PERFORMANCE EVALUATION OF NIFTY 50 NON-FINANCIAL COMPANIES IN INDIA: AN ENTROPY-BASED TOPSIS APPROACH

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Abstract: This study evaluates the financial performance of 39 non-financial companies listed on the Nifty 50 index in India for the financial year 2022-2023. The analysis employs the Entropy and TOPSIS approaches to assess the companies based on seven key financial ratios. The Entropy method determines each criterion's weight, objectively evaluating their relative importance. Subsequently, the TOPSIS method ranks the companies by comparing their financial performance against an ideal solution. The findings provide valuable insights into the relative performance of these companies, offering a comprehensive view of their financial health and operational efficiency during a period marked by economic volatility and post-pandemic recovery. This study aims to assist investors, financial analysts, and policymakers in making informed decisions by identifying top-performing companies and understanding the factors contributing to their success. The results also shed light on the critical financial metrics significantly influencing the company's performance in the Indian market. The entropy analysis showed that the debt-equity ratio is the most significant performance indicator, while the net profit margin (NPM) is the least significant criterion. Subsequently, TOPSIS analysis revealed that Nestle India Ltd. was the top performer during the study period. On the other hand, the company Bharti Airtel Ltd. has shown poor performance and requires more attention for improvement in some areas.

Keywords: Nifty 50, Non-Financial Companies, Performance, Financial, Entropy, TOPSIS

JEL Classification: C32, C44, L25

Introduction

Performance evaluation plays a significant role in the efficiency enhancement of any organization. An effective performance evaluation helps policymakers understand the barriers to economic development due to inefficiency in different sectors, i.e., which sector is thriving and which one requires more attention from policy-makers. The regulators can make sector-specific

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policies and can help in the optimum utilization of economic resources. Financial performance determines a company's competitiveness, business potential, revenue streams, and present and future aspects. Financial performance evaluation involves how well a business uses its resources—assets, shareholder equity, liabilities, revenue, and expenses while reaching its pre-defined goals. With India's growing integration into the global economy and increasing regulatory requirements, such analysis is essential for the management, shareholders, the general public, government regulators, credit facilitators, and the overall economy by identifying the sector's weaknesses and strengths (Alimohammadlou & Bonyani, 2017).

The analysis of financial ratios is an effective tool for assessing a company's stability. These ratios can be calculated from companies' income statements and balance sheets (Yalcin et al., 2012). Numerous research studies in the literature have demonstrated the advantages of financial ratios. These tools enable users to summarize and analyze data to make informed decisions. Financial ratios highlight the strengths and weaknesses of businesses in terms of profitability, earnings capacity, and solvency.

India, a developing country, has 41% of its Gross Fixed Capital formation (GFCF) is contributed by its non-financial sector. The sector is crucial for India's GDP growth and employment formation. Over the years, India has witnessed many structural and economic reforms. Following policies such as globalization and liberalization, many foreign competitors have entered India's financial and non-financial sectors. The foreign entrants made it difficult for manufacturers, local industries, small entrepreneurs, and the service sectors to compete with high technologies and advanced products. Thus, it is crucial to facilitate these sectors with financial assistance and proper subsidies from the government. Therefore, monitoring these sectors from time to time is also essential. Without proper monitoring, the financial crisis and areas of inefficiencies cannot be identified and tackled. Continuous performance evaluation helps companies mitigate risks related to market fluctuations, policy changes, and economic disturbances.

Researchers in the field of performance evaluation have used numerous evaluation methods. The DEA method, Regression analysis, time series analysis, panel data analysis, simple ratio analysis, and vice versa. Multi-criteria decision-making (MCDM) is a renowned approach used in decision-making and ranking of best alternatives among ample available alternatives. Currently, there is a limited study on ranking companies in the non-financial sector of India using MCDM tools based on their financial measures. Under MCDM, two methods are generally used for a complete analysis: weighing (e.g., Shannon entropy) and outranking methods (e.g., TOPSIS).

