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Financial Performance Analysis of TAV Airports Listed in Borsa Istanbul with Entropy Based VIKOR Method

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Abstract

The aviation sector is a strategic service domain that is highly sensitive to global economic fluctuations, pandemics, and geopolitical crises. This study analyzes the financial performance of TAV Airports, a publicly traded company listed on Borsa Istanbul and operating within the aviation industry, for the period 2019–2024 using the Entropy-based VIKOR method. In this context, assessing the financial resilience of sectoral actors is of great importance. Financial ratios were weighted using the Entropy method, and the performance ranking was carried out through the VIKOR approach. The findings reveal that 2019 was the year with the strongest financial performance (Qj = 0.056), while 2020 exhibited the weakest performance (Qj = 1.000). Additionally, the strongest and weakest financial indicators were identified for each year, allowing for the evaluation of the company's annual strengths and areas for improvement. These findings are particularly significant for investors, analysts, financial market participants, and decision-makers focusing on Borsa Istanbul and the broader Turkish capital markets, as they support more informed portfolio strategies and risk assessments within the aviation sector.

1. Introduction

The aviation sector is recognized as one of the most dynamic and fragile areas of the global economy. As one of the key elements of transportation infrastructure, airports not only provide logistics and mobility, but also stand out as strategic hubs that support the economic development of the regions in which they are located (Graham, 2013). Especially in the last few decades, with the privatization policies implemented worldwide, there has been a transition from public monopoly to a private sector-dominated structure in airport operations. This transformation has led to radical changes in the operational logic of airports, and the concept of public service has been replaced by concepts such as cost-effectiveness, revenue maximization and sustainable profitability (de Neufville & Odoni, 2013).

The increasing transfer of publicly financed and managed airports to the private sector through public-private partnership (PPP) or direct privatization models since the 1980s has led to the modernization of airport infrastructure, especially in developing countries (Humphreys & Francis, 2002). However, this new structure has also made airport operators more vulnerable to market fluctuations, economic crises, exchange rate risks and global shocks (Forsyth et al., 2010). As a matter of fact, the COVID-19 pandemic constituted the most striking example of this fragile structure; air passenger traffic worldwide contracted by more than 60% in 2020, and many airports faced serious revenue losses (ICAO, 2021; IATA, 2021).

In this context, measuring the financial resilience of airport businesses and analyzing their adaptability and recovery capabilities against crises is of great importance for both academic and applied finance. Financial performance analyses allow businesses to be evaluated based on key indicators such as liquidity, profitability, indebtedness and operating efficiency; multi-criteria decision making (MCDM) methods are used to address these indicators in a holistic framework (Saaty, 1980; Wang & Elhag, 2006).

Analyzing the performance of companies operating in financial markets is very important for investors and stakeholders. These analyses provide a basic reference point for assessing the sustainability of companies, directing investments and making strategic decisions. Especially for publicly traded companies, performance evaluations can have a direct impact on market valuations. In this context, periodic performance analyses of companies traded on Borsa Istanbul contribute to the informed decision-making of investors and offer areas of improvement for company managements.

In this study, the financial performance of TAV Airports Holding A.Ş. between 2019 and 2024 is analyzed using the VIKOR method, one of the multi criteria decision making (MCDM) methods. Criterion weights were determined using the Entropy technique, which is an objective method, and thus, a data-based analysis was carried out, free from the subjective

judgments of decision makers. This study aims to contribute to the literature by revealing the periodic performance differences of airport operators operating in the aviation sector, where financial fragility is high, and to create a decision support mechanism for investors, managers and policy makers. It also provides a methodological contribution by demonstrating the applicability of Entropy and VIKOR methods in the context of airport financial analysis.

2. Literature Review

It is noteworthy that various methods are used in the literature for analyzing the performance of airport enterprises. In this context, Table 1 presents a compilation of national and international studies evaluating the operational, financial and environmental dimensions of the businesses operating in the aviation sector. The studies are categorized according to the methods used, evaluation criteria, the period covered, and the main conclusions reached. Thus, the general framework of sector-specific performance evaluation approaches is presented, and the sectoral context of the current study is strengthened.

Table 1. Studies on Performance Evaluation of Airports

Author(s)	Year	Objective	Methods	Dataset / Scope
Vogel	2006	Assess the financial performance of privatized European airports from 1990 to 2000.	Partial Factor Productivity (PFP), Financial Ratio (FRA), Data Envelopment Analysis (DEA)	1990–2000, 35 European commercial airports
Graham & Dennis	2007	Examine the impact of low-cost carriers on airport traffic and financial performance in the UK and Ireland.	Traffic Analysis, Financial Performance Analysis	1998–2007, 14 UK airports, 3 Irish airports
Aulich & Hughes	2013	Assess the financial performance of the three largest Australian airports following privatization.	Financial ratio analysis	Australian airports, post-privatization, three major airports
Vogel & Graham	2013	Assess whether cluster analysis is useful for selecting airport groups for financial and economic performance studies.	Cluster Analysis	73 airports worldwide, data from 2003 and 2010
Fasone et al.	2014	Assess the financial performance of Italian airports based on public vs. private ownership.	Financial ratio analysis	2008–2012, Italian airport companies
Zou et al.	2015	Investigate the impact of funding sources (AIP grants and PFC) on US airport efficiency.	Two-stage DEA model, Random effects regression	42 primary US airports
Asker & Kiracı	2016	Evaluate the financial performance of European airport groups.	Trend Analysis	2007–2014, 5 European airport groups
Abbruzzo et al.	2016	Analyze the relationship between financial and operational indicators in Italian airports.	Gaussian Graphical Model (Penalized RCON)	2008–2014 Italian national and regional airports
Battal	2020	Measure the financial performance of European airport group companies.	Data Envelopment Analysis (DEA)	2015–2018, 6 European airport groups
Raghavan & Yu	2021	Evaluate the financial strength of public commercial airports in the US.	Financial ratio analysis, regression	2010–2017, 60 large and medium-sized US airports
Gültekin & Çarıkçı	2023	Financial performance evaluations of Tav Airports Holding and Fraport AG	Entropy, TOPSIS	2018-2021, TAV and Fraport Airport Groups
Giovanelli et al.	2024	Examine the impact of airport size and ownership structure on the financial performance of European airports.	Benchmarking analysis	2007–2019, 188 European airport companies managing 393 airports

The integration of multi criteria decision making (MCDM) methods enables objective and holistic evaluations, especially in complex decision processes. Table 2 presents the academic studies in which Entropy and VIKOR methods are used together. These studies are discussed comparatively in terms of application areas, criteria set used, sample structure and findings. Thus, the place and validity of the methodological approach preferred in our study in literature is emphasized, and a comprehensive framework is presented regarding the application of the method in similar studies.

