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Financial Performance of Indian NSE-Listed Companies Associated with Manufacturing Activities

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ABSTRACT

This study evaluated the financial performance of Indian manufacturing companies using an entropy-based COPRAS approach for 2022. A sample of 18 companies was selected from Nifty 50 firms and assessed based on five key financial ratios. The weights for each financial indicator were measured using the entropy method, and the rankings were performed using the COPRAS approach. It was observed that the debt-equity ratio is the most important performance indicator in the analysis, while the Current Ratio obtained the lowest weightage of 0.061. The ranking results indicate that Coal India Ltd. is the best performer during the period, followed by Bajaj Auto Ltd. and Eicher Motors Ltd. On the other hand, Bharat Petroleum Corpn. Ltd. received the lowest ranking based on the alternatives' performance score and degree of utility value. The study provides significant insights into the Indian manufacturing industry, efficiency, and areas for improvement for the companies in the sector. The application of MCDM in this context was limited, which encouraged this study.

Keywords: Financial performance, Manufacturing industry, India, MCDM, Entropy, COPRAS

1. Introduction

Manufacturing is the process of transforming raw materials into finished goods through the use of tools, human resources, machinery, and chemical processing. This structured approach involves a division of labor and can vary from small-scale artisanal production to large-scale industrial operations. The term 'manufacturing' comprises a spectrum of industries that differ in the mode of production, labor and capital dependency levels, and market rivalry (Abdel-Maksoud et al., 2005). The manufacturing sector is one of the key pillars of the Indian economy, contributing significantly to GDP, employment, exports, and overall industrial growth. The sector contributes approximately 17-18% of India's GDP, with efforts under the Make in India initiative aiming to increase this to 25%. It serves as a growth engine for industrial development and economic expansion. The sector supports allied industries such as logistics, supply chains, and small-scale enterprises, boosting employment. Manufacturing drives the demand for industrial infrastructure, such as power, transport, and communication. India has become an attractive destination for FDI in manufacturing, with sectors such as automobiles, electronics, and pharmaceuticals receiving substantial investment. Manufacturing also plays a key role in exports, helping India reduce trade deficits and boost global competitiveness. The sector includes a large base of Micro, Small, and Medium Enterprises (MSMEs), contributing around 30% of GDP and nearly 45% of total exports. Government initiatives such as Atmanirbhar Bharat and Production Linked Incentive (PLI) schemes promote local manufacturing and self-reliance. Strengthening domestic manufacturing helps reduce reliance on imports, especially in key sectors like electronics, defense, and pharmaceuticals. This enhances economic resilience and improves the trade balance.

Financial performance evaluation is crucial in the Indian manufacturing industry in this competitive environment, significantly increasing revenue growth (Abdel-Basset et al., 2020). Investors, including domestic and foreign stakeholders, rely on financial performance analysis to assess manufacturing firms' profitability, stability, and growth potential. Strong financial indicators attract investments, boosting capital formation in the sector. Financial evaluation helps identify production inefficiency, supply chain management, and resource utilization. Companies can optimize costs and improve productivity by analyzing financial ratios, e.g., return on assets (ROA) and operating margins. Evaluating financial stability allows businesses to anticipate risks related to debt, market fluctuations, and operational bottlenecks. A sound financial position ensures resilience against economic downturns and disruptions. A financially well-performing manufacturing firm has better access to credit, ensuring smooth operational and expansion plans.

The financial performance assessment is crucial for all companies, and a robust performance measure is imperative (Safaei et al., 2014). The performance evaluation includes multiple evaluation criteria; therefore, it is considered a multi-criteria decision-making (MCDM) problem (Dong et al., 2018; Varmazyar et al., 2016). Various methods and concepts have been applied in the field of performance analysis in different sectors. Many studies have emphasized a non-parametric assessment in outranking relation to get precise evaluation (Rabbani et a., 2014). Multi-attribute decision-making (MCDM) is an advanced mathematical model that comes under the branch of operations research and is effective in ranking the best alternatives out of a series of alternatives (Ban et al., 2020). MCDM ascertains the best alternative by considering more than one criterion that collectively affects the functions of the company (Gavalas et al., 2022). Accordingly, the present study aimed to rank the selected manufacturing companies listed under nifty 50 in India during 2022 using MCDM techniques. The dataset was gathered from the annual reports of the companies, and the relative importance (weights) of each criterion over another was ascertained for each criterion using the entropy method. The COPRAS method used the entropy weights to rank the companies based on their financial position.

