value, leading to an objective outcome by considering all indices (Guoliang and Qiang, 2007: 5501; Ecer, 2019:372). This method stands out for its exclusion of subjective judgments, relying solely on direct data during measurement. This characteristic enhances the realism and comparability of the results obtained (Guoliang and Qiang, 2007: 5501). The procedural steps of the Entropy Method are as follows:

Step 1: Creation of the decision matrix (D) specified in Equation (4.1), composed of x_{ij} values.

$$D = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{4.1}$$

In the decision matrix, m is the number of alternatives, n is the number of criteria, and x_{ij} is the value of the j. criterion of the i. alternative.

Step 2: The x_{ij} values are normalized using Equation (4.2) to form the normalized decision matrix.

$$p_{ij} = \frac{z'_{ij}}{\sum_{i=1}^{m} z'_{ij}}, \qquad \forall\, i,j \tag{4.2}$$

Step 3: Using the normalized values calculated in the previous step, Entropy values for each criterion are calculated using equation (4.3).

$$e_j = -k \sum_{i=1}^{m} p_{ij} \ln(p_{ij}), \qquad k = \frac{1}{\ln(m)}, \qquad \forall\, j \tag{4.3}$$

Step 4: Using Equation (4.4), the degree of difference for each criterion is calculated.

$$d_j = 1 - e_j, \qquad \forall\, j \tag{4.4}$$

Step 5: As a final step, the weight values of the criteria are calculated using equation (4.5).

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j}, \qquad \forall\, j \tag{4.5}$$

TOPSIS Method

Technique for Order Preference by Similarity to Ideal Solution-TOPSIS is a widely used multi-criteria decision-making method initially introduced by Hwang and Yoon (1981). Known for its simplicity, applicability, and reliable ranking capabilities, TOPSIS has become a preferred choice in various fields (Gómez-López et al., 2009: 1506). The method involves a series of steps explained below (Hwang and Yoon, 1981, pp.130-132).

Step 1: A decision matrix is formulated using Equation (4.6), where decision alternatives (m) represent the rows and decision criteria (n) constitute the columns of the matrix.

$$D = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{4.6}$$

Step 2: The normalized decision matrix is calculated by using vector normalization with Equation (4.7).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \qquad \forall\, i, j \tag{4.7}$$

Step 3: Using the predetermined weight values (w_j) and the values normalized by equation (4.7), a weighted normalized decision matrix is created by using equation (4.8).

$$v_{ij} = w_j r_{ij} \qquad \forall\, i, j \tag{4.8}$$

Step 4: The positive ideal solution values (A*) and negative ideal solution values (A-) are obtained using equations (4.9) and (4.10) respectively.

$$A^* = \{(\operatorname*{maks}_i v_{ij} \mid j \in J), (\min_i v_{ij} \mid j \in J') \mid i = 1,2,\ldots,m\} = \{v_1^*, v_2^*, \ldots, v_n^*\} \tag{4.9}$$

$$A^- = \{(\min_i v_{ij} \mid j \in J), (\operatorname*{maks}_i v_{ij} \mid j \in J') \mid i = 1,2,\ldots,m\} = \{v_1^-, v_2^-, \ldots, v_n^-\} \tag{4.10}$$

The equations, *J* represents the benefit criteria and *J'* represents the cost criteria.

Step 5: Using Equations (4.11) and (4.12), the distances of each alternative to the positive ideal solution and the negative ideal solution are calculated.

$$S_i^* = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^*\right)^2}, \qquad \forall\, i \tag{4.11}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2}, \qquad \forall\, i \tag{4.12}$$

Step 6: The relative closeness values of each alternative to the ideal solution are obtained using equation (4.13). It takes values between $0 \leq C_i \leq 1$.

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^*}, \qquad \forall i \qquad (4.13)$$

Step 7: Alternatives are ranked according to their C_i^* values. The alternative with the highest C_i^* value is the best.