The present study aimed to examine the financial performance of Nifty 50 companies (excluding the financial companies) in India during 2022-2023 and rank them under the MCDM method. The non-financial segment of India generally includes the manufacturing sector, the food and Agro-industry, the fast-moving consumer goods industry, Information technology, energy and utilities, transport and logistics, healthcare and pharmaceuticals, and vice versa. Each sector has several companies. The top 50 firms listed on India's National Stock Exchange (NSE) are among those under consideration for analysis. The financial data for the year 2022-2023 is collected from the ProwessIQ database. The study used an entropy-based TOPSIS approach to rank the alternatives.

This paper is organized into five major sections. Section 1, presents a brief introduction to the topic and the research objective. Section 2 presents a detailed literature review of the performance evaluation of different companies' performance measures and MCDM techniques focused on financial aspects. In Section 3, the research methodology consisting of the data source, sample selection, and methods used are presented and discussed; in the next section, in Section 4, the results of the analysis are discussed with adequate tables and figures, and finally, Section 5, concluded with a summary of findings, and suggestions for future studies.

Literature Survey

The studies on financial performance primarily focused on determining the relationships between financial measures and their impact on company performance. Regression models are frequently applied to demonstrate the extent to which financial measures explain company performance (Xu & Li, 2022). Many widely used approaches in the literature have been found for performance evaluation. These are the traditional ratio analysis, simple regression analysis, DEA, and other non-parametric approaches (Yalcin et al., 2012; Baran & ¯ak, 2014). As part of the traditional ratio analysis process, alternatives were evaluated using a variety of accounting ratios, including return on asset (ROA) and return on equity (ROE) (Avkiran, 2006). Nowadays, MCDM tools are gaining attention from researchers widely, they combine multiple conflicting attributes in a single heading in order to provide a comprehensive assessment of alternatives. Baren and Zak (2014) applied the Analytical Hierarchy Process (AHP) to assess ten transportation units operating in Polish agribusinesses. The study used eight main and eight sub-criteria for the analysis. Yadav and Sharma (2015) devised an approach that combines data envelopment analysis (DEA) with the analytical hierarchy process (AHP). Chang (2015) integrated the order of preference by similarity to the ideal solution (TOPSIS) method and the analytic network process (ANP) to develop a project selection model for nonprofit television stations. ANP was employed to calculate the criteria weights in this model, while TOPSIS was used to rank the alternatives. Verma et al. (2021) used an entropy-based approach to assess the manufacturing firms in India. Chand et al. (2020) evaluated India's mining and earthmoving equipment manufacturing companies based on the supply chain performance (SCP) indices. The study applied the Delphi technique to select critical SCP matrices and Decision-Making Trial and Evaluation Laboratory (DEMATEL) approaches to determine the interrelationship between selected criteria. At last, the Best-Worst method (BWM) technique was to rank the alternatives. Abdel-Basset et al. (2020) applied multiple MCDM techniques (AHP-VIKOR-TOPSIS) under a fuzzy environment to analyze the financial performance of steel manufacturing companies in Egypt. Varmazyar et al. (2016) employed different MCDM outranking tools such as the RAS, COPRAS, MOORA, and TOPSIS to prioritize Iran's research and technology organization. The study first used the ANP approach to determine the relative importance of attributes under the Balanced Scored Card (BSC) framework. Additionally, a DEMATEL approach was incorporated to check the intensity of the relation between the elements under BSC. Finally, the utility interval technique was utilized to integrate the rankings from different approaches. Wang (2008) evaluated the financial performance of Taiwan's container shipping lines using fuzzy multi-criteria group decision-making in conjunction with grey relation analysis. This study compared and ranked the units involved in a multi-criteria decision-making framework primarily using accounting-based financial performance indicators. In order to assess supplier performance in the automotive industry, Sarraf and Nejad (2020) compared two analytical approaches, DEA and GRA, in the performance measurement of 35 water and wastewater companies in Iran in 2017. The BSC framework was again followed to select the evaluation matrices. The weights for each criterion under BSC were determined using the Shannon entropy method. The research discovered that the GRA outranking method was more effective than the DEA technique. Chen et al. (2011) argue that the hybrid MCDM model gives managers a competitive edge over other approaches by enabling users to understand the appropriate arrangements to execute within the firm. Their study investigated the performance of hot spring hotels in Taiwan. The study applied an ANP-based DEMATEL model, incorporating 15 qualitative and quantitative performance indices. Keramati and Shapouri (2016) proposed an extensive approach for evaluating the performance of customer relationship management, or CRM, systems in Iranian Internet service providers. The approach employed DEMATEL to ascertain the interdependencies between the criteria and pinpoint key attributes impacting the performance, consequently adopting ANP to calculate the criteria weights. Finally, they applied TOPSIS to assess CRM performance, concluding that certain indicators play a crucial role in CRM success. Yalcin (2012) studied the performance evaluation of manufacturing companies in Turkey based on the financial aspects. The study employed the AHP-based VIKOR and