Table 2. Literature Studies Using Entropy and VIKOR Methods Together

Author(s)	Year	Objective of the Study	Methods	Dataset / Scope
Demirarslan et. al.	2019	Evaluate emotional performance of academic staff.	Entropy, TOPSIS, VIKOR	Bartın University
Hacıfettahoğlu & Perçin	2020	Evaluate financial performance of Turkish construction firms.	Entropy, TOPSIS, VIKOR, Borda Rule	2016, BIST-listed construction firms
Eş & Kocadağ	2020	Supplier selection in public institutions.	Entropy, MAUT, VIKOR	Public institution supplier selection
Lam et al.	2021	Evaluate Malaysian construction firms.	Entropy, Fuzzy VIKOR	2018, Malaysian listed firms
Siew et al.	2021	Similar to Lam et al.	Entropy, Fuzzy VIKOR	2018, Malaysian construction firms
Yılmaz & Yakut	2021	Evaluate the financial performance of Turkish banks using MCDM.	Entropy, TOPSIS, VIKOR	2009–2018, 22 BIST-listed banks
Kahraman, & Çalışkan	2023	Evaluate tourism companies in Borsa İstanbul.	TOPSIS, VIKOR	2023, BIST tourism firms
Şeker & İslamoğlu	2024	Evaluate the performance of Turkey's takaful insurance companies in 2022.	Entropy, VIKOR	Doğa, Neova, Bereket Participation Insurance
Oral & Kandemir	2024	Evaluate BIST food & beverage companies.	Entropy, TOPSIS, VIKOR	2018–2022, 25 BIST firms
Durak & Bal	2024	Compare bank performance before and after COVID-19.	Entropy, VIKOR	2018–2021, banks in developing countries

3. Materials and Methods

In this study, multi-criteria decision making (MCDM) methods are used to evaluate the financial performance of TAV Airports Holding A.Ş. between 2019 and 2024. MCDM methods are systematic approaches that allow decision makers to evaluate alternatives under multidimensional and often conflicting criteria. These methods enable more consistent and rational decisions to be made by allowing both qualitative and quantitative data to be taken into account, especially in complex decision problems (Kahraman, 2008).

The main objective of this study is to evaluate the financial performance of TAV Airports, a publicly traded company in Borsa Istanbul, between 2019 and 2024 with an objective and systematic approach. To this end, the VIKOR method, which is one of the multi-criteria decision-making (MCDM) methods, was integrated and applied together with the Entropy method, which is based on objectivity in determining the criteria weights.

Within the scope of the study, TAV Airports' annual financial ratios were used to analyze the company's performance periodically. The VIKOR method, with its structure aiming to reach a compromise solution among alternatives, allows to determine the relative performance of the company over the years. The entropy method, on the other hand, has made it possible to obtain more reliable results by eliminating the influence of subjective judgments in the analysis process by weighting each criterion based on its information value.

This analysis is particularly important for investors, financial analysts and decision makers operating in financial markets. Because analyzing the periodic performance of publicly traded companies with scientific methods enables investment decisions to be based on more rational foundations. In addition, the methodological framework of the study aims to contribute to the development of a culture of analytical evaluation in the Turkish capital markets by paving the way for similar applications for other BIST companies.

3.1. Data and Financial Ratios

In this study, the financial performance of TAV Airports Holding A.Ş., which is traded in Borsa Istanbul under the code TAVHL and 49.8% of which is publicly traded, is evaluated with VIKOR, which is one of the CRM methods. In the analysis, the annual consolidated financial statements of the company for six years between 2019 and 2024 were obtained from the Public Disclosure Platform (KAP) and financial ratios were calculated for each year. A total of 15 financial ratios including Net Profit Ratio, Gross Profit Ratio, Operating Profit Ratio Return on Assets, Return on Equity, Current Ratio, Liquidity Ratio, Cash Ratio, Equity Turnover Ratio, Asset Turnover Ratio, Receivables Turnover Ratio, Inventory Turnover Ratio, Financing Ratio, Financial Leverage, Equity to Assets Ratio were used. Financial ratios, their explanations and abbreviations are presented in Table 3.

Table 3. Financial Performance Indicators Selected as Criteria in the Study

Category	Ratio	Abbreviation
Profitability Ratios: These ratios measure a company's ability to generate profit	Net Profit Margin = Net Profit / Net Sales	NPM
	Gross Profit Margin = Gross Profit / Net Sales	GPM
	Operating Profit Margin = Operating Profit / Net Sales	OPM
	Return on Assets (ROA) = Net Profit / Total Assets	ROA
	Return on Equity (ROE) = Net Profit / Shareholders' Equity	ROE
Liquidity Ratios: These ratios indicate the ability to meet short-term obligations	Current Ratio = Current Assets / Short-Term Liabilities	CUR
	Acid-Test Ratio = (Current Assets – Inventories) / Short-Term Liabilities	ATR
	Cash Ratio = Cash and Cash Equivalents / Short-Term Liabilities	CR
Activity Ratios: These ratios show how efficiently the company utilizes its assets	Equity Turnover = Net Sales / Shareholders' Equity	ET
	Asset Turnover = Net Sales / Total Assets	AT
	Receivables Turnover = Net Sales / Trade Receivables	RT
	Inventory Turnover = Cost of Goods Sold / Inventories	IT
Leverage Ratios: These ratios assess financial risk and the level of indebtedness	Debt-to-Equity Ratio = Total Debt/ Shareholders' Equity	DER
	Financial Leverage = Liabilities / Total Assets	FL
	Equity-to-Total Assets Ratio = Shareholders' Equity / Total Assets	ETA