GRA Method

Grey Relational Analysis, a component of the grey system theory introduced by Deng in 1982, stands as a multi-criteria decision-making method particularly useful for tackling intricate problems with limited data (Kuo et al., 2008:81). The method's advantages lie in its ability to operate effectively with a small dataset, its comprehensibility, and the ease with which calculations can be performed (Chen and Ting, 2002: 849). The method follows the following steps (Fung, 2003:299-300; and Hamzaçebi and Pekkaya, 2011:9188-9189).

Step 1: A decision matrix is formulated, comprising x_{ij} values as specified in Equation (4.14).

$$\begin{bmatrix} x_1(1) & x_1(2) & \dots & x_1(n) \\ x_2(1) & x_2(2) & \dots & x_2(n) \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ x_m(1) & x_m(2) & \dots & x_m(n) \end{bmatrix} \qquad (4.14)$$

In the decision matrix, m is the number of alternatives, n is the number of criteria and x_{ij} is the value of the j. criterion of the i. alternative.

Step 2: In this step, the reference series is determined. The reference series is formed by taking the largest value for the benefit-based criteria in the decision matrix and the smallest value for the cost-based criteria, as shown in equation (4.15).

$$x_0 = (x_0(1), x_0(2), x_0(3), \dots\dots, x_0(n)) \qquad (4.15)$$

Step 3: Normalization is done in three different ways using Equations (3.16), (3.17) and (3.18) to create a normalized decision matrix represented by X^+

In the case of benefit;

$$x_i^*(j) \frac{x_i^o(j) - minx_i^o(j)}{maksx_i^o(j) - minx_i^o(j)} \qquad (4.16)$$

In the case of cost;

$$x_i^*(j) = \frac{minx_i^o(j) - x_i^o(j)}{maksx_i^o(j) - minx_i^o(j)} \qquad (4.17)$$

In the nominal case;

$$x_i^*(j) = 1 - \frac{|x_i^o(j) - x^o|}{maksx_i^o(j) - x^o} \qquad (4.18)$$

Step 4: The value of the difference between each alternative and the reference series is calculated with the help of equation (4.19) and the absolute value matrix is created.

$$\Delta_{0i} = |x_0^*(j) - x_i^*(j)| \tag{4.19}$$

Step 5: Gray relational coefficient values are calculated using equation (4.20).

$$\gamma(x_0^*(j), x_i^*(j) = \frac{\Delta_{min} + \zeta\Delta_{maks}}{\Delta_{min}(j) + \zeta\Delta_{maks}} \tag{4.20}$$

$$\Delta_{maks} = \max_{\forall j \in i} \max_{\forall k} |x_0^*(j) - x_j^*(j)|$$

$$\Delta_{min} = \min_{\forall j \in i} \min_{\forall k} |x_0^*(j) - x_j^*(j)|$$

The ζ parameter in Equation (4.21) is expressed as the discriminant coefficient and takes values in the range of [0,1]. The discriminant coefficient. ζ is generally used as 0.5 in the literature.

Step 6: In the last step, gray relational degrees are calculated. If the criteria are of equal importance, equality (4.30) is used.

$$\zeta(x_0^*(j), x_i^*(j) = \frac{1}{n}\sum_{j=1}^{n} ɣ\,(x_0(j), x_i\,(j)) \tag{4.21}$$

If each criterion has different importance values, gray relational values are calculated with equation (4.22).

$$\zeta(x_0^*(j), x_i^*(j) = \sum_{j=1}^{n} w_i(j)\varepsilon(x_0(j), x_i\,(j)) \tag{4.22}$$

After calculating the gray relational degrees, the alternatives are ranked according to the $\zeta(x_0^*(j), x_i^*(j)$ value. The alternative with the largest $\zeta(x_0^*(j), x_i^*(j)$ value is determined as the best alternative.