TOPSIS model in the fuzzy environment. The financial parameters ROA, ROE, EPS, and P/E ratio were used in the study. The results of the two models, AHP-VIKOR and AHP-TOPSIS, were compared, and significant differences in the ranking results of the two approaches were observed. Zhao et al. (2018) introduced an MCDM model that incorporates fuzzy Delphi and the best-worst method (BWM) to assess the performance of grid companies. Salimi and Rezaei (2018) used the BWM to analyze R&D performance and determine important metrics for R&D performance.

Data & Methodology

This study is an empirical research based on secondary data sources. The study considered the non-financial companies under Nifty 50 for 2022-23. Similarly, financial data was calculated from the CMIE database for one year. The study utilized the entropy-based TOPSIS approach to analyze the financial performance of selected companies based on seven indices. After that, the data cleaning was performed by accounting for any missing data, and companies with continuous missing data for multiple variables were not included in this study. To enhance the accuracy of the data, no approximation or rounding-off exercise has been carried out.

Table 1: Selected companies under Nifty 50

Codes	Name of Companies	Codes	Name of Companies
A1	Adani Enterprises Ltd.	A21	JSW Steel Ltd.
A2	Adani Ports & Special Economic Zone Ltd.	A22	Larsen & Toubro Ltd.
A3	Apollo Hospitals Enterprise Ltd.	A23	Ltimindtree Ltd.
A4	Asian Paints Ltd.	A24	Mahindra & Mahindra Ltd.
A5	Bajaj Auto Ltd.	A25	Maruti Suzuki India Ltd.
A6	Bharat Petroleum Corpn. Ltd.	A26	NTPC Ltd.
A7	Bharti Airtel Ltd.	A27	Nestle India Ltd.
A8	Britannia Industries Ltd.	A28	Oil & Natural Gas Corpn. Ltd.
A9	Cipla Ltd.	A29	Power Grid Corpn. Of India Ltd.
A10	Coal India Ltd.	A30	Reliance Industries Ltd.
A11	Divi'S Laboratories Ltd.	A31	Sun Pharmaceutical Inds. Ltd.
A12	Dr. Reddy'S Laboratories Ltd.	A32	Tata Consultancy Services Ltd.

A13	Eicher Motors Ltd.	A33	Tata Consumer Products Ltd.
A14	Grasim Industries Ltd.	A34	Tata Motors Ltd.
A15	HCL Technologies Ltd.	A35	Tata Steel Ltd.
A16	Hero Motocorp Ltd.	A36	Tech Mahindra Ltd.
A17	Hindalco Industries Ltd.	A37	Titan Company Ltd.
A18	Hindustan Unilever Ltd.	A38	Ultratech Cement Ltd.
A19	ITC Ltd.	A39	Wipro Ltd.
A20	Infosys Ltd.		