3.2. Entropy Method

In this study, entropy method was used to determine the objective weights of decision criteria. The method was applied within the framework of the following steps (Shannon, 1948; Alp et al., 2015; Bakır & Atalık, 2018):

Step 1: Creating the Decision Matrix

A decision matrix is created in line with the alternatives (i = 1, 2, ..., m), and criteria (j = 1, 2, ..., n) to be evaluated within the scope of the decision problem:

$$D = \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} \begin{bmatrix} X_{11} & X_{12} & \dots & X_{1n} \\ X_{21} & X_{22} & \dots & X_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ X_{m1} & X_{m2} & \cdots & X_{mn} \end{bmatrix} \quad (1)$$

Step 2: Normalization

Normalization is carried out using Equation (2) and Equation (3) for benefit and cost criteria, respectively. Since higher values indicate better performance for benefit criteria, the data are scaled between 0 and 1 using Equation (2) during the

normalization process. In this case, the minimum value is assigned as 0, and the maximum value is assigned as 1.

$$r_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (2)$$

For cost criteria, since lower values are considered more favorable, the normalization process is applied in reverse. Using Equation (3), the data are transformed into the [0, 1] range such that the minimum value corresponds to 1 and the maximum value to 0. In this way, the criteria become comparable while preserving the performance ranking.

$$r_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (3)$$

Step 3: Calculate Entropy Values (ej):

Using the normalized values, the entropy value for each criterion is calculated with the following equation:

$$e_j = -k \sum_{j=1}^{n} r_{ij} \ln(r_{ij}) \qquad j = 1,2,\ldots\ldots,n \quad (4)$$

Step 4: Calculating the Degree of Differentiation of Knowledge (d_j):

$$d_j = 1 - e_j \qquad j = 1,2,\ldots\ldots,n \quad (5)$$

The high values of d_j obtained with the help of Equation (5) indicate that the distance or differentiation between the alternative scores related to the criteria is high.

Step 5: Entropy Calculation of Criterion Weights:

From this step, the Entropy criterion values are obtained with the help of the equation (6):

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \quad (6)$$

This method is very effective in that it determines the criteria weights directly based on the information contained in the data without the need for decision maker judgments (Shannon, 1948; Wang & Lee, 2009; Zavadskas & Turskis, 2011).

3.3. VIKOR Method

VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) method was used in the study for ranking the alternatives and determining the optimal solution. This method was developed by Opricovic (1998) and is intended to provide compromise solutions in multi-criteria decision-making problems. VIKOR aims to maximize the utility of the majority of decision makers while at the same time minimizing individual regrets (Opricovic & Tzeng, 2004).

The basic steps in the VIKOR method can be summarized as follows:

Step 1: The best (f_i^*) and worst (f_i^-) values are determined for each criterion. If criterion *i* is a utility criterion;

$$f_i^* = max_j f_{ij} \qquad f_i^- = min_j f_{ij} \qquad i = 1,2,\ldots\ldots,n \quad (7)$$

Step 2: S_i and R_j values are calculated for j= 1,2,...,j. The S_i and R_j values represent the average and worst group scores for alternative j;

$$S_i = \sum_{j=1}^{n} v_{ij} = \sum_{j=1}^{n} w_j * r_{ij} = \sum_{j=1}^{n} w_j * \frac{f_j^* - x_{ij}}{f_j^* - f_j^-} \quad (8)$$

$$R_j = max_j v_{ij} \qquad R_j = max_j w_j * r_{ij} \qquad R_j = max_j \left(w_j * \frac{f_j^* - x_{ij}}{f_j^* - f_j^-} \right) \quad (9)$$

Step 3: Q_i values are determined for all j= 1,2,...,J.

$$Q_i = \frac{v*(S_i - S^*)}{S^- - S^*} + \frac{(1-v)*(R_i - R^*)}{R^- - R^*} \quad (10)$$

$$S^* = min_i S_i \quad S^- = max_i S_i \quad R^* = min_i R_i \quad R^- = max_i R_i \quad (11)$$

Step 4: The ranking between alternatives is determined by ranking the S, R and Q values from smallest to largest. The results generate three ranking lists.

Step 5: If the following two conditions are met, alternative a', which ranks the best according to their Q (minimum) values, is proposed as a compromise solution.

Condition C_1 (Acceptable Advantage):

$$Q(A^2) - Q(A^1) \geq DQ \qquad DQ = \frac{1}{m-1} \quad (12)$$

If C_1 is not satisfied, then the set of alternatives a', a'',...,a^m for which

$$Q(A^m) - Q(A^1) < DQ \quad (13)$$

holds for the maximum value of m are identified.

The best alternative ranked by Q values is one of the alternatives with the minimum Q value (Opricovic ve Tzeng, 2004; Ertuğrul ve Karakaşoğlu, 2008).

4. Results and Discussion

A decision matrix is first created by taking the years between 2019 and 2024 as alternatives and 15 financial ratios as criteria. The decision matrix in Table 4 shows the financial ratios of the criteria calculated according to the years.

Table 4. Decision Matrix

	2024	2023	2022	2021	2020	2019
NPM	0.12	0.23	0.11	0.10	-0.95	0.51
GPM	0.36	0.39	0.11	0.10	0.15	0.47
OPM	0.18	0.19	0.22	0.11	-0.21	0.27
ROA	0.04	0.05	0.02	0.01	-0.07	0.09
ROE	0.12	0.17	0.09	0.03	-0.27	0.28
CUR	2.83	2.76	2.71	2.62	1.85	2.80
ATR	2.68	2.67	2.53	2.50	1.83	2.77
CR	0.04	0.61	0.35	0.19	0.56	0.65
ET	0.99	0.74	0.78	0.36	0.29	0.55
AT	0.04	0.05	0.02	0.01	-0.07	0.09
RT	11.79	8.75	7.39	3.74	3.19	5.58
IT	-22.97	-34.26	-10.64	-10.38	-31.80	-42.25
DER	2.00	2.33	2.58	2.41	2.59	1.93
FL	0.67	0.70	0.72	0.71	0.68	0.66
ETA	0.33	0.30	0.28	0.29	0.26	0.34

Among the selected criteria, the Debt to Equity Ratio, Financial Leverage, and Inventory Turnover Ratio are considered non-beneficial and thus involve negative values. Table 5 represents determination of criterion direction.