COPRAS Method

Complex Proportional Assessment-COPRAS is a multi-criteria decision-making method devised by Zavadskas and Kaklauskas (1996), offering the capability to assess both quantitative and qualitative criteria. This method proves to be valuable in evaluating both useful and non-useful criteria separately in the evaluation process (Garg, 2019: 281). Noteworthy advantages of COPRAS include its short calculation time, clarity, user-friendliness, and transparency (Mulliner et al., 2013: 274). The application stages of the method are as follows; (Zavadskas et al., 2004:349; Kabak and Çınar, 2020: 186-187):

Step 1: The decision matrix in equation (4.23) is created, with decision alternatives (m) in the rows of the matrix and decision criteria (n) in the columns.

$$D = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{4.23}$$

Step 2: With Equation (4.24), x_{ij}values are normalized, and a normalized decision matrix is created.

$$X_{ij}^{*} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}}, \qquad \forall\, i,j \tag{4.24}$$

Step 3: Using the weight values (w_j) of the criteria and the normalized values with equation (3.24), a weighted normalized decision matrix is created with equation (3.25).

$$r_{ij} = w_j * x_{ij}^{*} \qquad \forall\, i,j \tag{4.25}$$

Step 4: Using the weighted normalized decision matrix obtained with Equation (4.25), useful criterion values are collected with Equation (4.26), and non-useful criterion values are collected with Equation (4.27).

$$S_i^{+} = \sum_{j=1}^{k} r_{ij} \qquad i = 1,2, \ldots., k \tag{4.26}$$

$$S_i^{-} = \sum_{j=1}^{k} r_{ij} \qquad i = k+1, k+2, \ldots., n \tag{4.27}$$

Step 5: The relative values of the alternatives are found with Equation (4.28).

$$Q_i = S_i^{+} + \frac{\sum_{i=1}^{m} S_i^{-}}{S_i^{-} \sum_{i=1}^{m} \frac{1}{S_i^{-}}} \qquad i = 1,2, \ldots., m \tag{4.28}$$

Step 6: The largest relative weight value is calculated as in Equation (4.29).

$$Q_{max} = \{Q_i\} \quad \forall\, i = 1,2, \ldots, m \tag{4.29}$$

Step 7: Step 7 involves the calculation of performance index (P_i) values for each alternative, as illustrated in Equation (4.30). Subsequently, the P_i values are arranged in descending order, with the alternative possessing the highest P_i value deemed to be the optimal choice.

$$P_i = \frac{Q_i}{Q_{max}} * \%100, \qquad i = 1,2, \ldots, m \tag{4.30}$$

8

MARCOS Method

Measurement Alternatives and Ranking according to Compromise Solution-MARCOS method, introduced by Stević et al. (2020), is a multi-criteria decision-making approach that evaluates alternative options by comparing their reference values to ideal values. The method's application involves the following steps (Stević et al., 2020:4-5):

Step 1: The decision matrix is created by determining the criteria and alternatives.

Step 2: As given in Equation (4.31), ideal and anti-ideal solutions are added to the initial matrix to create an expanded initial matrix.

$$D = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \\ AI \\ AAI \end{array} \begin{bmatrix} C_1 & C_2 & C_3 & C_4 \\ x_{11} & x_{12} & x_{13} & x_{14} \\ x21 & x22 & \cdots & x2n \\ . & . & . & . \\ x_{m1} & x_{m2} & x_{m3} & x_{mn} \\ x_{ai1} & x_{ai2} & x_{ai3} & x_{ain} \\ xaa1 & xaa2 & \cdots & x_{aan} \end{bmatrix} \tag{4.31}$$

The ideal solution (AI) represents the best alternative, while the anti-ideal solution (AAI) represents the worst alternative. AI and AAI are defined using Equations (4.32) and (4.33).

$$AI = \max x_{ij} \;\; Eğer\ j\ fayda\ kriteri\ ise\ \ ve\ minx_{ij}\ j\ maliyet\ kriteri\ ise \tag{4.32}$$

$$AAI = \min x_{ij} \;\; Eğer\ j\ fayda\ kriteri\ ise\ \ ve\ \max x_{ij}\ j\ maliyet\ kriteri\ ise \tag{4.33}$$

Step 3: A normalized expanded initial matrix is created using Equation (4.34) for benefit-based criteria and (Equation) (4.35) for cost-based criteria.