Source: Author's Compilation

After deducting the financial institutions, such as banks, NBFCs, and insurance companies, the remaining 39 companies were left for the analysis. The samples are listed in Table 1. Accordingly, based on the available literature (Kaya et al. 2024; Gavalas et al. 2022; Tavana et al. 2015; Abdel-Basset et al. 2020; Verma et al., 2021), variables are selected for this study, presented below in Table 2.

Table 2: Description of Selected Variables

Code	Attributes	Expected Outcome
C1	Net Profit Margin	Max
C2	Return on Net Worth	Max
C3	Return on Total Assets	Max
C4	Current Ratio	Max
C5	Debt to Equity Ratio	Min
C6	Earnings Per Share (EPS)	Max
C7	Price-Earnings (P/E) Ratio	Max

Source: Author's Compilation

Entropy Method

The term entropy is a weighing approach frequently used under MCDM in different fields to calculate the objective weights without concern about the conflicting preferences of the experts and multiple decision-makers (Verma et al., 2021).

The five main stages under the Shannon entropy weighing approach are as follows:

Step 1: Establishing the decision matrix for each alternative to each criterion

$$D = [C_{ij}]_{mn} = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{m1} & c_{m2} & \cdots & c_{mn} \end{bmatrix}$$

.... Eq. (1)

Step 2: Normalization of the decision matrix

$$x_{ij} = \frac{c_{ij}}{\Sigma C_{ij}} \text{ here, } i \in (1, \dots m) \text{ and } j \in (1, \dots, n)$$

.... Eq. (2)

Step 3: Calculating the entropy e_j for a set of indices j is

The Shannon entropy for each model is calculated using the following formula:

$$e_j = -P \sum_{i=1}^{n} x_{ij} \,.\, \text{In}(x_{ij})$$

.... Eq. (3)

Here, P represents a constant, $P = \frac{1}{1n(m)}$

Step 4: Calculation of the degree of divergence D_j

$$D_j = 1 - e_j$$ .... Eq. (4)

Step 5: Calculation of the entropy weights w_j

$$w_j = \frac{D_j}{\Sigma_{j=1}^{m} D_j}$$ .... Eq. (5)

TOPSIS method

The method TOPSIS is an outranking method under MCDM that ranks alternatives based on their closeness to an ideal or distance from the anti-ideal solutions. By following a structured methodology and utilizing robust data analysis techniques, the TOPSIS method provides a comprehensive and objective performance evaluation, aiding stakeholders in making informed decisions and driving strategic initiatives for the institution.

The following are the steps involved in the method (Sharma et al., 2021):

Step 1: Develop the normalized decision matrix

$$r_{ij} = \frac{x_{ij}}{\sqrt{\Sigma_{k=1}^{m} x_{kj}^2}}$$ ....Eq. (6)

Step 2: Determine the weighted normalized decision matrix V_j

$$V_j = w \,.\, r_{ij}$$ .... Eq. (7)

Step 3: Compute the most positive and most negative solutions

Calculate V^- which is the most negative ideal solution

$$V^+ = \left\{\left(\max_i vij \mid j \in J\right)\right\},\ i = 1, 2, \dots, m$$

$$V^- = \left\{\left(\min_i vij \mid j \in J\right)\right\},\ i = 1, \dots, m$$

.... Eq. (8)

Step 4: Calculate the distance from the most positive P_i^+ and negative N_i^- solutions

Where $P_i^+ = \sqrt{\Sigma_{j=1}^{n}\left(v_{ij} - v_j^+\right)^2}$, i = 1, …, m

.... Eq. (9)

Where $N_i^- = \sqrt{\Sigma_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2}$, i = 1, …, m ……………… Eq. (10)

Step 5: Calculate the TOPSIS scores based on the ideal solution

$Q_i = \frac{N_i^-}{\left(P_i^+ + N_i^-\right)}$, i = 1, …., m ……. Eq. (11)

Results and Discussion

The analysis took place in two stages; in the first phase, the entropy objective weighing approach was used on the selected criteria related to each alternative. The companies' performance scores were determined using the TOPSIS approach based on the entropy weights in the second phase.

