

Financial Performance of Nifty-50 Manufacturing Companies: An AHP-COPRAS Integrated Analysis

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ABSTRACT

The present study aims to develop a performance measurement model for Indian manufacturing companies, which can be used to analyze the success of the selected companies in terms of their relative financial position. An MCDM approach is required to aggregate the multiple financial criteria for a comprehensive overview of any sector. Therefore, the current study analyzed eight financial attributes using the AHP method and ranked the selected companies using the COPRAS method based on the AHP weights. The financial performance of 26 manufacturing companies under the Nifty 50 index was evaluated for the financial year 2023-2024. It was observed that ROE and ROA are the most significant indicators with the highest AHP weights. Following the utility values and aggregate performance scores in COPRAS, Coal India Ltd. is found to be the best alternative among the group. It excelled nearly across all criteria, followed by Nestle India Ltd. and Britannia Industries Ltd., acquiring second and third place.

Keywords: Manufacturing Companies, Performance, AHP, COPRAS, Financial Analysis.

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1. INTRODUCTION

Manufacturing is the process of converting raw materials into their ultimate form, making them readily available to users (Khan et al., 2022). This core function is integral to the efficiency and growth of the firms engaged in the manufacturing business. The current manufacturing environment is highly competitive due partly to global competition, rapidly evolving technologies, and shorter product life cycles. Businesses deal with a lot of uncertainty and globalized business environment, proper performance measurement of manufacturing companies is crucial (Yalcin et al., 2012). India aims to position itself in the global market as a global manufacturing hub and is taking significant initiatives such as 'Make in India.' Therefore, stability and efficiency in the manufacturing industry are essential to attract foreign direct investments (FDI) in the sector. Performance assessment is vital for companies and their current and potential future stakeholders.

To ensure the smooth functioning of these firms and to maintain an effortless business cycle, it is crucial to formalize an effective framework to evaluate the stability and long-term viability of manufacturing firms (Chand et al., 2020). A systematic performance evaluation framework may provide a foundation for continuous assessment corresponding to globalization, consistently rising competition, and customer demand. The performance evaluation framework is a structured system integrating multiple indices and methods to quantify the performance and efficiency of different alternatives

(Khan et al., 2022). Okoshi et al. (2019) argued that performance evaluation is a sequence of procedures to measure the accomplishment associated with the organization's goals.

We must consider several financial indicators demonstrating a company's competitiveness to assess its performance. According to Yurdakul & Ic, 2005, financial measures are essential to evaluate companies' current trends and future requirements in terms of profitability. They reflect the cumulative attainments of past series of operations and decisions made by the management. Managers of any institution must evaluate the financial stability of their organization (Darji & Dahiya, 2023; Kaya et al., 2024). In today's competitive world, it is an economic imperative to analyze the financial stability and performance of listed for both company management and their shareholders (Kaya et al., 2024). Accurate financial measurement matrices will help stakeholders understand the profitability, solvency, and growth in the sector. Companies must be assessed based on their financial performance to determine their relative position in the market. These will allow companies to overcome potential risks and improve their financial position (Darji & Dahiya, 2023). Nonetheless, the financial ratios are the effective evaluation units that efficiently convey the financial position of companies (Shaverdi et al., 2016; Darji & Dahiya, 2023; Kaya et al., 2024). Therefore, assessing the performance and financial stability of companies involved in core manufacturing activities in India is a crucial research area for both investors and researchers.

Financial performance analysis can be considered one of the multi-criteria decision-making problems since it incorporates several evaluation criteria or financial ratios (Varmazyar et al., 2016). Multi-criteria decision-making (MCDM) identifies the most optimal alternative by analyzing multiple attributes that collectively influence a company's overall performance, decision-making efficiency, and strategic growth (Gavalas et al., 2022). Consequently, the current study evaluates the financial viability of listed manufacturing companies in the Nifty 50 index in India for the year 2023. The study aimed to identify the most significant performance measurement criteria of the manufacturing companies in terms of their financial position and determine the relative ranking of the firms among the group using MCDM techniques. Subsequently, this study employs the Analytical Hierarchy Process (AHP) and the Complex Proportional Assessment (COPRAS) methods for the performance evaluation. The method AHP is used to calculate the weights for each attribute and the calculated AHP weights were then applied to the COPRAS method to rank companies according to their financial position. The data related to selected variables (criterion) are sourced from the CMIE-ProwessIQ database for the period 2023.

This study is structured into five key sections. The first section introduces the research, highlighting its significance and primary objectives. The second section presents a detailed review of relevant literature. The third section outlines the methodologies and analytical tools employed in the study. The empirical results and interpretations of the analysis are discussed in the fourth section. Finally, the fifth section summarizes the main findings, limitations, scope for future research, and policy implications.