$$n_{ij} = \frac{x_{ij}}{x_{ai}} \tag{4.34}$$

$$n_{ij} = \frac{x_{ai}}{x_{ij}} \tag{4.35}$$

Step 4: A weighted normalized decision matrix is created with the weight values of the criteria (w_{ij}) and equation (4.2).

$$v_{ij} = w_j * n_{ij} \qquad\qquad \forall\, i,j \tag{4.36}$$

Step 5: Using Equations (4.37) and (4.38), the benefit degrees of the alternatives are calculated according to the ideal and non-ideal solutions.

$$K_i^+ = \frac{S_i}{S_{ai}} \tag{4.37}$$

$$K_i^- = \frac{S_i}{S_{aai}} \tag{4.38}$$

The S_i value (i=1,2,...,m) represents the sum of weighted matrix elements. It is calculated using Equation (4.39).

$$S_i = \sum_{i=1}^{n} v_{ij} \tag{4.38}$$

Step 6: The benefit function of the alternatives is determined using the Equation (4.40). The benefit function is the compromise of the observed alternative into an ideal and a non-ideal solution.

$$(f)_{Ki} = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}} \tag{4.39}$$

Benefit functions based on ideal and non-ideal solutions are calculated with Equations (4.41) and (4.42).

$$f(K_i^-) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{4.40}$$

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{4.40}$$

Step 7: Alternatives are ranked based on the final values of the benefit functions. It is preferred that an alternative has the highest possible value of the benefit function. The alternative with the highest value is determined to be the best alternative.

5. Results

Table 3 displays the weight values for 29 indicators encompassing financial capital, manufactured capital, intellectual capital, human capital, natural capital, and social and relational capital elements of the banks considered in the study.

Table 3: Entropy Weight Values of Indicators for the 2020-2023 Period

INDICATORS	2020	2021	2022	2023
Financial Capital	**0,1107**	**0,2382**	**0,2403**	**0,3161**
FC1	0,0029	0,0060	0,0114	0,0081
FC2	0,0352	0,0908	0,0852	0,1155
FC3	0,0101	0,0496	0,0364	0,0686
FC4	0,0142	0,0623	0,0677	0,0692
FC5	0,0125	0,0108	0,0103	0,0042
FC6	0,0091	0,0044	0,0089	0,0105
FC7	0,0017	0,0014	0,0012	0,0020
FC8	0,0175	0,0061	0,0092	0,0214
FC9	0,0076	0,0069	0,0101	0,0166
Manufactured Capital	**0,0332**	**0,0342**	**0,0527**	**0,0380**
MC1	0,0154	0,0253	0,0257	0,0110
MC2	0,0031	0,0010	0,0068	0,0061
MC3	0,0147	0,0079	0,0202	0,0209
Intellectual Capital	**0,1536**	**0,0963**	**0,1774**	**0,1409**
IC1	0,1296	0,0764	0,1436	0,1162
IC2	0,0290	0,0200	0,0338	0,0247
Human Capital	**0,1086**	**0,1859**	**0,0567**	**0,0673**
HC1	0,0033	0,0025	0,0034	0,0030
HC2	0,0773	0,1557	0,0050	0,0204
HC3	0,0117	0,0142	0,0174	0,0160
HC4	0,0038	0,0045	0,0142	0,0116
HC5	0,0111	0,0082	0,0129	0,0129
HC6	0,0014	0,0007	0,0038	0,0034
Social and Relational Capital	**0,0339**	**0,0342**	**0,0709**	**0,0670**
SRC1	0,0237	0,0149	0,0265	0,0295
SRC2	0,0049	0,0025	0,0046	0,0101
SRC3	0,0053	0,0168	0,0399	0,0274
Natural Capital	**0,5550**	**0,4112**	**0,4020**	**0,3707**
NC1	0,0118	0,0089	0,0192	0,0113
NC2	0,0042	0,0042	0,0043	0,0092
NC3	0,0249	0,0559	0,0225	0,0172
NC4	0,0457	0,0451	0,0760	0,0574
NC5	0,2743	0,1840	0,1183	0,1292
NC6	0,1941	0,1130	0,1617	0,1464