The study first developed a 39×7 (m×n) decision matrix of 39 alternatives related to seven criteria. The values in the decision matrix were normalized to convert all the criteria into the same units. Each value in the decision matrix is divided by the column sum (Table 3).

Table 3: Normalized values of each attribute related to each alternative

	C1	C2	C3	C4	C5	C6	C7
A1	0.011	0.020	0.012	0.006	0.015	0.006	0.080
A2	0.000	0.000	0.000	0.009	0.113	0.000	0.000
A3	0.029	0.020	0.018	0.036	0.025	0.030	0.038
A4	0.022	0.032	0.038	0.036	0.005	0.017	0.044
A5	0.026	0.025	0.036	0.025	0.001	0.077	0.013
A6	0.008	0.008	0.005	0.011	0.058	0.006	0.016
A7	0.013	0.007	0.004	0.007	0.159	0.004	0.072
A8	0.023	0.075	0.048	0.017	0.057	0.032	0.037
A9	0.026	0.012	0.017	0.066	0.001	0.011	0.022
A10	0.123	0.098	0.125	0.048	0.001	0.010	0.006
A11	0.037	0.018	0.025	0.093	0.001	0.027	0.028
A12	0.027	0.016	0.021	0.044	0.001	0.062	0.020
A13	0.030	0.025	0.034	0.018	0.001	0.038	0.021
A14	0.017	0.007	0.008	0.017	0.008	0.014	0.033

A15	0.039	0.031	0.041	0.039	0.002	0.017	0.018
A16	0.018	0.021	0.025	0.025	0.001	0.057	0.011
A17	0.012	0.009	0.008	0.026	0.025	0.006	0.019
A18	0.029	0.023	0.028	0.020	0.002	0.017	0.042
A19	0.041	0.033	0.048	0.043	0.001	0.007	0.017
A20	0.031	0.038	0.045	0.027	0.005	0.022	0.017
A21	0.012	0.010	0.006	0.015	0.063	0.008	0.024
A22	0.015	0.013	0.009	0.021	0.018	0.021	0.028
A23	0.024	0.031	0.038	0.047	0.007	0.055	0.023
A24	0.017	0.019	0.019	0.017	0.009	0.022	0.015
A25	0.016	0.017	0.021	0.008	0.002	0.104	0.021
A26	0.017	0.012	0.007	0.013	0.090	0.006	0.009
A27	0.025	0.119	0.055	0.016	0.008	0.104	0.050
A28	0.042	0.021	0.025	0.009	0.007	0.014	0.003
A29	0.051	0.022	0.012	0.015	0.107	0.009	0.007
A30	0.017	0.011	0.011	0.013	0.031	0.026	0.025
A31	0.034	0.022	0.022	0.023	0.023	0.008	0.035
A32	0.033	0.056	0.062	0.034	0.006	0.041	0.021
A33	0.021	0.010	0.014	0.034	0.003	0.005	0.044
A34	0.012	0.017	0.010	0.007	0.059	0.004	0.032
A35	0.021	0.014	0.014	0.012	0.022	0.006	0.006
A36	0.020	0.020	0.024	0.026	0.002	0.018	0.017
A37	0.018	0.035	0.030	0.025	0.045	0.015	0.045
A38	0.017	0.012	0.012	0.012	0.013	0.065	0.031
A39	0.025	0.019	0.023	0.040	0.007	0.008	0.014

Source: Author's Calculation

In Table 3. the linear normalization is followed using Eq. (2), ensuring the values should be between 0 and 1. Next, the entropy values alternatively, each criterion is computed to measure the level of disorder or uncertainty. The degree of differentiation are then computed. Based on the values the entropy weights calculated and shown in Table 4.

