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Analysis of Companies' Intellectual Capital Performance Using the MEREC-Based MARCOS Method: The Case of the BIST Forest, Paper and Printing Index

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This study aims to measure and comparatively rank the intellectual capital performance of companies in the BIST Forest, Paper, and Printing Index by developing the MEREC–MARCOS integrated method, which will contribute to the literature in the field of multi-criteria decision making (MCDM).The study used decision matrices generated from financial data for the years 2020–2024. Criteria weights were determined using the MEREC method, and company performance rankings were performed using the MARCOS method. The reliability of the method was tested using comparative analysis using WASPAS, COPRAS, SAW, and MOOSRA methods, and the Spearman rank correlation coefficient. The analyses revealed that the criteria weights change periodically. While the Intangible Assets (K8) criterion was of the highest importance in 2020–2021, the Market Value–Book Value (K5) criterion gained prominence in subsequent years. In the company rankings, ALKA achieved the highest performance between 2022 and 2024, while DGNMO and MNDTR experienced a decline in performance. The Spearman correlation coefficient averaged 0.95, demonstrating high agreement between the methods. The MEREC–MARCOS method is an effective tool for objective, reliable, and comparative assessment of intellectual capital performance. The method can be adapted to different sectors and decision-making problems, and more flexible decision support systems can be developed by integrating it with fuzzy logic or artificial intelligence-based approaches.

KEYWORDS
BIST, multi-criteria decision making, intellectual capital

Şirketlerin Entelektüel Sermaye Performanslarının MEREC tabanlı MARCOS Yöntemi ile Analizi: BIST Orman, Kâğıt ve Basım Endeksi Örneği

Bu çalışma, çok kriterli karar verme (ÇKKV) alanında literatüre katkı sağlayacak MEREC–MARCOS bütünleşik yöntemini geliştirerek, BIST Orman, Kâğıt ve Basım Endeksi'ndeki şirketlerin entelektüel sermaye performanslarını ölçmeyi ve karşılaştırmalı olarak sıralamayı amaçlamaktadır. Araştırmada, 2020–2024 yıllarına ait finansal verilerden oluşturulan karar matrisleri kullanılmıştır. MEREC yöntemi ile kriter ağırlıkları belirlenmiş, MARCOS yöntemi ile şirket performans sıralamaları yapılmıştır. Yöntemin güvenilirliği, WASPAS, COPRAS, SAW ve MOOSRA yöntemleri ile karşılaştırmalı analiz ve Spearman sıra korelasyon katsayısı ile test edilmiştir. Analizler, kriter ağırlıklarının dönemsel olarak değiştiğini ortaya koymuştur. 2020–2021'de Maddi Olmayan Duran Varlıklar (K8) kriteri en yüksek öneme sahipken, sonraki yıllarda Piyasa Değeri–Defter Değeri (K5) kriteri öne çıkmıştır. Şirket sıralamalarında ALKA, 2022–2024 yıllarında en yüksek performansa ulaşırken, DGNMO ve MNDTR'nin performansında düşüş gözlenmiştir. Spearman korelasyon katsayısı ortalama 0,95 olup yöntemler arası yüksek uyum elde edilmiştir. MEREC–MARCOS yöntemi, entelektüel sermaye performansının nesnel, güvenilir ve karşılaştırmalı olarak değerlendirilmesinde etkili bir araçtır. Yöntem, farklı sektörler ve karar verme problemlerine uyarlanabilir; fuzzy mantık veya yapay zekâ tabanlı yaklaşımlarla bütünleştirilerek daha esnek karar destek sistemleri geliştirilebilir.

ANAHTAR KELİMELER
BIST, çok kriterli karar verme, entelektüel sermaye

1. INTRODUCTION

The accelerating technological advances and knowledge-based economic structures brought about by globalization have radically transformed how businesses achieve competitive advantage. In today's knowledge economy, the strategic importance of intangible assets, especially intellectual capital, as well as tangible assets, is increasing. Intellectual capital (IC) refers to all intangible assets that enable a business to sustain its activities and create value, and that are difficult to measure but produce high added value (Zor & Cengiz, 2013). IC, which consists of three basic components: human capital, structural capital and customer capital, is a holistic concept that includes the knowledge, skills and experiences of employees, organizational structure and processes, customer relations and brand value (Özdemir & Balkan, 2010).

Human capital is one of the most important factors determining a business's innovation and problem-solving capacity. Structural capital refers to the organizational infrastructure that enables the effective use of human capital in line with company objectives, while customer capital encompasses elements such as the business's relationships with the external environment, customer loyalty, and brand reputation. These components, together, are the fundamental value-creating resources that determine a company's long-term competitiveness (Özdemir & Balkan, 2010).

The forest products sector is one of the areas where intellectual capital is intensively applied. This sector, which processes wood, a renewable raw material, using mechanical and chemical methods in its production processes to produce semi-finished or finished products, boasts a wide range of products, including lumber, wood-based panels, paper and cardboard, furniture, and biofuels. In recent years, increasing global demand and environmental concerns have necessitated the adoption of a sustainable and environmentally friendly production approach in the sector (Yeşilkaya et al., 2023). In this context, elements of intellectual capital, such as innovative production techniques, R&D investments, supply chain management, and market development strategies, play a critical role in creating competitive advantage in the sector.

The management and measurement of intellectual capital has become a crucial requirement both in the strategic decision-making processes of businesses and in assessing the sector's overall performance. However, the abstract nature of IC makes it difficult to measure its performance. In this regard, multi-criteria decision-making (MCDM) methods offer the opportunity to objectively and comparatively analyze the intellectual capital performance of businesses by systematically evaluating different qualitative and quantitative indicators. MCDM is a powerful decision-making analysis method that allows for the simultaneous evaluation of multiple, often conflicting, criteria. Techniques such as AHP, MOORA, TOPSIS, VIKOR, ELECTRE, and DEMATEL have wide application in both determining criteria weights and ranking alternatives (Arslankaya & Göraltay, 2019).