Upon reviewing the Entropy values presented in Table 3, it is evident that among the capital element indicators outlined in the integrated reports of the banks, the highest importance and weight values correspond to the "Amount of Recycled Waste/Total Employees" (NC5), while the lowest indicator pertains to the "Ratio of Female Employees Returning to Work Post Maternity Leave" (HC6). Based on this, it can be argued that the indicator that has the greatest difference between banks is the amount of recyclable waste per employee. However, in 2023, the importance value for this indicator decreased and the difference started to decrease. The indicator with the least difference between banks is the rate of female employees returning from maternity leave.

Specifically, NC5 holds the highest weight value in 2020 and 2021, and "Paper Consumption/Total Employees" (NC6) takes precedence in 2022. Conversely, "Ratio of Female Employees Returning to Work Post Maternity Leave" (HC6) exhibits the lowest weight value in 2020 and 2021, with "Total Loans and Receivables/Total Deposits" (FC7) claiming this position in 2022. For the 2020-2022 period, the capital element with the highest weight value is identified as natural capital, followed by financial, human, intellectual, social, and relational capital in descending order. Analyzing weight values by years reveals that natural capital consistently holds the highest weight value, while manufactured capital consistently exhibits the lowest weight value.

Examining the weight values of capital elements over the years, it becomes apparent that financial, manufactured, and social and relational capital elements experience an increase in weight values. Notably, the weight value of intellectual capital undergoes a significant decrease in 2021 compared to 2020. This may probably be due to banks' restrictions on investments in intangible assets due to the pandemic effect. However, it was observed that it increased significantly again in 2022 and started to decrease slightly in 2023. Changing conditions in the banking sector after the pandemic have increased the importance of digitalization and digital transformation and may have led to differences in banks' adaptation to this process. However, the decrease in the importance weight value in the following year can be explained by the fact that banks adopted the transformation process and started to implement similar policies. Meanwhile, human capital's weight value peaks in 2021 before witnessing a significant decline in 2022 and 2023. The difference between banks may have emerged as a result of the use of different training models (hybrid, distance education, etc.) and the disruptions experienced during the pandemic in 2021, especially in employee training. However, in the following years, the integration of banks into new education models and the regular functioning of the system may have led to a decrease in this difference. Lastly, the significance of the natural capital element diminished over the years. This can be explained by the decrease in the importance values of indicators of natural capital elements and the decrease in the difference between banks as a result of banks following similar policies in energy, water, greenhouse gas emissions, waste and paper management within the scope of sustainability over the years.

Following the determination of weight values for the banks under investigation, the outcomes of applying the TOPSIS, GIA, MARCOS, and COPRAS methods to assess capital element indicators and rank bank performances concerning these elements are presented in the subsequent tables.

Table 4: 2020 MCDM Results

	TOPSIS		GRA		MARCOS		COPRAS	
	Score	Ranking	Score	Ranking	Score	Ranking	Score	Ranking
AKBNK	0,4080	2	0,5615	2	0,5807	2	0,6125	2
GARAN	0,3826	4	0,5260	3	0,4522	4	0,5832	4
HALKB	0,3252	6	0,5047	6	0,4800	3	0,5602	5
TIB	0,3285	5	0,5153	5	0,3809	6	0,4875	6
VAKBN	0,4006	3	0,5217	4	0,4042	5	0,5906	3
YKBNK	0,7268	1	0,7014	1	0,7130	1	1,0000	1
Mean	*0,4286*		*0,5551*		*0,5018*		*0,6390*	

Observing Table 4, YKBNK emerges as the top-ranked bank across all applied methods based on the scores and rankings obtained. Notably, HALKB occupies the last position according to the TOPSIS and GIA methods, while TIB holds the last spot according to the MARCOS and COPRAS methods. The average performance scores for banks fall within the range of 0.42-0.64. To explore the potential existence of a significant relationship between the results derived from the employed methods, a Spearman Rank Correlation test was conducted. The outcomes of this test are outlined in Table 5.