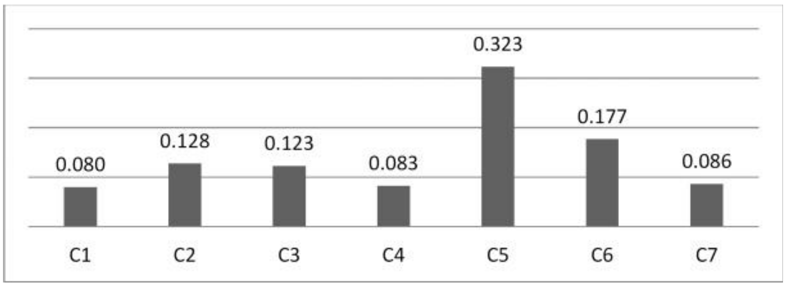
Table 4: Entropy Weights

C1	C2	C3	C4	C5	C6	C7
0.080	**0.128**	**0.123**	**0.083**	**0.323**	**0.177**	**0.086**

Source: Author's Computation

Table 4 depicts the relative importance (weights) of each criterion. Criteria with higher variability will have lower entropy, leading to higher weights. The weights are assigned to the criteria based on their entropy values. Criteria with more significant variation (lower entropy) are given higher importance, while those with less variation (higher entropy) receive lower weights.

Fig. 1: Relative importance of criteria



Source: Author's Compilation

Fig. 1 shows the importance level of different financial ratios (criterion). The C5 received the highest weightage, 0.323, which accounted for nearly one-third of the total importance of the criteria. This signifies that the C5 is the most crucial indicator in reflecting the financial performance of the selected alternatives. Therefore, the companies that perform better in C5 are likely to rank higher overall. C6 and C2 have received the second and third highest weights, 0.177 and 0.128. On the other hand, C1, C4, and C7 received the lowest weights, C1 among them being the least significant indicator.

Table 5: Distance from positive and negative ideal solutions

Companies	P_i^+	N_i^-	Qi	Companies	P_i^+	N_i^-	Qi
A1	0.131	0.171	0.566	**A21**	0.153	0.112	0.421
A2	0.196	0.053	0.213	**A22**	0.128	0.165	0.563
A3	0.117	0.160	0.577	**A23**	0.097	0.185	0.656
A4	0.111	0.183	0.623	**A24**	0.123	0.176	0.588
A5	0.097	0.194	0.666	**A25**	0.106	0.200	0.654
A6	0.153	0.117	0.433	**A26**	0.171	0.081	0.320
A7	0.228	0.033	0.127	**A27**	0.068	0.209	0.755
A8	0.115	0.133	0.537	**A28**	0.123	0.178	0.590
A9	0.124	0.186	0.599	**A29**	0.176	0.066	0.272
A10	0.083	0.212	0.718	**A30**	0.130	0.150	0.534
A11	0.111	0.190	0.632	**A31**	0.125	0.160	0.562
A12	0.105	0.191	0.645	**A32**	0.088	0.187	0.680
A13	0.108	0.187	0.634	**A33**	0.129	0.183	0.585
A14	0.132	0.176	0.572	**A34**	0.150	0.117	0.437
A15	0.110	0.186	0.628	**A35**	0.136	0.159	0.539
A16	0.108	0.189	0.637	**A36**	0.121	0.183	0.602
A17	0.138	0.156	0.531	**A37**	0.125	0.137	0.523
A18	0.117	0.185	0.612	**A38**	0.114	0.177	0.609
A19	0.112	0.188	0.625	**A39**	0.125	0.177	0.587
A20	0.107	0.183	0.632				