There are many studies on the application of multi-criteria decision-making methods in the fields of forestry and forest industry. Özel et al. (2014) conducted research using the Analytical Hierarchy Process Method regarding the location selection of afforestation works to be carried out with red pine and stone pine species in the Bartın basin. Azizi et al. (2016) determined the indicators affecting sustainable development in Iran's wooden furniture industry and prioritized these indicators with the AHP method. Urmak et al. (2017) evaluated forestry activities in Türkiye on a provincial basis using multi-criteria decision-making methods such as AHP, MAUT and SAW. Yesilkaya (2018) attempted to determine the most optimal location among five candidate cities for paper factory location with AHP, TOPSIS, and PROMETHEE techniques. Yılmaz et al. (2020) aimed to determine the most effective mass media tools in conveying forestry activities to the public by considering the preferences and expectations of local stakeholders in the context of Isparta Regional Directorate of Forestry, using the Analytical Hierarchy Process (AHP) method. The work performances of forest cadastre commissions in Bartın province were prioritized by Daşdemir and Gençay (2021) using the AHP technique. Kurt et al. (2021) determined the financial performance of fifteen companies in the Turkish paper products, forest products and furniture sectors using entropy-based PROMTHEE. Abedi (2022) identified the most effective criteria for preventing forest fires in the Arasbaran forests of Iran and analyzed these criteria using TOPSIS and SAW methods. Yeşilkaya et al. (2022) analyzed the industrial wood production of the provinces in Türkiye using TOPSIS and VIKOR methods. Akay and Demir (2022) tried to reveal the weight values of the criteria that are effective in selecting the most suitable vehicle types in forest products transportation using the hybrid fuzzy multi-criteria decision-making method and to determine the most suitable vehicle alternative according to criteria such as environmental damage, cost and operational performance under different scenarios. Deng et al. (2023) aimed to develop an indicator and method system (BWM and VIKOR) to evaluate SFM performance in economic, social and environmental dimensions by transferring the concept of Sustainable Forest Management (SFM) from macro level to micro level forestry enterprises, to analyze five-year performance by applying this model to a forestry enterprise in China and to emphasize the importance of environmental factors by offering policy recommendations and improvement suggestions. Singer and İlçe (2024) focused on presenting a decision framework for material combination selection in furniture production based on an integrated BWM-WASPAS technique. Chavenetidou et al. (2025) evaluated the suitability of eight softwood species most used in the Greek timber industry in terms of quality criteria and determined the most suitable species using PROMETHEE and AHP methods. Diker (2025) examined the sustainability performance of enterprises in the forest products and furniture sectors and identified their strengths and areas requiring development and evaluated the sustainability reports in the Public Disclosure Platform using content analysis and grey relational analysis.

This study aims to measure and comparatively analyze the intellectual capital performance of businesses operating in the forest products sector using MCDM-based methods. In this way, a scientific contribution will be made to the strategic management processes of enterprises by revealing which intellectual capital components are priorities in the sector.

Various methods are used in literature to measure and evaluate intellectual capital performance. Recently, evaluation models based on MCDM methods have been frequently used in national and international academic studies to provide a more holistic perspective on intellectual capital performance.

Chen and Chen (2010) attempted to overcome the challenges faced through effective knowledge management within the framework of the sector's structural development and profitability goals, identify critical assessment criteria for intellectual capital, and establish the best benchmark within the sector based on these criteria. For this purpose, they adopted a hybrid Multi-Criteria Decision Making (MCDM) approach, comprising DEMATEL, ANP, and VIKOR methods. Saeedi et al. (2012) applied the Fuzzy TOPSIS method to prioritize the intellectual capital (IC) components in Sapco company. They also offered various strategic recommendations to improve the company's intellectual capital and intangible asset management. Sekhar et al. (2015) aimed to develop a decision-making framework for prioritizing intellectual capital indicators and identifying critical indicators. The study focuses on manufacturing units of SMEs operating in the north-central region of India. The Delphi–AHP–TOPSIS approach, in which Delphi, AHP and TOPSIS methods are used in an integrated manner, was adopted. Wudhikarn (2018) aimed to provide a comprehensive assessment of the identification of important elements in intellectual capital (IC) management with the help of a hybrid approach based on the integration of ideational and non-ideational IC model, Delphi method and ANP. Lu and Wudhikarn (2022) aimed to propose a new and holistic model for developing intellectual capital (IC) performance indicators. To this end, the researchers integrated intellectual capital management with the MCDM approach and tested this improved model in a case study of a financial shared services center where intellectual capital management practices were inadequate. In the study, a total of 34 intellectual capital performance indicators were identified using a combination of a survey method and an intellectual capital process model. To determine the importance of these indicators, the BWM was applied, and the indicators were prioritized. Akgün and Günay (2021) examined the relationship between intellectual capital and business performance of two companies in the BIST Health Services index using ELECTRE, MAPPAC, ORESTE, TOPSIS and WSA methods. In the analysis conducted by Çevik and Arslan (2022) using the fuzzy AHP method to evaluate the intellectual capital of ship management companies, it was revealed that the most important element is human capital. Tamosiuniene and Sajaviciute (2022) determined the attractiveness levels of companies by considering the components of intellectual capital and applied the TOPSIS method to rank the companies. For this purpose, they identified eight criteria. Soylu and Zafari (2024) evaluated the intellectual capital performance of companies in the Metal Goods, Machinery, Electrical Equipment, and Transportation Vehicles sectors traded on the BIST using the CRITIC-based Gray Relational Analysis method. The criteria were the number of employees, R&D expenses, marketing expenses, capital employed, Market Value-Book Value, and net sales. Liu et al. (2024) attempted to develop a scientifically based decision-making structure to assess companies' intellectual capital. First, the Delphi method was used, and then the GDANP method was applied by integrating Grey DEMATEL and ANP to determine the relative weights of the indicators. Finally, the effectiveness and applicability of the proposed intellectual capital assessment index was tested using the TOPSIS method using data from thirty new technology companies operating in China.

There are studies on different fields using MEREC-based MARCOS methods, and studies in recent are summarized in Table 1.

Table 1. *Studies using the MEREC based MARCOS method in recent*

Authors	Problem	Method
Simic et al. (2022)	Analysis of the Impact of Urban Transportation on Climate Change	MEREC and MARCOS
Ivanovic et al. (2022)	Selection of truck mixer concrete pump	MEREC and DNMARCOS
Ersoy (2022)	Analysis of innovative performance of countries	MEREC and MARCOS
Sumerli Sarıgül et al. (2023)	Evaluation of airport service quality	MEREC, MARCOS and CoCoSo
Mastilo et al. (2024)	Evaluation of financial indicators	MEREC and MARCOS
Stilic et al. (2024)	Analysis of the Travel and Tourism Development Index of European countries	MEREC and MARCOS
Mondal et al. (2024)	Sustainable forest resources management	Pythagorean fuzzy MEREC and MARCOS
Sehgal et al. (2025)	Cost-effective optimization of hybrid renewable energy system	MEREC and MARCOS
Kumar et al. (2025)	Coating material selection	MEREC, TOPSIS, WASPAS, CODAS, MARCOS, TODIM, COPRAS, AMR, EDAS and MABAC
Arıkan Kargı (2025)	Evaluation of companies' performance	MEREC and MARCOS

2. MATERIAL AND METHOD

2.1. Material

This study aims to measure and evaluate the intellectual capital performance of companies listed in the BIST Forest, Paper, and Printing Index using the MEREC-based MARCOS method and their financial statements for the period 2020-2024. Furthermore, the reliability and consistency of the method were tested using different multi-criteria decision-making methods.