Table 5: 2020 Spearman Rank Correlation Test Results

Spearman's rho		TOPSIS	GRA	MARCOS	COPRAS
TOPSIS	Correlation Coefficient	1,000	,943	,600	,943
	p value	,000	,005	,208	,005
	N	6	6	6	6
GRA	Correlation Coefficient	,943	1,000	,657	,886
	p value	,005	,000	,156	,019
	N	6	6	6	6
MARCOS	Correlation Coefficient	,600	,657	1,000	,771
	p value	,208	,156	,000	,072
	N	6	6	6	6
COPRAS	Correlation Coefficient	,943	,886	,771	1,000
	p value	,005	,019	,072	,000
	N	6	6	6	6

The correlation coefficient and p significance values presented in Table 5 reveal a noteworthy and statistically significant correlation between the TOPSIS-GIA and TOPSIS-COPRAS methods at the 1% significance level. Additionally, a significant correlation is observed between the GIA-COPRAS methods, at the 5% significance level. This suggests that these three methods TOPSIS, GIA, and COPRAS can be interchangeably applied when assessing the indicators related to banks' capital elements for the year 2020.

Table 6: 2021 MCDM Results

	TOPSIS		GRA		MARCOS		COPRAS	
	Score	Ranking	Score	Ranking	Score	Ranking	Score	Ranking
AKBNK	0,3369	4	0,5579	3	0,5491	3	0,6477	5
GARAN	0,3399	3	0,5465	5	0,5706	2	0,7871	3

HALKB	0,5049	2	0,5691	2	0,5003	5	0,8442	2
TIB	0,3269	5	0,5560	4	0,5019	4	0,7271	4
VAKBN	0,3057	6	0,5383	6	0,3737	6	0,5782	6
YKBNK	0,5680	1	0,6297	1	0,6502	1	1,0000	1
Mean	***0,3970***		***0,5662***		***0,5243***		***0,7640***	

Upon reviewing Table 6, it is evident that YKBNK consistently secures the top position, while VAKBN consistently ranks at the bottom across all methods. Although there are some variations in scores and rankings obtained from different methods, the banks at the first and last places remain unchanged. The average performance scores for banks fall within the range of 0.40 to 0.76. To assess the presence of a significant relationship between the results obtained from the employed methods, a Spearman Rank Correlation test was conducted, and the outcomes are detailed in Table 7.

Table 7: 2021 Spearman Rank Correlation Test Results

Spearman's rho		TOPSIS	GRA	MARCOS	COPRAS
TOPSIS	Correlation Coefficient	1,000	,829	,657	,943
	p value	,000	,042	,156	,005
	N	6	6	6	6
GRA	Correlation Coefficient	,829	1,000	,486	,771
	p value	,005		,329	,072
	N	6	6	6	6
MARCOS	Correlation Coefficient	,657	,486	1,000	,600
	p value	,156	,329	,000	,208
	N	6	6	6	6
COPRAS	Correlation Coefficient	,943	,771	,600	1,000
	p value	,005	,072	,208	,000
	N	6	6	6	6

Based on the correlation and p significance values, a significant relationship is observed between the TOPSIS-COPRAS methods at the 1% significance level, between the TOPSIS-GRA methods at the 5% significance level, and between the GRA-COPRAS methods at the 10% significance level. Consequently, it can be inferred that the results obtained from assessing indicators for the year 2021 using these methods are likely to be closely aligned.