Source: Calculated by the author

Distance from Positive Ideal Solution (PIS) represents a company's distance from the best possible scenario. A smaller value indicates that the company is closer to the ideal scenario. Distance from Negative Ideal Solution (NIS) represents a company's distance from the worst possible scenario. A higher value indicates that the company is further away from the worst scenario, which is desirable. Qi ranges between 0 and 1. A value closer to 1 indicates that the company is closer to the ideal solution, while a value closer to 0 indicates proximity to the worst possible outcome. A higher Qi value indicates a company's better overall performance relative to the others when all criteria are considered. The P_i^+ and N_i^-

values are calculated using Eq. (9) and (10). Accordingly, the Qi i.e., the performance scores of each alternative determined based on Eq. (11).

Table 5 shows that companies such as A27 (Qi = 0.755), A10 (Qi = 0.718), and A7 (Qi = 0.666) have the highest Qi values, indicating they are closer to the ideal solution in terms of the criteria used. A27 has a very low value (0.068) and a high value (0.209), which is close to the ideal or best solution and distant from the worst. Companies like A7 (Qi = 0.127), A29 (Qi = 0.272), and A26 (Qi = 0.320) have the lowest Qi values, suggesting they are further from the ideal performance compared to other companies. A7, for instance, has the highest value (0.228) and the lowest value (0.033), indicating that it is far from the ideal and close to the worst scenario. Companies such as A21 (Qi = 0.421) and A34 (Qi = 0.437) have moderate Qi values, indicating they are neither close to the ideal nor the worst solution. They perform reasonably well but require improvement. A34 has balanced (0.150) and (0.117) values, which leads to its moderate Qi.

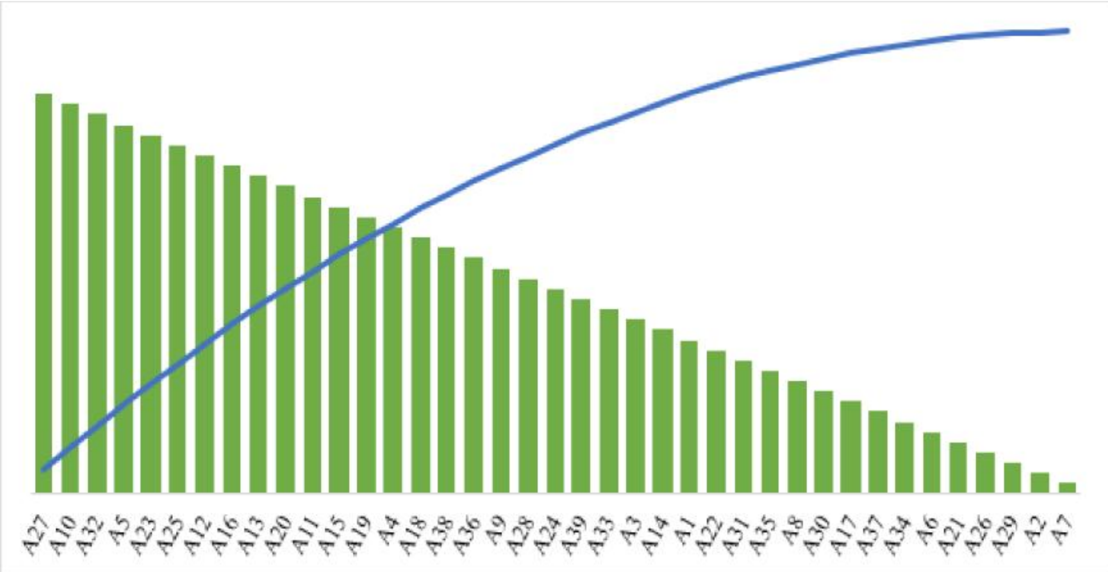
Table 6: Ranking of Alternatives

Companies	Ranks	Companies	Ranks
A1	25	**A21**	35
A2	38	**A22**	26
A3	23	**A23**	5
A4	14	**A24**	20
A5	4	**A25**	6
A6	34	**A26**	36
A7	39	**A27**	1
A8	29	**A28**	19
A9	18	**A29**	37
A10	2	**A30**	30
A11	11	**A31**	27
A12	7	**A32**	3
A13	9	**A33**	22
A14	24	**A34**	33
A15	12	**A35**	28
A16	8	**A36**	17
A17	31	**A37**	32
A18	15	**A38**	16
A19	13	**A39**	21
A20	10		