As a result of the literature review, indicators associated with intellectual capital were identified and used as criteria (Lu et al., 2010; Costa, 2012; Chang et al., 2013; Soylu, 2020; Soylu & Zafari, 2024). The criteria are presented in detail in Table 2. The criteria presented in Table 2 were obtained from the companies' financial statements, through the Public Disclosure Platform (2025). Market value data for the companies was obtained from the İş Yatırım (2025) database. There are 20 companies included in the BIST Forest, Paper, Printing Index, but the study was conducted with 14 companies because the market value criteria could not be reached by all companies or was missing in some years. The companies included in the study are presented in Table 3. R&D expenses, one of the indicators related to intellectual capital, were also excluded from the study because information on R&D expenses was not available in the financial statements of most companies within the scope of the study.

Table 2. *Criteria used in the study*

Criteria	Abbreviations	Direction of criteria
Number of employees	C1	Minimum
Administrative expenses	C2	Minimum
Marketing expenses	C3	Minimum
Foreign liabilities	C4	Minimum
Market value-Book value	C5	Maximum
Net sales	C6	Maximum
Capital employed	C7	Minimum
Intangible assets	C8	Maximum
Equity	C9	Maximum

Table 3. *Companies used in the study*

Abbreviations	Names of companies
DGNM0	DOĞANLAR Furniture Group Manufacturing Industry and Trade Inc.
GENTS	GENTAŞ Decorative Surfaces Industry and Trade Inc.
ORMA	ORMA Forest Products Integral Industry and Trade Inc.
SUMAS	SUMAŞ Chipboard and Furniture Industry Inc.
YONGA	YONGA Furniture Industry and Trade Inc.
ALKA	ALKIM Paper Industry and Trade Inc.
BAKAB	BAK Packaging Industry and Trade Inc.
DURDO	DURAN DOĞAN Printing and Packaging Industry Inc.
KAPLM	KAPLAMIN Packaging Industry and Trade Inc.
KARTN	KARTONSAN Cardboard Industry and Trade Inc.
MNDTR	MONDI TURKEY Corrugated Cardboard Paper and Packaging Industry Inc.
PRZMA	PRIZMA PRES Printing Publishing Industry and Trade Inc.
SAMAT	SARAY Printing, Paper Making, Stationery Trade and Industry Inc.
VKING	VIKING Paper and Cellulose Inc.

2.2. Method

2.2.1. MEREC Method

The MEREC (Method based on the Removal Effects of Criteria) method, developed by Keshavarz-Ghorabaee et al. (2021), is classified among objective weighting methods in multi-criteria decision-making (MCDM). The core principle of MEREC lies in measuring the impact of removing each criterion on the overall performance of the alternatives (Mastilo et al., 2024). The MEREC method was chosen to determine the criteria weights due to its objective and unbiased weighting, its reflection of the true impact of the criteria, and its mathematical and ease of application. Moreover, it contributes to consistent and balanced decisions by providing more average results and lower variances than other objective weighting methods, such as entropy (Keshavarz-Ghorabaee et al., 2021; Saidin et al., 2023; Keleş, 2023; Elsayed, 2024). This method has an application process consisting of six steps (Keshavarz-Ghorabaee et al. 2021).

Step 1. Creation of the initial decision matrix

A initial decision matrix consists of alternatives and criteria. The alternatives are in the rows of the matrix, and the criteria are in the columns.

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

Step 2. Normalization of the initial decision matrix

To obtain the normalized values of the initial decision matrix, equation (2) is used for the benefit criterion and equation (3) is used for the cost criterion.

$$r_{ij} = \frac{min x_{ij}}{x_{ij}} \tag{2}$$

$$r_{ij} = \frac{x_{ij}}{max_{ij}} \tag{3}$$

Step 3: Calculating total performance value

The total performance values of the alternatives were calculated with the help of equation (4).

$$S_i = \ln\left(1 + \left(\frac{1}{m}\sum_j \left|In\left(r_{ij}\right)\right|\right)\right) \tag{4}$$

Step 4: Calculating the performance values of the alternatives by removing each criterion

The equation for this step is similar to the equation for step 3. The only difference between step 4 and step 3 is that new performance values for the alternatives are calculated using a new set of criteria created by removing each criterion.

$$S'_{ij} = \ln\left(1 + \left(\frac{1}{m}\sum_{k,k\neq j} \left|In\left(r_{ij}\right)\right|\right)\right) \tag{5}$$

Step 5. Calculating total absolute deviation

The total absolute deviation values of the criteria were calculated with the help of equation (6).

$$E_j = \sum_i \left|S'_{ij} - S_i\right| \tag{6}$$

Step 6. Calculating the weights of the criteria

The weight values of the criteria were calculated with the help of equation (7).

$$w_j = \frac{E_j}{\sum_{j=1} E_j} \tag{7}$$

In the MEREC method, when the logarithms of the negative values in the decision matrix are taken, infinite and complex numbers are obtained. In such cases, the values are converted to positive using the Z-Score standardization method proposed by Zhang et al. (2014). Equations (8) and (9) are used for this process.

$$z_{ij} = \frac{x_{ij-}\overline{x_j}}{\sigma_j} \tag{8}$$

$$ZA_{ij} = z_{ij} + A \quad \left(A > \left|minz_{ij}\right|\right) \tag{9}$$

where, $z_{ij}$is the z-score value of the j criterion of the i alternative, x_{ij} is the value of the j criterion of the i alternative, $\overline{X}_j$is the mean of the j criterion, σ_j is the standard deviation of the j criterion and A is a value very close to the $minz_{ij}$ value.

2.2.2. MARCOS Method

The MARCOS (Measurement Alternatives and Ranking according to Compromise Solution) method determines the ranking of alternatives based on their relation to reference points—specifically, the ideal and anti-ideal solutions (Stević et al., 2020). This method uses a utility function to evaluate the relative performance of alternatives. A utility function reflects how close an alternative is to the ideal solution and how far it is from anti-ideal one. Therefore, the best alternative is the one closest to the ideal and farthest from the anti-ideal (Stanković et al., 2020; Stević et al., 2020). The MARCOS method is one of the chosen methods in multi-criteria decision analyses due to its reference-based comparison approach, its ability to examine alternatives from both an "ideal" and "anti-ideal" perspective; its ability to provide consistent rankings and stable results through sensitivity analysis; its flexible structure and broad application potential; its relatively straightforward structure; and its novel and research-ready nature (Trung, 2022a; Trung, 2022b; El-Araby, 2023; El-Araby et al., 2024).

The implementation of the MARCOS method involves the following steps (Stevic et al., 2020):

Step 1. Creation of the initial decision matrix

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots . & \cdots . & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{10}$$

Step 2: Extension of the decision matrix.