The study consists of five sections. Section 1 outlines the introduction, significance, and primary objective. Section 2 provides a comprehensive review of the literature that pertains to studies and research on the performance analysis of manufacturing companies. Section 3 provides a description of the tools and methods used. Section 4 presented the empirical results and discussions. The fifth and final section discusses the significant findings, recommendations, and conclusions.

2. Literature Review

Different methods under MCDM have been applied to the performance evaluation of companies in different sectors in India. However, the application of MCDM tools in exploring the financial performance of the Indian manufacturing industry is limited to date. Yurdakul and Ic (2005) evaluated Turkish companies in the fabric industry using the AHP-based TOPSIS approach from 2001-2003. The study used some non-financial indicators to examine the operational efficiency in the sector. Leachman et al. (2005) examined the manufacturing performance of companies in the automobile industry. The study applied the DEA approach, incorporating some input-output qualitative and quantitative variables. The study observed a strong relationship between R&D expenditure and compressed production time on manufacturing sectors' efficiency. Chen et al. (2011) evaluated the hot spring hotels in Taiwan under a balanced scorecard (BSC) framework. The study employed ANP and DEMATEL and suggested that an integrated MCDM model helps an organization identify areas for improvement and achieve goals. Yalcin (2012) investigated the financial performance of manufacturing companies in Turkey. The study involved textile, paper, metal, and non-metal manufacturing companies and compared their performance using the AHP-VIKOR and AHP-TOPSIS approaches in a fuzzy environment. The results indicated a similar outcome using the two approaches. Digalwar et al. (2013) studied the green manufacturing performance of Indian companies using 12 non-financial matrices and methods other than MCDM. Baran and Zak (2013) evaluated ten transportation units operating in Polish agribusinesses using the AHP method. Shaverdi et al. (2014) evaluated the seven Iranian petrochemical companies using a fuzzy AHP approach based on some financial indicators. Rabbani et al. (2014) investigated the oil-producing companies in Iran based on new integrated sustainability balanced scorecard and MCDM approaches (ANP and COPRAS). The study employed some linguistic variables. Safaei et al. (2014) studied the performance of six automotive companies listed on the Tehran Stock Exchange. The study used AHP as a weighing method and multiple outranking techniques (i.e., VIKOR, ARAS, and COPRAS) integrated with fuzzy sets. The study incorporated some accounting and value-based ratios as financial measures. The ranks obtained using the three methods were combined using mean ranks, and it was found that the economic value-based measures were more significant compared to other financial ratios. 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.

Anthony et al. (2019) assessed seven chemical companies in India using different MCDM tools such as TOPSIS, COPRAS, and DEA. The Shannon entropy method was used to obtain the weights of financial attributes. Sarraf and Nejad (2020) studied Iran's water and wastewater companies under the BSC framework. The study used the DEA and GRA methods for ranking and the Shannon entropy method to determine the weights of each criterion. It was concluded that the GRA method was more effective compared to the DEA method. Kamble et al. (2020) employed an exploratory and empirical research design to identify the performance metrics pertinent to assessing smart manufacturing systems in India for small, medium, and micro enterprises that manufacture auto components. According to the study, an SMS-enabled by Industry 4.0 provides more advantages than a conventional manufacturing system. Chand et al. (2020) studied mining and earthmoving equipment manufacturing companies in India using a Dellphi-BWM-DEMATEL approach. The criteria weights and interaction were identified using the DEMATEL approach, and the ranking was performed using BWM and Delphi techniques. Finally, the ranks were combined using the utility interval technique. Abdel-Ban et al. (2020) studied the listed manufacturing companies in Rome during 2011-2015. The study examined 15 financial and non-financial indicators, assessed them using the AHP, and ranked the alternatives using the TOPSIS approach in a fuzzy environment. Basset et al. (2020) investigated the financial performance of ten steel manufacturing companies in Egypt using the AHP-VIKOR and AHP-TOPSIS approach. The AHP was applied to determine the criteria weights, and the other two methods were utilized to rank the companies. The results of the two approaches were identical.