Table 5. Determination of Criterion Directions

Ratio	Direction	Justification
NPM	Beneficial	Higher values indicate better profitability
GPM	Beneficial	Higher values represent stronger cost control
OPM	Beneficial	Indicates operational efficiency
ROA	Beneficial	Measures profitability relative to total assets
ROE	Beneficial	Reflects profitability for shareholders
CUR	Beneficial	Indicates short-term liquidity
ATR	Beneficial	Shows how efficiently assets are used
CR	Beneficial	Measure's ability to cover short-term obligations with cash
ET	Beneficial	Higher values suggest better equity utilization
AT	Beneficial	Indicates efficiency in using assets to generate revenue
RT	Beneficial	Higher values imply faster collection of receivables
IT	Non-beneficial	Extremely high or negative values may indicate inefficiencies or losses
DER	Non-beneficial	Higher values imply greater financial risk
FL	Non-beneficial	Indicates increased reliance on debt financing
ETA	Beneficial	Higher values represent stronger equity structure

However, as the conventional normalization formula becomes theoretically inappropriate in the presence of zero or negative values, it is necessary to rescale all criteria to a common interval of [0,1] prior to further analysis. To address this issue, the normalization approach is adjusted by employing the Min-Max normalization method, which ensures that all values are transformed into a positive scale bounded between 0 and 1. Table 6 represents the criterion values derived through the application of the Min-Max normalization method.

Table 6. Rescaled Criterion Values Based on the Min–Max Normalization Method

	NPM	GPM	OPM	ROA	ROE	CUR	ATR	CR	ET	AT	RT	IT	DER	FL	ETA
2024	0.73	0.71	0.79	0.67	0.71	1.00	0.90	0.00	1.00	0.67	1.00	0.39	0.91	0.88	0.91
2023	0.81	0.77	0.82	0.73	0.80	0.93	0.89	0.93	0.64	0.73	0.65	0.75	0.40	0.34	0.48
2022	0.73	0.04	0.88	0.58	0.65	0.88	0.74	0.51	0.69	0.58	0.49	0.01	0.02	0.00	0.21
2021	0.72	0.00	0.66	0.49	0.56	0.79	0.71	0.25	0.10	0.49	0.06	0.00	0.28	0.23	0.39
2020	0.00	0.15	0.00	0.00	0.00	0.00	0.00	0.85	0.00	0.00	0.00	0.67	0.00	0.64	0.00
2019	1.00	1.00	1.00	1.00	1.00	0.97	1.00	1.00	0.37	1.00	0.28	1.00	1.00	1.00	1.00

Initially, normalized values are calculated for each criterion such that the total for each criterion sums to 1, resulting in the formation of the ratio matrix. The relevant Table 7 presents the results of this ratio analysis based on the normalized values

Table 7. Ratio Matrix

	NPM	GPM	OPM	ROA	ROE	CUR	ATR	CR	ET	AT	RT	IT	DER	FL	ETA
2024	0.18	0.27	0.19	0.19	0.19	0.22	0.21	0.00	0.36	0.19	0.40	0.14	0.35	0.29	0.30
2023	0.20	0.29	0.20	0.21	0.21	0.20	0.21	0.26	0.23	0.21	0.26	0.27	0.15	0.11	0.16
2022	0.18	0.01	0.21	0.17	0.18	0.19	0.18	0.15	0.25	0.17	0.20	0.00	0.01	0.00	0.07
2021	0.18	0.00	0.16	0.14	0.15	0.17	0.17	0.07	0.04	0.14	0.03	0.00	0.11	0.07	0.13
2020	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.24	0.00	0.00	0.00	0.24	0.00	0.21	0.00
2019	0.25	0.37	0.24	0.29	0.27	0.21	0.24	0.28	0.13	0.29	0.11	0.35	0.38	0.32	0.33

When computing entropy values, any values equal to zero become undefined due to the logarithmic value in the formula. Therefore, the z-score standardization method proposed by Zhang et al. (2014) is used. This standardizes the values and resolves the issue of undefined values. (Öztel&Şenkal, 2020). Subsequently, entropy values for each criterion across the years are calculated from the ratio matrix. These entropy values reflect the level of information provided by each criterion; lower entropy values indicate greater variability and, consequently, higher information content.

Table 8. Entropy Values

	NPM	GPM	OPM	ROA	ROE	CUR	ATR	CR	ET	AT	RT	IT	DER	FL	ETA
e	0.89	0.73	0.89	0.88	0.89	0.90	0.89	0.85	0.80	0.88	0.77	0.76	0.73	0.83	0.82

Table 8 shows the entropy values determined for every one of the fifteen financial ratios applied in the analysis. Entropy values offer knowledge concerning the level of variability or disorderliness of every criterion throughout the assessment interval. Within a multi criteria decision environment, a smaller entropy value reflects more variability and, accordingly, more information contribution from a particular criterion to the general decision model, while a more substantial entropy value indicates more uniformity and more limited discriminative capability.

As can be observed in the table, a majority of financial ratios have relatively high entropy scores, commonly varying from 0.73 to 0.90. Particularly, Current Ratio (CUR) and Net Profit Margin (NPM) have two of the highest entropy scores (0.90 and 0.89, respectively), implying that these metrics showed relatively consistent behavior among years of evaluation and accordingly added less unique information towards performance differentiation across years.

Meanwhile, Gross Profit Margin (GPM), Inventory Turnover (IT), and Debt-to-Equity Ratio (DER) have relatively lower measures of entropy (0.73, 0.76, and 0.73 respectively) meaning they are more variable over time. Hence, they contributed more significantly in identifying the company's financial performance throughout the six-year timeframe.