The initial decision matrix is expanded by incorporating reference values: the ideal solution (AI) and the anti-ideal solution (AAI).

$$X' = \begin{bmatrix} x_{aa1} & x_{aa2} & \cdots & x_{aan} \\ x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots . & \cdots . & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \\ x_{ai1} & x_{ai2} & .. & x_{ain} \end{bmatrix} \tag{11}$$

The anti-ideal solution (AAI) represents the worst alternative, whereas the ideal solution (AI) represents the best alternative. AAI and AI were determined using the following equations.

$$AAI = \min_i x_{ij} \;\; if\; j \in B \; and \; \max_i x_{ij} \;\; if \; j \in C \tag{12}$$

$$AI = \max_i x_{ij} \;\; if\; j \in B \; and \; \min_i x_{ij} \;\; if \; j \in C \tag{13}$$

where, B is a benefit group of criteria, while C is a group of cost criteria.

Step 3. Normalization of the extended decision matrix

In the expanded decision matrix, the data are normalized using equations (14) and (15).

$$r_{ij} = \frac{x_{ai}}{x_{ij}} \quad if\ j \in C \tag{14}$$

$$r_{ij} = \frac{x_{ij}}{x_{ai}} \quad if\ j \in B \tag{15}$$

Step 4. Creation of weighted normalize decision matrix

The weighted normalized decision matrix is created by multiplying the normalized value with the weight coefficients of criterion obtained by the MEREC method.

$$v_{ij} = x_{ij} * w_j \tag{16}$$

Step 5. Calculating the utility degree of alternatives

In this step, the S_i values of the alternatives are first calculated using equation (17). Then, the utility degrees of the alternative relative to the anti-ideal and ideal solutions are calculated using equations (18) and (19).

$$S_i = \sum_{j=1}^{n} v_{ij} \tag{17}$$

$$K_i^- = \frac{S_i}{S_{aai}} \tag{18}$$

$$K_i^+ = \frac{S_i}{S_{ai}} \tag{19}$$

Step 6. Calculating the utility function of alternatives

Firstly, utility functions in relation to the ideal and anti-ideal solution are calculated using equations (20) and (21). Then, the utility function of alternatives is calculated using equation (22).

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{20}$$

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{21}$$

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1-f(K_i^+)}{f(K_i^+)} + \frac{1-f(K_i^-)}{f(K_i^-)}} \tag{22}$$

The final ranking of alternatives is determined by the utility function value ($f(K_i)$) achieved by each alternative. In this context, the highest possible utility value for an alternative means that it is closest to the ideal solution and farthest from the anti-ideal solution. Thus, it ensures that the alternative is considered the most preferable option.

3. RESULTS

3.1. Evaluation of Criteria Using the MEREC Method

When the decision matrix in Table 4 is examined, the K5 criterion (Market Value-Book Value) contains a negative value. Negative values in the decision matrix are generally not used directly in the MEREC method because this method requires positive values when evaluating the importance weights of the criteria. Therefore, negative values must be converted to positive values. For this purpose, criteria containing negative data were normalized using the Z-score developed by Zhang et al. (2014).

Table 4. *Decision matrix for 2024*

Companies	C1	C2	C3	C4	C5	C6	C7	C8	C9
DGNM0	2547	662992194	3,125E+09	6,637E+09	641463203	1,184E+10	4,277E+09	398846844	3,195E+09
GENTS	830	292206531	236928027	1,327E+09	513700075	3,91E+09	2,662E+09	12664551	2,582E+09
ORMA	399	163366754	256699732	2,855E+09	-283266872	3,41E+09	5,751E+09	9260116	5,549E+09
SUMAS	82	27861485	5766948	126696047	1,672E+09	463520476	397646050	1331695	381710618
YONGA	185	48687356	22795362	511567070	518747565	360406762	583499406	10699781	455252435
ALKA	231	117753888	88589011	754257404	5,041E+09	2,727E+09	1,808E+09	5592270	1,677E+09
BAKAB	701	262051357	169833179	2,096E+09	320833824	4,383E+09	3,044E+09	79618238	2,33E+09
DURDO	395	189189069	207730549	1,056E+09	719424429	2,003E+09	1,549E+09	10534354	1,355E+09
KAPLM	225	78186398	190052498	1,039E+09	2,698E+09	1,76E+09	1,246E+09	694718	1,052E+09
KARTN	214	168954568	206581812	1,148E+09	4,123E+09	3,871E+09	2,848E+09	22620385	2,777E+09
MNDTR	1465	1,313E+09	960875413	3,823E+09	-605489440	1,236E+10	7,016E+09	65644513	6,721E+09
PRZMA	32	9229239	990244	89810478	171918167	50143054	355771997	12333536	336081833
SAMAT	68	3658621	2393290	168326422	289631607	179669853	446383256	43673782	419368393
VKING	170	102583635	135417389	2,528E+09	1,381E+09	809669976	418989295	5076120	36768712

Table 5. *The values of the criteria after Z-score calculation for 2024*

Companies	C1	C2	C3	C4	C5	C6	C7	C8	C9
DGNM0	2.9962	1.2354	3.4478	2.8336	-0.3694	2.1997	0.9618	3.5045	0.5829
GENTS	0.4344	0.1377	-0.2073	-0.2302	-0.4498	0.1239	0.1705	-0.3581	0.2678
ORMA	-0.2087	-0.2437	-0.1822	0.6513	-0.9511	-0.0071	1.6844	-0.3922	1.7947
SUMAS	-0.6816	-0.6449	-0.4998	-0.9224	0.2790	-0.7788	-0.9395	-0.4715	-0.8647
YONGA	-0.5280	-0.5833	-0.4782	-0.7004	-0.4466	-0.8058	-0.8484	-0.3778	-0.8269
ALKA	-0.4593	-0.3788	-0.3950	-0.5604	2.3980	-0.1861	-0.2484	-0.4289	-0.1982
BAKAB	0.2419	0.0484	-0.2922	0.2136	-0.5711	0.2477	0.3573	0.3115	0.1380
DURDO	-0.2146	-0.1673	-0.2442	-0.3864	-0.3204	-0.3756	-0.3750	-0.3794	-0.3640
KAPLM	-0.4683	-0.4959	-0.2666	-0.3961	0.9240	-0.4393	-0.5239	-0.4779	-0.5196
KARTN	-0.4847	-0.2272	-0.2457	-0.3331	1.8207	0.1135	0.2613	-0.2586	0.3679
MNDTR	1.3818	3.1599	0.7089	1.2097	-1.1538	2.3364	2.3044	0.1718	2.3980
PRZMA	-0.7562	-0.7001	-0.5058	-0.9437	-0.6648	-0.8871	-0.9600	-0.3615	-0.8882
SAMAT	-0.7025	-0.7166	-0.5041	-0.8984	-0.5907	-0.8531	-0.9156	-0.0480	-0.8453
VKING	-0.5503	-0.4237	-0.3357	0.4629	0.0959	-0.6882	-0.9290	-0.4340	-1.0422