Source: Computed by the author

Table 6 shows the ranking of 39 selected companies based on the TOPSIS approach. The Qi values rank the alternatives; the higher the value, the better the performance. Similarly, company A27 ranked 1st with a Qi value of 0.755, followed by A10 and A32, with Qi values of 0.718 and 0.680, and ranked 2nd and 3rd. Company A7 received the last position with a Qi value of 0.127.

Fig. 2: Relative performance of selected companies



Source: Author's Compilation

The Fig 2. Reflects the performance level of non-financial companies under NIFTY 50. Company A7, A2, A29, and A26 came at the bottom of the chart, receiving the lowest ranking. On the other side, the alternatives A27, A10, A32, A5, and A25 made a place in the top five based on their performance scores. Alternatives A12, A16, and A19 have balanced performance, reflecting a need for improvement in various ratios.

Conclusion

This study utilized the entropy-based TOPSIS approach to evaluate the financial performance of 39 companies under the non-financial sector among the top 50 companies listed on the Indian National Stock Exchange. The study examined seven financial ratios selected from the available literature. The computed weights indicate that Debt to Equity Ratio (C5) is the most important criterion in determining the overall ranking of the companies, followed by earnings Per Share (C6). Companies that excel in these criteria are likely to outperform their peers. Return on Net Worth (C2) and Return on Total Assets (C3) are also important but less so than

Debt to Equity Ratio (C5) and EPS (C6), while the ratios Net Profit Margin (C1), Current Ratio (C4), and Price-Earnings Ratio (C7) have the most negligible impact individually. This weighting provides a clear guide for companies on where to focus their improvement efforts to maximize their performance and ranking. The attribute Debt to Equity Ratio (C5) with a maximum entropy value of 0.323 should be the primary focus for companies seeking to improve their overall ranking. Investments, strategies, and operational improvements in this area are likely to yield the highest returns in terms of overall performance. The criterion EPS (C6) also requires significant attention, as it plays a crucial role in the evaluation with an entropy score of 0.177. It is further observed that the companies Nestle India Ltd. (A27), Coal India Ltd. (A10), and Tata Consultancy Services Ltd. (A32) are the three best performers during the study period, while the Bharti Airtel Ltd. (A7), Adani Ports & Special Economic Zone Ltd. (A2), Power Grid Corpn. Of India Ltd. (A29) has received the lowest ranking. The High Qi companies (i.e., A27, A10) are likely more attractive for investors and stakeholders due to their proximity to the ideal performance. These companies are likely well-managed or operate in favorable conditions, making them reliable investments. Low Qi companies (e.g., A7, A29) may require strategic overhauls or targeted improvements. These companies might face challenges that must be addressed to move closer to the ideal performance. Companies with low Qi values may also represent higher risks. They might be more susceptible to external pressures or internal inefficiencies that prevent them from reaching ideal performance levels. The TOPSIS analysis provides a clear ranking of the companies based on their proximity to the ideal solution.

Companies like A27 and A10 emerge as leaders, performing well across the criteria. In contrast, companies like A7, A2, and A29 are identified as underperformers with significant space for improvement.

This analysis can guide decision-making in optimizing performance across multiple criteria. Finally, the financial performance analysis of India's non-financial sector is a barometer for the country's overall health, featuring the significant implications for investments, managerial decisions, employment, policy making, and economic stability.

Conflict of Interests

The author declares that there is no conflict of interests that are directly or indirectly related to this research work.

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