Methodology and data

3.1 Sample and Variables Selection

The study attempted to assess the financial performance of manufacturing companies operating in India during the financial year 2022 using an integrated MCDM approach. Accordingly, the data was collected from the CMIE-ProwessIQ database for the year 2022. A total of 18 companies operating in core manufacturing activities are selected from Nifty 50 index firms. The study applied entropy and COPRAS techniques to determine the criteria weights and rank the selected companies based on their financial performance. Table 1 demonstrates the selected firms for the analysis.

Table 1: Selected Manufacturing Companies

Code	Companies	Code	Companies
M1	Bajaj Auto Ltd.	**M10**	Mahindra & Mahindra Ltd.
M2	Bharat Petroleum Corpn. Ltd.	**M11**	Maruti Suzuki India Ltd.
M3	Coal India Ltd.	**M12**	NTP C Ltd.
M4	Eicher Motors Ltd.	**M13**	Oil & Natural Gas Corpn. Ltd.
M5	Grasim Industries Ltd.	**M14**	Power Grid Corpn. Of India Ltd.
M6	Hero Motocorp Ltd.	**M15**	Reliance Industries Ltd.
M7	Hindalco Industries Ltd.	**M16**	Tata Motors Ltd.
M8	JSW Steel Ltd.	**M17**	Tata Steel Ltd.
M9	Larsen & Toubro Ltd.	**M18**	Ultratech Cement Ltd.

Source: Compiled by the authors

Although the underlying rationale relates to core manufacturing, which readily makes products available to consumers, the companies are segregated into different industries. For instance, M1, M4, M6, M10, M11, and M16 are companies involved in automotive manufacturing process; while, M7, M8, and M17 concerned with steel and metal manufacturing. Similarly, M5 and M18 are associated with manufacturing items related to industrial infrastructure and construction materials. The companies M2, M3, M12, M13, M14, and M15 produce oil, gas, and energy. Finally, M9 deals in infrastructure and engineering.

Table 2: Selected Variables

Code	Criteria	Description	Index
C1	Return on Total Assets	$\frac{Net\ Income}{Total\ Assets}$	Max
C2	Return on Networth	$\frac{Net\ Income}{Total\ Shareholders'Fund}$	Max
C3	Current Ratio	$\frac{Current\ Assets}{Current\ Liabilities}$	Max
C4	Debt to Equity Ratio	$\frac{Total\ debt}{Ttal\ equity}$	Min
C5	Debt to Assets Ratio	$\frac{Total\ Debt}{Total\ Assetss}$	Min

Source: Compiled by the authors

Table 2 outlines the selected criterion for the assessment. Multiple ratios must be employed to analyze the financial viability of any sector (Shaverdi et al., 2016). Accordingly, this study incorporated five financial ratios and data gathered from the company's annual reports. The variables were selected based on an extensive review of available literature (Yalcin et al., 2012; Parvadavardini et al.,2016; Shaverdi et al., 2016; Anthony et al., 2019). MCDM deals with criteria in maximizing and minimizing in nature and combines them in a single heading. The criteria shown in Table 2 can be categorized as profitability, liquidity, and solvency ratios.

3.2 Entropy method

Shannon and Weaver first proposed the term 'Entropy' in 1947.
The Entropy Weighing comprises the following five steps:

Step 1: Construct the decision matrix

$$X = [x_{ij}]_{mn} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

where x_{ij} $denotes\ the\ perfroamance\ of\ ith\ alternative\ related\ to\ jth\ criteria. here,$,$i \in (1, \ldots m)$ and $j \in (1, \ldots, n)$.

Step 2: Normalization of the decision matrix X

$$r_{ij} = \frac{x_{ij}}{\sum x_{ij}} \quad (2)$$

Step 3: Determination of entropy e_j for the set of attributes j is

$$e_j \quad (3)$$

Step 4: Calculation of the degree of divergence d_j

$$d_j = 1 - e_j \quad (4)$$

Step 5: Calculation of the entropy weights w_j

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \quad (5)$$

3.3 COPRAS

The Complex Proportional Assessment (COPRAS) approach was introduced by Zavadskas et al. (2008) and was first applied in their research on multi-criteria decision-making in construction and civil engineering projects. The method selects the alternatives, considering the best and worst ideal solutions and the significance and utility degree of selected alternatives (Das et al., 2012).