Table 8: 2022 MCDM Results

	TOPSIS		GRA		MARCOS		COPRAS	
	Score	**Ranking**	**Score**	**Ranking**	**Score**	**Ranking**	**Score**	**Ranking**
AKBNK	0,7825	1	0,6179	2	0,8465	1	1,0000	1
GARAN	0,4830	4	0,5891	4	0,5456	4	0,7258	4
HALKB	0,1716	6	0,4828	6	0,4155	6	0,4881	6
TIB	0,6243	2	0,6124	3	0,6926	2	0,9067	2
VAKBN	0,3437	5	0,5440	5	0,4494	5	0,5508	5
YKBNK	0,5839	3	0,6620	1	0,6626	3	0,8495	3
Mean	***0,4982***		***0,5847***		***0,6020***		***0,7535***	

Analyzing the scores and rankings in Table 8, it is evident that AKBNK secures the top position according to the TOPSIS, MARCOS, and COPRAS methods, while YKBNK claims the first place based on the GRA method. Conversely, HALKB consistently ranks at the bottom across all methods. Despite some variations in scores, a general assessment indicates that the results are closely aligned in terms of rankings. The average performance scores for banks fall within the range of 0.50 to 0.75. To explore the potential existence of a significant relationship between the scores and rankings obtained from the applied methods, a Spearman Rank Correlation test was conducted, and the outcomes are detailed in Table 9.

Table 9: Spearman Rank Correlation Test Results for 2022

Spearman's rho		TOPSIS	GRA	MARCOS	COPRAS
TOPSIS	Correlation Coefficient	1,000	,829	1,000	1,000
	p value	,000	,042	,000	,000
	N	6	6	6	6
GRA	Correlation Coefficient	,829	1,000	,829	1,000
	p value	,042	,000	,042	,000
	N	6	6	6	6
MARCOS	Correlation Coefficient	1,000	,829	1,000	1,000
	p value	,000	,042	,000	,000
	N	6	6	6	6
COPRAS	Correlation Coefficient	1,000	,829	1,000	1,000
	p value	,000	,042	,000	,000
	N	6	6	6	6

According to the correlation and significance values in Table 9, a significant and high relationship is observed between the TOPSIS-COPRAS-MARCOS methods at the 1% significance level, and between the GRA-COPRAS-MARCOS methods at the 5% significance level. Consequently, it can be inferred that all methods employed for evaluating indicators in 2022 can be applied interchangeably.

Table 10: 2023 MCDM Results

	TOPSIS		GRA		MARCOS		COPRAS	
	Score	**Ranking**	**Score**	**Ranking**	**Score**	**Ranking**	**Score**	**Ranking**
AKBNK	0,8732	1	0,6276	2	0,8882	1	1	1
GARAN	0,4984	4	0,5918	4	0,6464	3	0,7083	3
HALKB	0,1680	6	0,4701	6	0,3948	6	0,4032	5
TIB	0,5520	2	0,6193	3	0,6777	2	0,7396	2
VAKBN	0,1848	5	0,5721	5	0,4082	5	0,3880	6
YKBNK	0,5201	3	0,6569	1	0,6184	4	0,6777	4
Mean	***0,4661***		***0,5896***		***0,6056***		***0,6528***	

Analyzing the scores and rankings in Table 10, it is evident that AKBNK secures the top position according to the TOPSIS, MARCOS, and COPRAS methods, while YKBNK claims the first place based on the GRA method. Conversely, HALKB occupies the last position according to the TOPSIS, GIA and MARCOS methods, while VAKBN holds the last spot according to the COPRAS method. Despite some variations in scores, a general assessment indicates that the results are closely aligned in terms of rankings. The average performance scores for banks fall within the range of 0.47 to 0.65. To explore the potential existence of a significant relationship between the scores and rankings obtained from the applied methods, a Spearman Rank Correlation test was conducted, and the outcomes are detailed in Table 11.

Table 11: Spearman Rank Correlation Test Results for 2023

Spearman's rho		TOPSIS	GRA	MARCOS	COPRAS
TOPSIS	Correlation Coefficient	1,000	,829	,943	,886
	p value	,000	,042	,005	,019
	N	6	6	6	6
GRA	Correlation Coefficient	,829	1,000	,657	,600
	p value	,042		,156	,208
	N	6	6	6	6
MARCOS	Correlation Coefficient	,943	,657	1,000	,943
	p value	,005	,156		,005
	N	6	6	6	6
COPRAS	Correlation Coefficient	,886	,600	,943	1,000
	p value	,019	,208	,005	,000
	N	6	6	6	6

According to the correlation and p significance values in Table 11, there is a significant and high relationship between the TOPSIS-MARCOS, MARCOS-COPRAS methods at the 1% significance level and between the TOPSIS-GIA, TOPSIS-COPRAS methods at the 5% significance level. Based on this, it can be argued that the results obtained from the methods used in evaluating the indicators for 2023 will be used interchangeably to a large extent.