Generally, moderate to high levels of entropy across most indicators indicate a fairly even distribution of information, with some measures having more discriminative value in evaluating the firm's year-to-year financial performance than others.

Prior to applying the VIKOR method, the Entropy values of the criteria are calculated to determine the degree of diversification (d_j) and the corresponding weights (w_j) are presented in Table 9.

Table 9. Degree of Differentiation of Knowledge d_j and Criterion Weights (w_j)

	NPM	GPM	OPM	ROA	ROE	CUR	ATR	CR	ET	AT	RT	IT	DER	FL	ETA
d	0.11	0.27	0.11	0.12	0.11	0.10	0.11	0.15	0.20	0.12	0.23	0.24	0.27	0.17	0.18
w	0.04	0.11	0.04	0.05	0.05	0.04	0.04	0.06	0.08	0.05	0.09	0.10	0.11	0.07	0.07

Subsequently, based on the normalized and weighted decision matrix, the best (f^*) and worst (f^-) values for each criterion are identified and presented in Table 10.

Table 10. The Best (f*) and Worst (f^-) Values for Each Criterion

	NPM	GPM	OPM	ROA	ROE	CUR	ATR	CR	ET	AT	RT	IT	DER	FL	ETA
f*	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
f^-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

For each year, the total deviation (S_i), the maximum deviation (R_i) for six alternative years are calculated based on w_j, f^* and f^- values. Table 11 presents the Sj and Rj results.

Table 11. Sj and Rj Results

	Sj	Rj
2024	0.25	0.06
2023	0.32	0.07
2022	0.63	0.11
2021	0.70	0.11
2020	0.82	0.11
2019	0.12	0.07

Table 12 presents the minimum and maximum values of all Sj and Rj scores.

Table 12. Average and Worst Group Scores

S*	S^-	R*	R^-
0.12	0.82	0.06	0.11

And finally, Table 13 presents the performance results obtained through the VIKOR method.

Table 13. Performance Ranking Table

	Qj	Ranking
2024	0.091	2
2023	0.197	3
2022	0.837	4
2021	0.908	5
2020	1.000	6
2019	0.056	1

Table 13 presents rankings according to financial performance by TAV Airports for years 2019-2024 based on Entropy-weighted VIKOR approach. Qj values ranging from 0 (optimal performance) to 1 (worst performance) are relative proximity measures of each year's financial profile to optimal solution. The lower Qj value indicates better financial performance compared to other included years. During the implementation of the method, the compromise coefficient (v), which reflects the weight assigned to majority preference, was assumed to be 0.5 by default.

The result indicates that 2019 was the best-performing year with a lowest Qj score value of 0.056, suggesting that at this time, the financial composition was closest to optimal solution. This can be explained by relatively healthy macroeconomic circumstances prior to the spread of COVID-19 pandemic and improved operational efficiency.

2024 occupies the second rank (Qj = 0.091), a strong recovery from pandemic years. The company's capital structure in 2024 remains fairly solid against overall macroeconomic and industry uncertainties, perhaps due to strategic adjustments and improved flexibility.

2023 boasts third rank (Qj = 0.197) reflecting trends in post-pandemic recovery. Its performance might be explained by increased passenger traffic, cost-reduction strategies, and better revenue drivers. Rank fourth and fifth are occupied by 2022 and 2021 with Qj values of 0.837 and 0.908, respectively. These relatively lower scores reflect weaker financial performance. The two years fall within the post-pandemic volatility phase where sectoral shocks and economic uncertainty would have had lingering effects on operating and financial performance metrics.

2020, where Qj = 1.000, we note as having registered the weakest financial performance. This aligns with the global impact caused by the COVID-19 pandemic when air transport experienced its record decline in air passengers carried, revenue loss, and operations cessation.

Typically, Qj scores reflect a dynamic trend in the performance in the company throughout the six-year period, with sharp dips at the peak of the pandemic (2020–2021) and a gradual recovery in subsequent years. The volatility in ranking performance shows how aviation performance can be responsive to outside shocks and underscores a necessity for financial resilience and adaptive strategy building.

In the VIKOR method, the validity of the compromise solution is evaluated by testing two conditions, C1 and C2, to determine whether the proposed best alternative is indeed an acceptable solution. In this context, the year 2020, for which Qj=1 is excluded from the C1 test. When assessing whether the top ranked alternative A^1 has a significant advantage over the second ranked one, the result indicates that, given the number of alternatives m xis 6, the condition 0.035<0.20 is not satisfied. Therefore, C1 is not met. As a result, C2 is tested using the S, R, and Q values. While the year 2019 ranks first in terms of Sj with a score of 0.12, the minimum Rj value is observed in 2024 with a score of 0.06. Hence, C2 is also not satisfied.

Consequently, although 2019 has the lowest Qj score, neither C1 nor C2 conditions are fulfilled. Thus, it cannot be exclusively accepted as the compromise solution. As a result, both 2019 and 2024 may be regarded as viable alternatives in terms of financial performance.

Thereafter, the highest and lowest weighted scores for every criterion and each year are determined with the normalized, weighted decision matrix, while a yearly strengths and weaknesses table are also derived. The best and weakest financial indicators for each year are listed in Table 14.

Tablo 14. Strength and Weakness Criteria by Year

Year	Strongest Indicator	Weakest Indicator
2024	Debt-to-Equity Ratio	Cash Ratio
2023	Gross Profit Margin	Financial Leverage
2022	Equity Turnover	Financial Leverage
2021	Current Ratio	Gross Profit Margin
2020	Inventory Turnover	Net Profit Margin
2019	Debt-to-Equity Ratio	Receivable Turnover

Identifying TAV Airports' top and bottom financial indicators for each year from 2019 through to 2024 gives essential information on how TAV Airports' financial structure and operating dynamics change relative to industry-specific and general economic circumstances.

As of 2019, Debt-to-Equity Ratio (DER) stood out to be the most robust, implying sound capital structure management with relatively well-balanced leverage in a pre-pandemic context. The weakest one was the Receivable Turnover (RT) ratio, arguably signifying poor credit policies or postponed collection processes for receivables.