The method involves the following steps:

Step 1: *Calculate the normalized decision matrix*

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (6)$$

Step 2: *Determine the weighted normalized matrix*

$$v_{ij} = r_{ij} w_j \quad (7)$$

Step 3: *Calculating the maximizing and minimizing indexes for each alternative*

$$S_{+i} = \sum_{j=1}^{k} v_{ij} \quad (8)$$

$$S_{-i} = \sum_{j=k+1}^{n} v_{ij} \quad (9)$$

Step 4: *Determine the relative significance of alternatives*

$$Q_i = S_{+i} + \frac{\min\limits_i s_{-i} \sum_{i=1}^{m} s_{-i}}{s_{-i} \sum_{i=1}^{m} \left(\frac{\min\limits_i s_{-i}}{s_{-i}} \right)} \quad (10)$$

Step 5: *Rank alternatives based on the quantitative utility (U_i) values*

$$U_i = \frac{Q_i}{Q_{max}} \times 100 \quad (11)$$

3. Results and Discussion

The study commenced with evaluating criteria weights of different financial indicators using the entropy method; later, the study employed the COPRAS technique to rank the selected companies.

The study first developed an 18×5 (m×n) decision matrix of 18 alternatives related to five attributes. The values in the decision matrix are the data incorporated from the annual financial reports of the selected companies for the year 2022. The values in the decision matrix were normalized to convert all the criteria into the same units. Each value in the decision matrix was divided by the column sum (Table 3).

Table 3: Normalized values

	C1	C2	C3	C4	C5
M1	0.071	0.095	0.079	0.003	0.005
M2	0.020	0.010	0.037	0.112	0.092
M3	0.290	0.338	0.153	0.001	0.003
M4	0.072	0.089	0.057	0.003	0.006
M5	0.015	0.019	0.053	0.015	0.031
M6	0.058	0.065	0.081	0.003	0.005
M7	0.021	0.018	0.082	0.048	0.065
M8	0.025	0.015	0.047	0.123	0.108
M9	0.034	0.022	0.068	0.035	0.037
M10	0.053	0.049	0.056	0.017	0.025
M11	0.047	0.055	0.026	0.004	0.008
M12	0.030	0.016	0.043	0.174	0.148

Source: Calculated by the authors

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

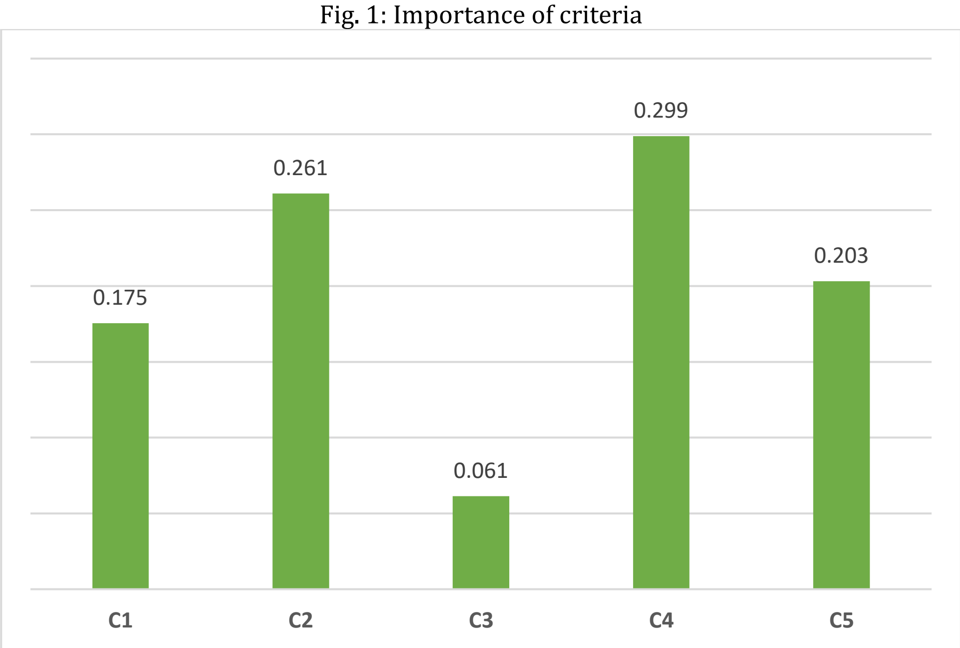
Table 4: Entropy Weights

C1	C2	C3	C4	C5
0.175	0.261	0.061	0.299	0.203

Source: Calculated by the authors

Table 4 shows the weights of each criterion or the relative significance of the selected financial indices. Criteria with higher d_j will have lower e_j, leading to higher weights. The weights are assigned to the criteria based on their entropy values.