Table 6. *Decision matrix for 2024 (positive value converted version)*

Companies	C1	C2	C3	C4	C5	C6	C7	C8	C9
DGNM0	4.1562	2.3954	4.6078	3.9936	0.7906	3.3597	2.1218	4.6645	1.7429
GENTS	1.5944	1.2977	0.9527	0.9298	0.7102	1.2839	1.3305	0.8019	1.4278
ORMA	0.9513	0.9163	0.9778	1.8113	0.2089	1.1529	2.8444	0.7678	2.9547
SUMAS	0.4784	0.5151	0.6602	0.2376	1.4390	0.3812	0.2205	0.6885	0.2953
YONGA	0.6320	0.5767	0.6818	0.4596	0.7134	0.3542	0.3116	0.7822	0.3331
ALKA	0.7007	0.7812	0.7650	0.5996	3.5580	0.9739	0.9116	0.7311	0.9618
BAKAB	1.4019	1.2084	0.8678	1.3736	0.5889	1.4077	1.5173	1.4715	1.2980
DURDO	0.9454	0.9927	0.9158	0.7736	0.8396	0.7844	0.7850	0.7806	0.7960
KAPLM	0.6917	0.6641	0.8934	0.7639	2.0840	0.7207	0.6361	0.6821	0.6404
KARTN	0.6753	0.9328	0.9143	0.8269	2.9807	1.2735	1.4213	0.9014	1.5279
MNDTR	2.5418	4.3199	1.8689	2.3697	0.0062	3.4964	3.4644	1.3318	3.5580
PRZMA	0.4038	0.4599	0.6542	0.2163	0.4952	0.2729	0.2000	0.7985	0.2718
SAMAT	0.4575	0.4434	0.6559	0.2616	0.5693	0.3069	0.2444	1.1120	0.3147
VKING	0.6097	0.7363	0.8243	1.6229	1.2559	0.4718	0.2310	0.7260	0.1178

After converting the negative values in the decision matrix to positive values, the data were normalized using the benefit-oriented criteria equation (2) and the cost-oriented criteria equation (3). Then, total performance values were calculated using the normalized data and equation (4). The normalized data and total performance values are presented in Table 7.

Table 7. *Normalized decision matrix for 2024 and total performance (S_i) values*

Companies	C1	C2	C3	C4	C5	C6	C7	C8	C9	S_i
DGNM0	1.0000	0.5545	1.0000	1.0000	0.0078	0.0812	0.6125	0.1462	0.0676	0.8963
GENTS	0.3836	0.3004	0.2068	0.2328	0.0087	0.2126	0.3840	0.8506	0.0825	0.9849
ORMA	0.2289	0.2121	0.2122	0.4536	0.0297	0.2367	0.8210	0.8884	0.0399	0.9322
SUMAS	0.1151	0.1192	0.1433	0.0595	0.0043	0.7159	0.0636	0.9907	0.3989	1.1176
YONGA	0.1521	0.1335	0.1480	0.1151	0.0087	0.7705	0.0899	0.8720	0.3536	1.0439
ALKA	0.1686	0.1808	0.1660	0.1501	0.0017	0.2802	0.2631	0.9330	0.1225	1.1101
BAKAB	0.3373	0.2797	0.1883	0.3440	0.0105	0.1939	0.4380	0.4635	0.0908	0.9927
DURDO	0.2275	0.2298	0.1987	0.1937	0.0074	0.3479	0.2266	0.8738	0.1480	1.0097
KAPLM	0.1664	0.1537	0.1939	0.1913	0.0030	0.3787	0.1836	1.0000	0.1839	1.0661
KARTN	0.1625	0.2159	0.1984	0.2071	0.0021	0.2143	0.4103	0.7567	0.0771	1.0983
MNDTR	0.6116	1.0000	0.4056	0.5934	1.0000	0.0781	1.0000	0.5122	0.0331	0.6675
PRZMA	0.0972	0.1065	0.1420	0.0542	0.0125	1.0000	0.0577	0.8542	0.4334	1.0861
SAMAT	0.1101	0.1026	0.1423	0.0655	0.0109	0.8892	0.0705	0.6134	0.3743	1.0956
VKING	0.1467	0.1704	0.1789	0.4064	0.0049	0.5784	0.0667	0.9395	1.0000	0.9783

After calculating the total performance value (S_i) of each alternative, the performance of the alternatives (S_{ij}) was calculated by removing each criterion obtained using Equation (5). The S_{ij} values are presented in Table 8.

Table 8. *S_{ij} values for 2024*

Companies	C1	C2	C3	C4	C5	C6	C7	C8	C9
DGNM0	0.8963	0.8692	0.8963	0.8963	0.6481	0.7755	0.8739	0.8051	0.7660
GENTS	0.9443	0.9337	0.9172	0.9225	0.7658	0.9185	0.9444	0.9782	0.8756
ORMA	0.8656	0.8620	0.8620	0.8971	0.7652	0.8671	0.9236	0.9271	0.7803
SUMAS	1.0358	1.0372	1.0444	1.0094	0.8970	1.1054	1.0121	1.1173	1.0836
YONGA	0.9673	0.9618	0.9662	0.9555	0.8385	1.0336	0.9449	1.0385	1.0023
ALKA	1.0427	1.0454	1.0421	1.0381	0.8453	1.0624	1.0600	1.1075	1.0301
BAKAB	0.9469	0.9388	0.9214	0.9477	0.7850	0.9227	0.9581	0.9605	0.8886
DURDO	0.9479	0.9483	0.9420	0.9409	0.7882	0.9660	0.9477	1.0042	0.9292
KAPLM	0.9950	0.9918	1.0013	1.0007	0.8144	1.0283	0.9991	1.0661	0.9992
KARTN	1.0286	1.0398	1.0365	1.0381	0.8384	1.0395	1.0647	1.0879	0.9985
MNDTR	0.6390	0.6675	0.6147	0.6373	0.6675	0.5104	0.6675	0.6286	0.4515
PRZMA	0.9946	0.9984	1.0101	0.9703	0.9067	1.0861	0.9730	1.0802	1.0543
SAMAT	1.0101	1.0072	1.0204	0.9888	0.9118	1.0912	0.9919	1.0773	1.0584
VKING	0.8947	0.9015	0.9037	0.9399	0.7274	0.9551	0.8582	0.9757	0.9783

Finally, the sum of deviations (E_j) was calculated using Equation (6) and the weights coefficients (w_j) of the criteria were calculated using Equation (7). The values of E_j and w_j are presented in Table 9.