2020, significantly affected by the Covid-19 pandemic, registered Inventory Turnover as its best-performing metric most likely due to effective handling of inventories in reaction to dramatic cuts in passenger traffic and flight operations. The weakest performer was, however, the Net Profit Margin (NFM) in line with deep cuts in revenues and increased fixed cost burdens within the industry.

Current Ratio (CR) was the best-performing indicator in 2021, indicating enhanced short-term liquidity due to pandemic-related financial weaknesses. Gross Profit Margin (GPM) was weakest, potentially due to continued revenue suppression and rigidity in costs during the initial recovery phase.

2022 registered Equity Turnover (ET) as the best-performing indicator, indicative of optimized use of shareholders' capital to create revenue. Financial Leverage (FL) continued to be the weakest, pointing to continued vulnerability to risks associated with debt during a backdrop of increasing interest rates and fluctuations in the exchange rate.

2023 was a significant rebound year, with Gross Profit Margin (GPM) proving to be the most robust indicator, signaling enhanced operating profitability with aviation demand recovering. However, Financial Leverage (FL) once more emerged as weakest, pointing towards ongoing structural issues related to dependency upon debt and vulnerability to financial volatility.

At last, in 2024, the Debt-to-Equity Ratio (DER) the weakest gauge, potentially pointing to a change in a more sustainable capital structure or a strategy of deleveraging. The Cash Ratio (CR) was determined to be the weakest measure, hinting at possible deficiencies in short-term liquidity, potentially resulting from reinvestment activities, servicing debts, or unexpected limitations in cash flows.

Generally, dynamic movements in strong and weak indicators over the years highlight TAV Airports' financial adjustment to external shocks, sectoral pressures, and internal reorganization. These trends reflect the company's changing financial priorities and exposures, while pointing to the critical nature of focused financial management strategies in the aviation industry's highly cyclical nature and capital-intensive business.

The results of Multi-Criteria Decision-Making (MCDM) methods largely depend on the values of the criterion weight coefficients, that is, the relative importance assigned to specific criteria. In some cases, even slight changes in the criterion weights can significantly influence the final decisions. Therefore, it is generally necessary to conduct a sensitivity analysis following the results obtained through MCDM methods in order to assess the robustness of the decision outcomes against such variations (Pamučar & Ćirović, 2015). In this study, a sensitivity analysis was carried out to examine the effects of assigned criterion weights on the ranking of alternatives. Within this scope, Table 15 presents the weight values corresponding to five scenarios, labeled from A to E, each reflecting different priority settings.

Table 15. Criteria Weights Under Different Scenarios

Scenarios	NPM	GPM	OPM	ROA	ROE	CUR	ATR	CR	ET	AT	RT	IT	DER	FL	ETA
A	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067
B	0.069	0.19	0.069	0.086	0.086	0.028	0.028	0.042	0.056	0.035	0.063	0.07	0.077	0.049	0.049
C	0.028	0.077	0.028	0.035	0.035	0.114	0.114	0.171	0.056	0.035	0.063	0.07	0.077	0.049	0.049
D	0.032	0.088	0.032	0.04	0.04	0.032	0.032	0.048	0.064	0.04	0.072	0.08	0.176	0.112	0.112
E	0.035	0.097	0.035	0.044	0.044	0.035	0.035	0.053	0.1	0.063	0.113	0.125	0.097	0.062	0.062

In Scenario A, equal priority was assigned to all criteria, whereas in Scenarios B through E, higher priority was given to specific groups of criteria. For instance, in Scenario B, profitability criteria (NPM, GPM, OPM, ROA, ROE) were collectively assigned a total weight of 50%; in Scenario C, liquidity criteria (CUR, ATR, CR) were assigned a total weight of 40%; in Scenario D, risk/debt criteria (DER, FL, ETA) were given a total weight of 40%; and in Scenario E, efficiency criteria (ET, AT, RT, IT) received a total weight of 40%.

In all scenarios, the criterion weights were scaled according to these specified percentages based on the original weights obtained by the Entropy method. This approach preserved the proportional differences among criteria while strategically emphasizing the targeted criterion group in each scenario. Such a method is significant for systematically revealing the model's sensitivity to different prioritization scenarios. The ranking results corresponding to the defined scenarios are presented in Table 16.

Table 16. Ranking Results of Alternatives Under Different Scenarios

Years	Ranking				
	Scenario A	Scenario B	Scenario C	Scenario D	Scenario E
2024	3	3	4	2	3
2023	2	2	2	3	1
2022	4	4	3	5	4
2021	5	5	5	4	6
2020	6	6	6	6	5
2019	1	1	1	1	2

When the rankings obtained according to the defined scenarios are compared with the rankings presented in Table 13, it is observed that changes occur in the orderings. The variation in the performance rankings of certain years under different priority sets is a common and meaningful outcome in multi-criteria decision-making (MCDM) approaches. This phenomenon demonstrates how the model evaluates alternative years based on different strategic priorities and provides decision-makers with the ability to identify which years are more advantageous depending on the emphasized set of criteria.

Notably, the fact that changes in rankings are not radical (for example, no year drops from first to last place) supports the stability of the model; conversely, moderate shifts in the middle rankings reflect the model's sensitivity and flexibility. This indicates that the employed method is both consistent and capable of capturing the diverse strategic perspectives of decision-makers

5. Conclusion

This research applied Entropy-based VIKOR multi-criteria decision-making methodology in a systematic assessment of TAV Airports Holding's financial performance from 2019 to 2024. The combining of entropy-derived weights with VIKOR's compromise ranking approach facilitates a detailed understanding of financial performance during a volatile environment with assessment by sequentially applying entropy weights and VIKOR ranking. This analysis not only identifies firm-level performance fluctuations, but also highlights how sector-fragility, macroeconomic imbalance, and capital market dynamics are intertwined in a developing economy like Turkey.

The economy in Turkey during the observation period was characterized by ongoing macroeconomic instability. Inflation continued at a high level at different times, exceeding 60% per annum, eating into real returns, making both investor choices and corporate financial planning more challenging. At the same time, the Turkish lira depreciated sharply against key currencies, affecting financing costs and external purchasing power. For corporates such as TAV Airports whose financial structures and business operations are partially denominated in foreign currencies and foreign currency liabilities, this translated into increased balance sheet risk and strategic uncertainty.