Fig. 1: Importance of criteria



Source: Compiled by the authors

Fig. 1 shows a significant variation in criteria importance. The criteria C4 received the highest weightage, 0.299, followed by C2 (0.261) and C5 (0.203) receiving second and third highest weightage. This implies that the C4, C2, and C5 are the most significant indicators reflecting the accurate financial performance of manufacturing companies. Therefore, the companies that perform better in these indices are likely to rank higher in the group. Conversely, C3 obtained the lowest weightage of 0.061, followed by C1 (0.175) and C2 (0.261), which received the lowest weights.

Table 5. Maximum and minimum values of cost-benefit criteria

Companies	**S+**	**S-**	**S-min/S-**
M1	0.0421	0.0026	0.7623
M2	0.0084	0.0515	0.0390
M3	0.1485	0.0020	1.0000
M4	0.0394	0.0029	0.6916
M5	0.0109	0.0115	0.1741
M6	0.0322	0.0028	0.7211
M7	0.0134	0.0274	0.0733
M8	0.0111	0.0576	0.0349
M9	0.0158	0.0182	0.1102
M10	0.0255	0.0107	0.1886
M11	0.0243	0.0037	0.5400
M12	0.0120	0.0804	0.0250
M13	0.0292	0.0096	0.2098
M14	0.0215	0.0928	0.0217
M15	0.0146	0.0342	0.0587
M16	0.0155	0.0537	0.0374
M17	0.0180	0.0249	0.0807
M18	0.0155	0.0156	0.1284

Source: Calculated by the authors

In the next stage, the entropic weights are used to determine the ranks using the COPRAS method. The method starts with normalizing the values in the decision matrix for each alternative related to each criterion. The normalized values in COPRAS are determined using Eq. (6). Next, the entropic weights are multiplied by the values in the normalized decision matrix, and a weighted normalized matrix has been prepared using Eq. (7).

After weighted normalization, further computations treated benefit and cost criteria separately. The maximizing S_{+i} and minimizing S_{-i} indexes for each alternative were then obtained using Eq. (8-9). Higher value of S_{+i} indicates a better performance of alternatives in beneficial aspects, while the maximum S_{-i} shows poor performance of the alternative, i.e., an increase in non-beneficial or cost criteria. Next, the min S_{-i} was determined, which were then divided by S_{-i} values for each cell (m*n). The values are presented in Table 5.

Table 6. Performance scores of rankings

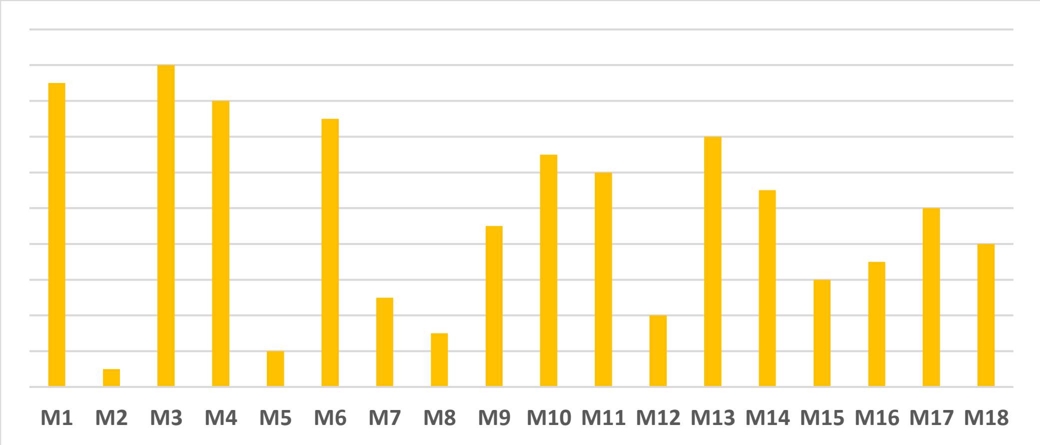
Companies	**Qi**	**Ui**	**Rank**
M1	0.0424	0.2849	2
M2	0.0085	0.0572	18
M3	0.1486	1.0000	1
M4	0.0395	0.2657	3
M5	0.0110	0.0742	17
M6	0.0324	0.2176	4
M7	0.0135	0.0909	14
M8	0.0112	0.0755	16
M9	0.0159	0.1070	10
M10	0.0257	0.1726	6
M11	0.0244	0.1641	7
M12	0.0122	0.0819	15
M13	0.0293	0.1971	5
M14	0.0217	0.1457	8
M15	0.0147	0.0990	13
M16	0.0156	0.1048	12
M17	0.0181	0.1219	9
M18	0.0157	0.1053	11