Table 9. *Sum of absolute deviations (E_j) and weight of criteria (w_j)*

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**
E_i	0.8706	0.8767	0.9011	0.8966	2.8780	0.7176	0.8604	0.2253	1.1834
w_j	0.0925	0.0932	0.0957	0.0953	0.3060	0.0762	0.0914	0.0239	0.1257

According to Table 9, the evaluation criterion with the highest importance weight for 2024 is the Market Value-Book Value (K5) criterion with a weight of 0.3060, while the evaluation criterion with the lowest weight is the Intangible Assets as (K8) criterion with a weight of 0.0239. The order of importance weights for the criteria in 2024 is as follows: K5>K9>K3>K4>K2>K1>K7>K6>K8.

All steps of the MEREC method applied for 2024 were also applied for the other years within the scope of the study and are presented in Table 10.

Table 10. *E_j and w_j values for 2020-2023*

Years		C1	C2	C3	C4	C5	C6	C7	C8	C9
2020	E_j	0.9195	1.0135	1.2810	0.9030	1.1922	1.4834	0.6709	1.8400	0.7605
	w_j	0.0914	0.1007	0.1273	0.0897	0.1185	0.1474	0.0667	0.1828	0.0756
2021	E_j	0.9466	1.2089	1.2698	0.9805	1.1853	1.3002	0.7967	1.7493	0.9703
	w_j	0.0910	0.1162	0.1220	0.0942	0.1139	0.1249	0.0766	0.1681	0.0932
2022	E_j	0.8324	0.8758	0.8686	0.7608	3.7991	0.6252	0.8538	0.2022	0.6455
	w_j	0.0880	0.0925	0.0918	0.0804	0.4014	0.0661	0.0902	0.0214	0.0682
2023	E_j	0.8022	0.7961	0.8443	0.7421	2.3893	0.4204	0.6734	0.1547	0.4673
	w_j	0.1100	0.1092	0.1158	0.1018	0.3278	0.0577	0.0924	0.0212	0.0641

When Table 10 is analyzed, the Intangible Assets (K8) criterion was determined as the criterion with the highest importance weight in 2020 and 2021, while the Capital Employed (K7) criterion was determined as the criterion with the lowest importance weight. The K5 criterion was determined as the criterion with the highest importance weight in 2022 and 2023, while the K8 criterion was determined as the criterion with the lowest importance weight. Therefore, criteria importance weights change over the years.

3.2. Evaluation of Alternatives Using the MARCOS Method

The decision matrix used in the MEREC method was used as the decision matrix. The extended decision matrix was created by adding the ideal (AI) and anti-ideal (AAI) solution values to the decision matrix and it is presented in Table 11. Ideal values are calculated using Equation (13), and anti-ideal values are calculated using Equation (12).

Table 11. *Extended decision matrix for 2024*

Companies	C1	C2	C3	C4	C5	C6	C7	C8	C9
AAI	4.1562	4.3199	4.6078	3.9936	0.0062	0.2729	3.4644	0.6821	0.1178
DGNMO	4.1562	2.3954	4.6078	3.9936	0.7906	3.3597	2.1218	4.6645	1.7429
GENTS	1.5944	1.2977	0.9527	0.9298	0.7102	1.2839	1.3305	0.8019	1.4278
ORMA	0.9513	0.9163	0.9778	1.8113	0.2089	1.1529	2.8444	0.7678	2.9547
SUMAS	0.4784	0.5151	0.6602	0.2376	1.4390	0.3812	0.2205	0.6885	0.2953
YONGA	0.6320	0.5767	0.6818	0.4596	0.7134	0.3542	0.3116	0.7822	0.3331
ALKA	0.7007	0.7812	0.765	0.5996	3.5580	0.9739	0.9116	0.7311	0.9618
BAKAB	1.4019	1.2084	0.8678	1.3736	0.5889	1.4077	1.5173	1.4715	1.2980
DURDO	0.9454	0.9927	0.9158	0.7736	0.8396	0.7844	0.785	0.7806	0.7960
KAPLM	0.6917	0.6641	0.8934	0.7639	2.0840	0.7207	0.6361	0.6821	0.6404
KARTN	0.6753	0.9328	0.9143	0.8269	2.9807	1.2735	1.4213	0.9014	1.5279
MNDTR	2.5418	4.3199	1.8689	2.3697	0.0062	3.4964	3.4644	1.3318	3.5580
PRZMA	0.4038	0.4599	0.6542	0.2163	0.4952	0.2729	0.2000	0.7985	0.2718
SAMAT	0.4575	0.4434	0.6559	0.2616	0.5693	0.3069	0.2444	1.1120	0.3147
VKING	0.6097	0.7363	0.8243	1.6229	1.2559	0.4718	0.2310	0.7260	0.1178
AI	0.4038	0.4434	0.6542	0.2163	3.5580	3.4964	0.2000	4.6645	3.5580

If the data in the expanded decision matrix is benefit-oriented, it is normalized using equation (15) and if it is cost-oriented, it is normalized using equation (14). The results are presented in Table 12.

Table 12. *Normalized decision matrix for 2024 (MARCOS method)*

Companies	C1	C2	C3	C4	C5	C6	C7	C8	C9
AAI	0.0972	0.1026	0.1420	0.0542	0.0017	0.0781	0.0577	0.1462	0.0331
DGNMO	0.0972	0.1851	0.1420	0.0542	0.2222	0.9609	0.0943	1.0000	0.4899
GENTS	0.2533	0.3417	0.6867	0.2326	0.1996	0.3672	0.1503	0.1719	0.4013
ORMA	0.4245	0.4839	0.6691	0.1194	0.0587	0.3297	0.0703	0.1646	0.8304
SUMAS	0.8441	0.8608	0.9909	0.9104	0.4044	0.1090	0.9070	0.1476	0.0830
YONGA	0.6389	0.7689	0.9595	0.4706	0.2005	0.1013	0.6418	0.1677	0.0936
ALKA	0.5763	0.5676	0.8552	0.3607	1.0000	0.2785	0.2194	0.1567	0.2703
BAKAB	0.2880	0.3669	0.7539	0.1575	0.1655	0.4026	0.1318	0.3155	0.3648
DURDO	0.4271	0.4467	0.7143	0.2796	0.2360	0.2243	0.2548	0.1673	0.2237
KAPLM	0.5838	0.6677	0.7323	0.2832	0.5857	0.2061	0.3144	0.1462	0.1800
KARTN	0.5980	0.4753	0.7155	0.2616	0.8377	0.3642	0.1407	0.1932	0.4294
MNDTR	0.1589	0.1026	0.3500	0.0913	0.0017	1.0000	0.0577	0.2855	1.0000
PRZMA	1.0000	0.9641	1.0000	1.0000	0.1392	0.0781	1.0000	0.1712	0.0764
SAMAT	0.8826	1.0000	0.9974	0.8268	0.1600	0.0878	0.8183	0.2384	0.0884
VKING	0.6623	0.6022	0.7936	0.1333	0.3530	0.1349	0.8658	0.1556	0.0331
AI	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

After the normalization process, the importance weight values obtained with the MEREC method were multiplied by the normalized values to create a weighted normalized decision matrix. The weighted normalized decision matrix is presented in Table 13.