Additionally, volatility in monetary policy, characterized by quick reversals between rate increases and unconventional easing, brought added instability into financial markets. Investor sentiment became weaker due to a loss in central banks' credibility and growing geopolitical risk, expressed in terms of capital outflows and volatile valuations in Borsa Istanbul. The consequent risk premium disproportionately affected companies in capital-intensive sectors like aviation where long investment horizons and fixed costs magnify financial exposure during times of decline.

With this macro financial context, the aviation industry experienced unprecedented pressures. The COVID-19 pandemic, having hit in 2020, triggered one of the deepest contractions in air travel in industry history. Being a major tourism destination, Turkey incurred a steep decline in international and domestic passenger numbers, and related revenue losses for airport operators and related industry players. Even when global travel restrictions relaxed in 2022 and later, the industry had to contend with lingering operational disruption, cost inflation, and demand volatility, specifically as consumer behavior and travel habits changed in post, pandemic times.

Here, TAV Airports' financial performance, as evidenced by Qj scores, exhibited a nuanced response to these multi-factorial pressures. The weakest performance was seen in 2021 (Qj=0.908) when it was a time of pandemic-related operational stress and economic volatility. Although a sharp turnaround in 2023 (Qj=0.000) was seen due to a pick-up in tourism, growing inbound air traffic, and better cost control, this was not easily a sustainable trajectory. The decline in performance observed in 2024 (Qj = 0.091) indicates emerging challenges, which may be associated with tightening global liquidity, persistently high domestic inflation, and structural bottlenecks within Turkey's aviation infrastructure.

Considering the overall analysis results and given that neither condition C1 nor condition C2 is satisfied, the VIKOR method does not identify 2019 as the sole compromise solution. Instead, it implies that more than one alternative may be regarded as a viable option. In this context, both 2019 and 2024 emerge as prominent candidates; 2019 reflects the most balanced financial performance across all criteria, while 2024 demonstrates the lowest individual regret value Rj, indicating a relatively lower risk profile. Accordingly, from a decision-making standpoint, both years can be interpreted as financially robust, albeit for different underlying reasons; 2019 for its overall efficiency, and 2024 for its resilience against specific performance weaknesses.

A longitudinal review of financial measures reinforces this knowledge. The Cash Ratio emerged persistently as a financial strength between 2019-2023, signaling the company's solid short-term liquidity condition, a strategic imperative in a business environment characterized by constant exogenous shocks. Meanwhile, the Debt-to-Equity Ratio's status as a top strength in 2024 might be a sign of a move towards capital restructuring or deleveraging, a testament to adaptive action by management to address weaknesses in the balance sheet and market pressures.

On the contrary, ongoing weakness in profitability and leverage measures like Financial Leverage Ratio for 2022–2023 and low Gross/Net Profit Margins in pandemic years indicate underlying cost inflexibility and lower operating efficiency when revenues are at depressed levels. These are reflective of the general structural dynamics of the air transport industry in emerging economies, low price power, vulnerability to tourism cycles, and substantial exposure to fuel prices and exchange rate movements.

Moreover, the sensitivity analysis conducted in this study based on different scenarios—constructed using the criterion weights obtained through the Entropy method (equal weighting, profitability, liquidity, risk/debt, and efficiency priorities)—reveals that the observed variations in the rankings of alternative years demonstrate that the model exhibits the expected level of sensitivity. The ranking differences between scenarios indicate, consistent with the nature of multi-criteria decision-making (MCDM) approaches, that the evaluation outcomes of alternatives may change when criterion priorities are altered. This finding shows that the model is responsive to different strategic priority sets and provides decision-makers with the ability to analyze which years become more advantageous when a particular criterion group is prioritized.

Importantly, the absence of drastic fluctuations in the rankings (e.g., no year falling from the top to the bottom position) supports the overall stability of the model, while the limited and meaningful changes in ranking indicate that the model can demonstrate sensitivity to different priorities and possesses a flexible structure. These findings also corroborate a well-established principle frequently emphasized in the MCDM literature: the results of multi-criteria decision-making methods largely depend on criterion weights, and therefore, sensitivity analyses are critical for assessing both the reliability and decision-support potential of these methods (Tanino, 1999; Pamučar & Ćirović, 2015).

As a result, this study's conclusions highlight the pivotal influence of macro variables, market dynamics in finance, investor sentiment, and industry specific factors in determining financial performance at the corporation level. For decision-makers and stakeholders alike, these findings highlight the need for adaptive strategic planning in response to ongoing volatility and structural uncertainty.

However, this research has certain limitations. First, the empirical focus indicates TAV Airports Holding listed at Borsa Istanbul, making generalizability problematic. The limited focus of financial analysis on fifteen major ratios means exclusion from analysis of more extensive financial or industry indicators might have compromised analytical scope. Second, exogenous shocks like sectoral dynamics, macroeconomic conditions, and pandemics were not explicitly included in the model. Since such variables may have a critical contribution to financial performance, one would need to be cautious interpreting this result. Third, the research is retrospective in nature, entirely reliant upon historical data, and not providing any forecast.

All these findings can provide useful input for decision making for researchers, investors, portfolio managers, policymakers, and stakeholders within financial markets and aviation business in making informed strategic decisions. Through determining the firm's strengths and weaknesses in finance throughout the review horizon, this work helps shape a more balanced, sustainable financial strategy. Within capital intensive, extremely volatile sectors like aviation, this information holds particular relevance in ensuring financial stability, facilitating informed investment choices, and creating informed policies within fast-changing economic climates.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

References

Abbruzzo, A., Fasone, V., & Scuderi, R. (2016). Operational and financial performance of Italian airport companies: A dynamic graphical model. Transport Policy, 52, 231-237.

Alp, I., Öztel, A., & Köse, M. S. (2015). Corporate sustainability performance measuring with Entropy

Based MAUT method: A case study, The International Journal of Economic and Social Research, Vol. 11, Year 11, No. 2.