Source: Calculated by the authors

The comprehensive performance score Q_i and the quantitative utility values U_i was then determined using Eq.10-11 and shown in Table 6. Q_i indicates a measure of overall performance combining benefit and cost criteria for each alternative. U_i is the utility degree for each alternative, which indicates the relative performance of each alternative (companies), where a higher score is preferred.

Table 6 presents the relative ranking of the selected companies based on their performance scores Qi and Ui values. From Table 6, it is observed that M3 has the highest Qi = 0.1486 and Ui = 1. Conversely, M2 received the lowest Qi = 0.0085 and Ui = 0.0572, thus emerging at the bottom of the list. On the other hand, M1 (Qi = 0.0424, Ui = 0.2849) and M4 (Qi = 0.0395 and Ui = 0.2657) received the second and third highest performance scores.

Fig.2. Performance of the alternatives



Source: Compiled by the authors

Fig. 3 demonstrates the relative performance of each company using the entropy-COPRAS approach. M3 is the top performer with the highest performance scores and rankings (table 6). Subsequently, M2 received the lowest ranking in terms of performance and utility value (tabl6) across the alternatives. Companies M1, M4, and M6 reflect moderately strong performance scores with areas for improvement. Other alternatives, such as M5, M8, and M12, show a relatively low degree of utility and the least efficiency in the sector.

4. Conclusion

The manufacturing industry is the backbone of India's economic growth and is crucial to GDP contribution, employment, exports, and technological development. Strengthening this sector through policy reforms and innovation will be essential for India's goal of becoming a global manufacturing hub. The manufacturing sector significantly contributes to India's GDP. Assessing its financial performance helps policymakers and industry leaders understand its health and make informed decisions to enhance growth. In the highly competitive world, evaluating financial performance is fundamental for the stakeholders and long-term growth in the sector. Therefore, this study evaluated the financial aspects of 18 selected manufacturing companies in India from a list of the top 50 companies listed in the National Stock Exchange (NSE) for 2022. The weighing approach entropy was used to calculate the criteria weights for the five selected financial indices, and a method called COPRAS was used to rank the companies based on the entropy weights.

Entropy scores depict that the criteria of the debt-to-equity ratio received the highest weightage, 0.299, followed by the return on net worth and debt-to-assets ratio, which received the second and third highest weightage. This implies that these are the most significant indicators reflecting the accurate financial performance of companies. Therefore, the companies that perform better in these indices are likely to rank higher in the group. Conversely, the Current Ratio obtained the lowest weightage of 0.061, followed by the Return on Total Assets, which received the lowest weight.

COPRAS results have shown Coal India Ltd. as the top performer with the highest performance scores and ranking—subsequently, Bharat Petroleum Corpn. Ltd. received the lowest ranking in performance and utility value among the alternatives. Companies such as Bajaj Auto Ltd., Eicher Motors Ltd., and Hero Motocorp Ltd. reflect moderately strong performance scores with areas for improvement. Other alternatives, such as Grasim Industries Ltd., JSW Steel Ltd., and NTP C Ltd., show a relatively low degree of utility and the least efficiency in the sector.

Financial performance matrices are instruments in strategic planning. These help businesses optimize resource allocation. Moreover, the combined model provides a clear quantitative ranking of the manufacturing companies listed on the Indian stock exchange, which will help stakeholders identify strengths, weaknesses, and market opportunities. Furthermore, the regulatory body may use the study findings to shape industrial policies, provide incentives to poor performers, and implement reforms. Future studies may consider other MCDM tools, e.g., AHP and SWARA, for determining the relative weights of criteria and different outranking tools such as VIKOR, TOPSIS, ELECTRE, and PROMETHEE for ranking alternatives. Moreover, the sample size and the study period can be extended for future work.

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