2. LITERATURE REVIEW

As a subjective weighing tool, the AHP is used to develop a multi-level hierarchical framework that identifies the objective at the top and the criteria, sub-criteria, and alternatives at the bottom of the structure. To obtain the criteria weights, the method applies a pair-wise comparison between the criterion and the study alternatives (Guru & Mahalik, 2019). The AHP technique may effectively deal with the complexity of the decision-making process by considering both financial and non-financial variables simultaneously. Since the decision is based on expert judgment, it provides a more precise evaluation framework (Yurdakul & Ic, 2005; Pipatprapa et al., 2018). Several MCDM outranking measures were utilized to evaluate performance and efficiency across various sectors in India. Nevertheless, there are limited applications of renowned MCDM approaches specifically for investigating the performance of the manufacturing sector in India in terms of their financial position and viability. Yurdakul and Ic (2005) applied an AHP and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) integrated model to explore the operational efficiency of nineteen companies in the fabric industry in Turkey from 2001 to 2003. Yalcin et al. (2012) evaluated selected Turkish manufacturing companies using the MCDM methods based on some basic financial ratios. The AHP technique was employed in the fuzzy environment to determine the relative significance of value-based and accounting-based criteria. The outranking tools TOPSIS and VIKOR were used to obtain the ranking of the companies. It was observed that sector-wise ranking results of companies were similar under the two methods. Digalwar et al. (2013) assessed Indian green manufacturing companies using methods other than MCDM based on 12 non-financial performance indices. Moghimi and Anvari (2014) examined eight selected Iranian cement companies based on their financial strength and weaknesses, applying an AHP-based TOPSIS approach under a fuzzy environment. The study incorporated multiple financial indicators under the dimensions of profitability ratios, activity, average ratios, liquidity, and growth ratios. Baran and Zak (2014) investigated the transportation efficiency performance of selected agri-business companies using the AHP model. Accordingly, the importance of stakeholders' participation in decision-making was emphasized in their study. Varmazyar et al. (2016) combined multiple MCDM tools (ARAS, COPRAS, MOORA, and TOPSIS) to rank Iran's research and technology environment. The study also employed the Analytical Network Process (ANP) technique to prioritize the evaluation criteria; the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method was further employed to determine the interaction within selected indicators (financial ratios). Finally, the utility interval technique was used to combine the rankings obtained under different approaches. Yazdani et al. (2017) used DEMATEL and COPRAS techniques in green supplier selection problems using criteria related to environmental performance aspects. The quality function development (QFD) method was employed to establish a central relationship matrix and identify the degree of relationship among criteria. Finally, the method of COPRAS was used to prioritize the alternatives based on their relative performance. Kusumah and Fabianto (2018) investigated the financial performance before and after implementing ISO 9000 for manufacturing companies listed on the Indonesian

stock exchange. The study employed McNemer and Cochran's Q test to check the impact. It was found that the impact on the performance of selected companies was insignificant. Anthony et al. (2019) assessed the long-term financial viability of Indian chemical companies from 2010-2018. The study applied a Shannon entropy-based MCDM approach combining the TOPSIS, COPRAS, and DEA methods in weighing and ranking 12 financial criteria and selecting seven companies. Sarraf and Nejad (2019) compared two approaches, DEA and GRA, in the performance analysis of water and wastewater companies in Iran. The study used the entropy method to measure the relative importance of indices under the BSC framework to identify significant criteria. The GRA method under MCDM was found to be more efficient than DEA. Chand et al. (2020) examined the supply chain performance (SCP) of companies in India involved in producing mining and earth-moving tools. The study employed a hybrid MCDM approach combining the BWM, Delphi, and DEMATEL techniques. The Delphi technique and DEMATEL were applied to select and evaluate the SCP matrices. Finally, the BWM (Best-Worst Method) approach was used to rank the alternatives. In conclusion, the importance of cross-functional and inter-organizational performance management is highlighted. Liou et al. (2021) developed a green supplier selection model under a novel MCDM model. The study evaluated 13 parameters combining fuzzy BWM and fuzzy TOPSIS. Gavalas et al. (2022) assessed the shipbuilding industry using three approaches under MCDM, e.g., ANP, MOORA, and DEMATEL. Khan et al. (2022) measured the overall performance of steel manufacturing companies in India. Three main and 18 sub-criteria were evaluated using the BWM approach. It was observed that the indicator 'operational efficiency' was significantly reflecting the performance level of the companies. Darji and Dahiya (2023) evaluated the companies involved in textile manufacturing in India using the Data Envelopment Analysis (DEA) approach. Multiple data envelopment analysis (DEA) techniques and a return-to-scale technique were employed in the study. Results depict that the textile industry in Haryana had a poor financial position. It was further observed that the public sector companies were technically more efficient than companies in private undertakings. Kaya et al. (2024) used nine MCDM tools to rank the selected companies besides banks in Borsa Istanbul across eight financial criteria for the year 2021. The current ratio was found to be the most significant criterion. The authors concluded that evaluating corporate financial performance is vital in performance measurement.

3. DATA AND METHODOLOGY

The analysis includes 26 companies involved in manufacturing activities listed on the NIFTY-50 in India. The data relating to selected variables (criterion) are sourced from the CMIE-ProwessIQ database for a one-year period, i.e., the financial year 2023-2024. In order to rank the companies according to their relative performance across multiple financial measures, the study used the AHP-based COPRAS model within the MCDM framework. The AHP method is applied to calculate the weights for each attribute, and the calculated AHP weights are then incorporated into the COPRAS method to rank

companies according to their financial position. Various industries fall under the manufacturing sector, with differences in labor, overheads, capital intensity, production techniques, and market competitiveness (Abdel-Maksoud et al., 2005).