Table 13. *Weighted normalized decision matrix for 2024*

w_j	0.0925	0.0932	0.0957	0.0953	0.306	0.0762	0.0914	0.0239	0.1257
Companies	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**
AAI	0.0090	0.0096	0.0136	0.0052	0.0005	0.0059	0.0053	0.0035	0.0042
DGNMO	0.0090	0.0173	0.0136	0.0052	0.0680	0.0732	0.0086	0.0239	0.0616
GENTS	0.0234	0.0318	0.0657	0.0222	0.0611	0.0280	0.0137	0.0041	0.0504
ORMA	0.0393	0.0451	0.0640	0.0114	0.0180	0.0251	0.0064	0.0039	0.1044
SUMAS	0.0781	0.0802	0.0948	0.0868	0.1238	0.0083	0.0829	0.0035	0.0104
YONGA	0.0591	0.0717	0.0918	0.0449	0.0614	0.0077	0.0587	0.0040	0.0118
ALKA	0.0533	0.0529	0.0818	0.0344	0.3060	0.0212	0.0201	0.0037	0.0340
BAKAB	0.0266	0.0342	0.0721	0.0150	0.0506	0.0307	0.0120	0.0075	0.0459
DURDO	0.0395	0.0416	0.0684	0.0266	0.0722	0.0171	0.0233	0.0040	0.0281
KAPLM	0.0540	0.0622	0.0701	0.0270	0.1792	0.0157	0.0287	0.0035	0.0226
KARTN	0.0553	0.0443	0.0685	0.0249	0.2564	0.0278	0.0129	0.0046	0.0540
MNDTR	0.0147	0.0096	0.0335	0.0087	0.0005	0.0762	0.0053	0.0068	0.1257
PRZMA	0.0925	0.0899	0.0957	0.0953	0.0426	0.0059	0.0914	0.0041	0.0096
SAMAT	0.0816	0.0932	0.0955	0.0788	0.0490	0.0067	0.0748	0.0057	0.0111
VKING	0.0613	0.0561	0.0760	0.0127	0.1080	0.0103	0.0791	0.0037	0.0042
AI	0.0925	0.0932	0.0957	0.0953	0.3060	0.0762	0.0914	0.0239	0.1257

Then, S_i values were calculated using equation (17). With the help of calculated S_i values and using equations (18) and (19), alternative utility scores were calculated. Using the calculated utility scores, equations (20) and (21), the utility function scores for the ideal solution and the anti-ideal solution were calculated. Finally, the total utility scores of the alternatives were calculated using equation

(22). The alternatives were ranked based on their total utility scores. The results are presented in Table 14.

ALKA was the company with the highest intellectual capital performance in 2024. ALKA company is followed by SUMAS, KARTN, PRZMA and SAMAT. The bottom five companies in terms of intellectual capital performance are DGNMO, MNDTR, BAKAB, GENTS, ORMA, respectively.

Table 14. *MARCOS results and rankings for 2024*

Companies	S_i	K_i-	K_i+	f(K_i-)	f(K_i+)	f(K_i)	Rank
AAI	0.0567						
DGNMO	0.2803	4.9420	0.2803	0.0537	0.9463	0.2795	14
GENTS	0.3005	5.2985	0.3005	0.0537	0.9463	0.2996	11
ORMA	0.3176	5.6000	0.3176	0.0537	0.9463	0.3167	10
SUMAS	0.5688	10.0293	0.5689	0.0537	0.9463	0.5671	2
YONGA	0.4109	7.2458	0.4110	0.0537	0.9463	0.4097	8
ALKA	0.6074	10.7100	0.6075	0.0537	0.9463	0.6056	1
BAKAB	0.2948	5.1972	0.2948	0.0537	0.9463	0.2939	12
DURDO	0.3209	5.6573	0.3209	0.0537	0.9463	0.3199	9
KAPLM	0.4631	8.1650	0.4631	0.0537	0.9463	0.4617	6
KARTN	0.5486	9.6724	0.5486	0.0537	0.9463	0.5470	3
MNDTR	0.2810	4.9544	0.2810	0.0537	0.9463	0.2802	13
PRZMA	0.5270	9.2917	0.5270	0.0537	0.9463	0.5254	4
SAMAT	0.4964	8.7516	0.4964	0.0537	0.9463	0.4949	5
VKING	0.4114	7.2528	0.4114	0.0537	0.9463	0.4101	7
AI	0.9999						

All steps of the MACOS method applied for 2024 were also applied to the other years within the scope of the study, and the f(K_i) and ranking results for each year are presented in Table 15.

Table 15. *f(K_i) values and ranking of alternatives for 2020-2023.*

Years	2020		2021		2022		2023	
Companies	f(Ki)	RANK	f(Ki)	RANK	f(Ki)	RANK	f(Ki)	RANK
DGNMO	0.3358	5	0.2657	5	0.2754	13	0.4175	12
GENTS	0.1617	9	0.1076	11	0.2774	12	0.4840	11
ORMA	0.1346	12	0.1164	10	0.2284	14	0.3948	13
SUMAS	0.3641	4	0.2963	4	0.5211	3	0.7152	3
YONGA	0.1375	11	0.1171	9	0.4157	8	0.6229	6
ALKA	0.1636	8	0.1287	8	0.7183	1	0.7856	1
BAKAB	0.2174	7	0.1554	7	0.3075	11	0.4867	10
DURDO	0.1102	14	0.0981	13	0.3075	10	0.5471	9
KAPLM	0.1293	13	0.1072	12	0.4331	7	0.6181	7
KARTN	0.3657	3	0.2970	3	0.6011	2	0.6863	5
MNDTR	0.3037	6	0.2998	2	0.4332	6	0.3391	14
PRZMA	0.4534	1	0.4916	1	0.5018	4	0.7105	4
SAMAT	0.4141	2	0.2348	6	0.5014	5	0.7385	2
VKING	0.1434	10	0.0838	14	0.3993	9	0.6085	8

According to Table 15, the company with the highest intellectual capital performance in 2020 and 2021 was PRZMA, while the companies with the lowest performance in 2020 and 2021 were DURDO and VKING, respectively. In 2020, PRZMA was followed by SAMAT, KARTN, SUMAS and DGNMO, respectively, while in 2021, PRZMA was followed by MNDTR, KARTN, SUMAS and DGNMO, respectively. ALKA emerged as the company with the highest intellectual capital performance in 2022 and 2023. This company is followed by KARTN, SUMAS, PRZMA, and SAMAT in 2022, and SAMAT, SUMAS, PRZMA, and KARTN in 2023. The five companies with the lowest performance in 2022 are ORMA, DGNMO, GENTS, BAKAB, DURDO, respectively, while the five companies with the lowest performance in 2023 are MNDTR, ORMA, DGNMO, GENTS, and BAKAB, respectively. It is a remarkable result that ALKA company's intellectual capital performance was in the middle in 2020 and 2021, but ranked first in 2022, 2023 and 2024. Another remarkable result is that DGNMO, which was in the top five in 2020 and 2021 in terms of intellectual capital performance, ranked 13th, 12th and 14th in 2021. The last remarkable result is that MNDTR, which was ranked 2nd in 2021, will be ranked 14th and 13th in 2023 and 2024, respectively.