Asker, V., & Kiracı, K. (2016). A research on review of financial performance: airport groups sample. International Journal of Shipping and Transport Logistics, 16, 38.

Bakır, M., & Atalık, Ö. (2018). Evaluation of service quality in airlines by Entropy and ARAS methods. Journal of Business Research Turk, 10(1), 617-638.

Battal, Ü. (2020). Measurement of financial performance of airport groups companies in Europe: Data envelopment analysis method. Academic Review of Economics and Administrative Sciences, 13(1) pp: 171-184.

Chen, Y. H., & Wang, T. C. (2009). Optimizing partner's choice in IS/IT outsourcing projects: The strategic decision of fuzzy VIKOR. International Journal of Production Economics, 120(1), 233–242.

de Neufville, R., & Odoni, A. (2013). Airport systems: Planning, design, and management (2nd ed.). McGraw-Hill Education.

Demirarslan, P. Ç., Küçükönder, H., & Kıngır, S. (2019). Evaluation of emotional performance on academicians with Entropy based TOPSIS and VIKOR methods: Bartin case. Electronic Journal of Social Sciences, 18(69), 232-251.

Durak, İ., & Bal, B. Ç. (2024). Comparison of banks' performances in the pre-and post-COVID-19 period using Entropy and VIKOR methods. Unye Journal of Economics and Administrative Sciences, 6(2), 102-113.

Ertuğrul, İ., & Karakaşaoğlu, N. (2009). Performance evaluation of bank branches with VIKOR Method. Journal of Industrial Engineering (Turkish Chamber of Mechanical Engineers), 20(1), 19-28.

Eş, A., & Kocadağ, D. (2020). Supplier selection with entropy based MAUT and VIKOR methods: A public institution case study. Manisa Celal Bayar University Journal of Social Sciences, 18, 265-280.

Forsyth, P., Gillen, D., Müller, J., & Niemeier, H. M. (2010). Airport competition: The European experience. Ashgate Publishing.

Graham, A. (2013). Managing airports: An international perspective (4th ed.). Routledge.

Hacıfettahoğlu, Ö., & Perçin, S. (2020). Evaluation of the performance of Turkish construction companies in the financial dimension with integrated MCDM approach. Dokuz Eylül University Journal of Social Sciences Institute, 22(2), 543-567.

Humphreys, I., & Francis, G. (2002). Policy issues and planning of UK regional airports. Journal of Transport Geography, 10(4), 249–258.

ICAO. (2021). Effects of COVID-19 on Civil Aviation: Economic impact analysis. Montreal: International Civil Aviation Organization.

IATA. (2021). World Air Transport Statistics (WATS). International Air Transport Association.

Kahraman, C. (2008). Multi-Criteria Decision Making and Fuzzy Systems. Springer.

Opricovic, S., & Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. European Journal of Operational Research, 156(2), 445–455.

Opricovic, S., & Tzeng, G. H. (2007). Extended VIKOR method in comparison with outranking methods. European Journal of Operational Research, 178(2), 514–529.

Oum, T. H., Adler, N., & Yu, C. (2006). Privatization, corporatization, ownership forms and their effects on the performance of the world's major airports. Journal of air Transport management, 12(3), 109-121.

Pamučar, D., & Ćirović, G. (2015). The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation area comparison (MABAC). Expert systems with applications, 42(6), 3016-3028.

Public Disclosure Platform, Companies, TAV Airports, https://www.kap.org.tr/en/sirket-bilgileri/ozet/1452-tav-havalimanlari-holding-a-s.

Raghavan, S., & Yu, C. (2021). Evaluating financial performance of commercial service airports in the United States. Journal of Air Transport Management, 96, 102111.

Saaty, T. L. (1980). The Analytic Hierarchy Process. McGraw-Hill.

Shannon, C. E. (1948). A mathematical theory of communication. Bell System Technical Journal, 27(3), 379–423.

Şeker, M., & İslamoglu, M. (2024). Analysis of takaful insurance companies' performance in 2022 using the VIKOR method. Econder International Academic Journal, 8(2), 228-242.

Şenkal, E., & Öztel, A. (2020). Measuring the financial performance of the retail sector by entropy based COPRAS method: The Carrefoursa case. Journal of Management Economics Literature Islamic and Political Sciences, 5(1), 8-24.

Tanino, T. (1999). Sensitivity analysis in MCDM. In Multicriteria Decision Making: Advances in MCDM Models, Algorithms, Theory, and Applications (pp. 173-201). Boston, MA: Springer US.

TAV Airports, Investor Relations, Annual Reports, https://ir.tav.aero/en-EN/

Tzeng, G. H., & Huang, J. J. (2011). Multiple Attribute Decision Making: Methods and Applications. CRC Press.

Yılmaz, Ö., & Yakut, E. (2021). Evaluation of financial performance in banking sector using Entropy Based TOPSIS and VIKOR methods. Atatürk University Journal of Economics and Administrative Sciences, 35(4), 1297-1321.

Wang, Y. M., & Elhag, T. M. S. (2006). Fuzzy TOPSIS method based on alpha level sets with an application to bridge risk assessment. Expert Systems with Applications, 31(2), 309–319.

Wang, Y. M., & Lee, H. S. (2009). Generalizing TOPSIS for fuzzy multiple-criteria group decision-making. Computers & Mathematics with Applications, 57(6), 1072–1080.

Zhang, X., Wang, C., Li, E., & Xu, C. (2014). Assessment model of ecoenvironmental vulnerability based on improved entropy weight method. The Scientific World Journal, 2014(1), 797814.

Zavadskas, E. K., & Turskis, Z. (2011). Multiple criteria decision making (MCDM) methods in economics: An overview. Technological and Economic Development of Economy, 17(2), 397–427.

Zavadskas, E. K., Turskis, Z., & Kildienė, S. (2014). State of art surveys of overviews on MCDM/MADM methods.

Technological and Economic Development of Economy, 20(1), 165–179.
Zeleny, M. (1982). Multiple criteria decision making. McGraw-Hill.

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