6. Conclusion

This study aimed to assess the indicators of capital elements found in banks' integrated reports, utilizing weight values obtained through the Entropy Method. The analysis revealed that the most crucial indicator for the banks under consideration is the amount of waste recycled per employee, while the least significant indicator is the ratio of female employees returning to work after maternity leave. Comparatively, the analysis suggests that the disparity between banks in the amount of waste recycled per employee is higher than that in the ratio of female employees returning to work after maternity leave. Notably, the indicator with the highest variation between banks reached its peak in 2020 but experienced a decline in 2021, 2022 and 2023. This decline may be attributed to increased environmental awareness among banks, leading to enhanced waste management practices. The adoption of similar policies within the mandatory zero-waste framework and increased sensitivity to recyclable waste could be contributing factors, reducing the variation between banks over the years.

Analyzing the weight values of banks' capital elements reveals noteworthy trends. The natural capital element, which exhibited the highest importance value in 2020 with significant variations between banks, has shown a declining trend in subsequent years. This decline may be attributed to increased societal and organizational awareness toward environmental issues aligned with sustainability development goals and the increasing emphasis of banks on energy, water, waste, and emission management, coupled with awareness-raising activities among employees, likely contributed to reduced differences in natural capital indicators among banks. In contrast, there is an observed increase in the difference between banks concerning the weight values of the financial capital element in 2021, 2022 and 2023. This variance may stem from the differential impact of economic conditions and macroeconomic factors on public, private, and foreign-owned banks. Examining intellectual capital, the highest disparity between banks was recorded in 2020, followed by a substantial decrease in 2021 and an increase again in 2022. The onset of the COVID-19 pandemic in March 2020 accelerated digitalization in the banking sector, leading to differences in banks' adaptability. The fluctuation in intellectual capital weight values may reflect the sector's diverse responses to the pandemic, with potential restrictions on investments in intangible assets contributing to the decline in 2021. Contrary to intellectual capital, human capital's weight values peaked in 2021. Notably, there is a significant difference in the average training hours per employee indicator among banks in that year. This discrepancy is attributed to variations in banks' adaptation processes amid the rapidly changing education model during the pandemic. With the integration and implementation of banks into this educational paradigm in 2022, differences between banks decreased in this regard.

In a comprehensive assessment of the integrated reporting performance scores derived from the evaluation of capital element indicators among banks in the study, several noteworthy trends emerge. Yapı and Kredi Bank, a private capital bank, consistently secured the top rank in 2020 and 2021, while Akbank claimed the first position in 2022 and 2023. On the other hand, Halkbank, a public bank, ranked 6th in both 2020, 2022 and 2023, and Vakıflar Bank held the 6th position in 2021. The overall performance of banks during the 2020-2022 period was deemed average, with the highest performance observed in 2022. The observed shifts in rankings and the increasing performance scores may be attributed to increased societal awareness of sustainability and evolving expectations. Banks are now placing greater emphasis on non-financial indicators alongside financial indicators to meet societal expectations. This suggests that indicators related to capital elements, disclosed within the framework of integrated reporting, are evolving. Banks in the service sector are striving to promptly respond to the changing needs of both society and the state. Consequently, it can be stated that there has been a rise in the adoption of integrated reporting within the banking sector. This reporting method enables the presentation of both financial and non-financial indicators together. In future studies on this subject, different sectors can be addressed and the indicators of capital elements in the integrated reports of companies operating in these sectors can be analyzed with different multi-criteria decision-making methods. Additionally, different indicators can be added to the indicators used in this study and the study period can be expanded in the following years.

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