3.3. Sensitivity Analysis

To evaluate the validity and applicability of the proposed MEREC-MARCOS methodology, the ranking results obtained by this method were compared with other multi-criteria decision making (MCDM) methods, namely WASPAS, COPRAS, SAW and MOOSRA approaches. The findings of this comparison are presented in Table 16, where it is seen that ALKA company has the highest ranking in all methods. This demonstrates that the MEREC-MARCOS approach can produce consistent and reliable results in ranking companies' intellectual capital performance.

Moreover, to evaluate the ranking accuracy of the model, the rankings obtained from different multi-criteria decision making (MCDM) approaches and the ranking of the proposed model were compared through Spearman rank correlation coefficient and the results of this analysis are presented in Figure 1. According to the Spearman correlation analysis, similarity rates of 96%, 88%, 100%, and 96% were obtained between the original ranking generated by the proposed method and the rankings of the other four MCDM approaches, respectively. These rates indicate a high level of agreement between the methods. Considering all methods, the overall average Spearman rank correlation coefficient was calculated as 0.95, strongly supporting the high reliability and consistency of the ranking performance of the proposed model.

Table 16. *Comparison of the MARCOS method with other MCDM methods*

Companies	MARCOS	WASPAS	COPRAS	SAW	MOOSRA
DGNM0	14	13	9	14	14
GENTS	11	10	12	11	10
ORMA	10	12	13	10	12
SUMAS	2	3	3	2	3
YONGA	8	7	7	8	7
ALKA	1	1	1	1	1
BAKAB	12	11	14	12	11
DURDO	9	9	10	9	9
KAPLM	6	4	4	6	4
KARTN	3	2	2	3	2
MNDTR	13	14	11	13	13
PRZMA	4	5	5	4	6
SAMAT	5	6	6	5	5
VKING	7	8	8	7	8

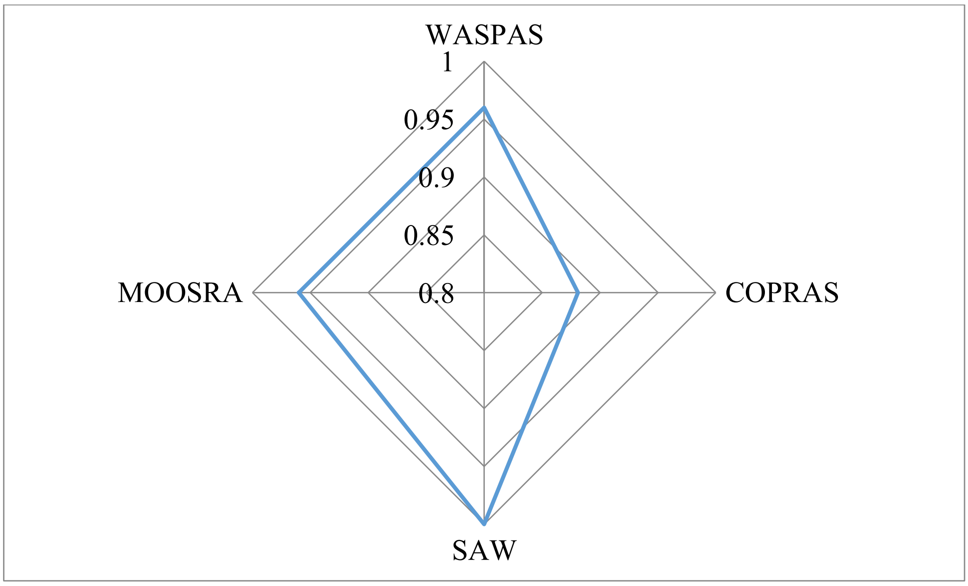

Figure 1. *Spider diagram of Spearman rank coefficient correlation for 4 methods*

4. CONCLUSION

In this study, the MEREC-MARCOS integrated method, which provides a new contribution to literature in the field of multi-criteria decision making (MCDM), is proposed for the purpose of measuring and comparatively ranking the intellectual capital performances of companies included in the BIST Forest, Paper and Printing Index. To test the applicability of the method, decision matrices were created based on financial data of companies between 2020 and 2024, and performance analyses were conducted by year.

The study findings revealed that criteria importance levels vary over time. While the Intangible Assets (K8) criterion received the highest weight in 2020 and 2021, the Market Value - Book Value (K5) criterion gained prominence in subsequent years. This variability reflects the changing impact of companies' intellectual capital components across different periods, depending on sectoral and economic conditions.

One notable result in terms of company rankings is that ALKA had the highest intellectual capital performance in 2022, 2023, and 2024. However, it ranked in the middle in 2020 and 2021. Similarly, DGNMO and MNDTR, which were top ranked in 2020 and 2021, fell to the bottom in subsequent years, indicating performance fluctuations and the long-term effects of management strategies.

The validity and reliability of the proposed MEREC-MARCOS methodology were tested by comparing the ranking results with other common MCDM methods, namely WASPAS, COPRAS, SAW, and MOOSRA. The fact that ALKA company ranks first in all methods supports the consistency of the model. Furthermore, similarity rates between rankings were assessed using the Spearman rank correlation coefficient, and high correlations were obtained at 96%, 88%, 100%, and 96%. The average correlation coefficient was calculated as 0.95, and this result revealed that the proposed model was highly stable, consistent and reliable.

The MEREC-MARCOS method can be used by decision-makers and managers as an effective tool for rationally and objectively assessing intellectual capital performance. This method can be applied to decision problems across different sectors to test its general validity. Furthermore, more comprehensive models can be developed by integrating new weighting techniques into the method. The model's performance can be tested by considering different sectors, geographic regions, or macroeconomic variables. Furthermore, more flexible decision support systems can be developed by combining it with fuzzy logic or artificial intelligence-based approaches.

Author Declarations and CRediT Roles

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