Table 1: Selected Alternatives (Companies)

Index	Alternatives	Index	Alternatives
A1	Asian Paints Ltd.	A14	ITC Ltd.
A2	Bajaj Auto Ltd.	A15	JSW Steel Ltd.
A3	Bharat Electronics Ltd.	A16	Larsen & Toubro Ltd.
A4	Bharat Petroleum Corpn. Ltd.	A17	Mahindra & Mahindra Ltd.
A5	Britannia Industries Ltd.	A18	Maruti Suzuki India Ltd.
A6	Cipla Ltd.	A19	Nestle India Ltd.
A7	Coal India Ltd.	A20	Oil & Natural Gas Corpn. Ltd.
A8	Dr.Reddy's Laboratories Ltd.	A21	Reliance Industries Ltd.
A9	Eicher Motors Ltd.	A22	Sun Pharmaceutical Inds. Ltd.
A10	Grasim Industries Ltd.	A23	Tata Motors Ltd.
A11	Hero Motocorp Ltd.	A24	Tata Steel Ltd.
A12	Hindalco Industries Ltd.	A25	Titan Company Ltd.
A13	Hindustan Unilever Ltd.	A26	Ultratech Cement Ltd.

Source: Authors' compilation

Table 1 outlines the selected companies involved in large-scale manufacturing in India listed on India's National Stock Exchange (NSE). The companies are divided into distinct industries, although the primary aim is connected to core manufacturing, which provides consumers with easy access to readily available products. For example, businesses in A2, A9, A11, A17, A18, and A23 are engaged in the automotive manufacturing process, whereas A15, A24, and A12 are focused on the production of steel and metal. In a similar vein, A10, A16, and A26 are linked to the production of goods for infrastructure, construction materials, and industrial equipment. A7 is a coal mining company that produces and manufactures coal-based products. A6, A8, and A22 manufacture products for pharmaceuticals and healthcare. A1, A5, A13, A14, A19, A25 manufactures consumer goods and FMCGs. Finally, A3 is associated with electronics and technological equipment. A4, A20, A21 deals with oil, gas, and petrochemical manufacturing.

Table 2: Selected Variables (Criterion)

Index	Criterion	Formula	Expected Values
C1	Return on Total Assets (ROA)	Net Income/Total Assets	Max
C2	Net Profit Margin (NPM)	Net Profit /Sales	Max

C3	Current Ratio (CR)	Current Assets / Current Liabilities	Max
C4	Quick Ratio (QR)	(Current Assests -Inventory)/ Current Liabilities	Max
C5	Earning Per Share (EPS)	Net Income/ Number of Outstanding Shares	Max
C6	Return on Equity (ROE)	Net Income/ Total Equity	Max
C7	Debt to Assets Ratio (DA)	Total Debt/ Total Assests	Min
C8	Debt to Equity Ratio (D/E)	Total Debt/Equity	Min

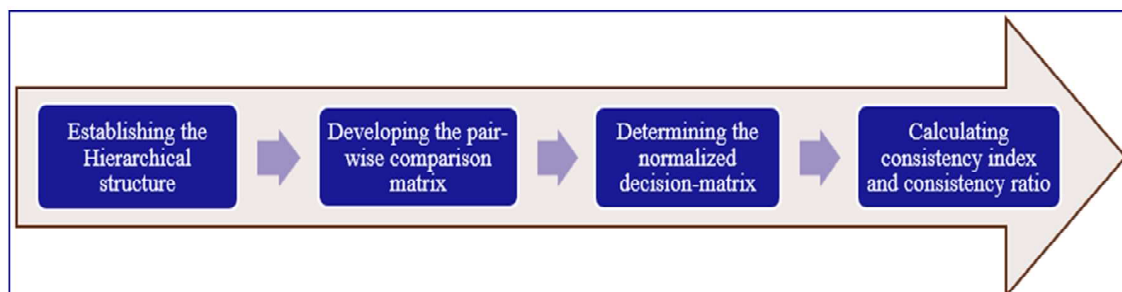
Source: *Compiled by the authors*

We must consider several financial indicators demonstrating a company's competitiveness to assess its performance (Moghimi & Anvari, 2014). Similarly, this study selected eight criteria or financial ratios based on the available literature on related studies (Ertuđrul & Karakapođlu, 2009; Yalcin et al., 2012; Moghimi & Anvari, 2014; Parvadavardini et al., 2016; Anthony et al., 2019; Darji & Dahiya, 2023; Kaya et al., 2024). The selected criteria presented in Table 2 represent specific areas of a company's financial performance, for instance, profitability indicators (ROA, NPM), liquidity indicators (CR, QR), market-based indicators (EPS, ROE), and solvency ratios (DA, D/E). MCDM combines multiple criteria that are usually conflicting, i.e., maximizing or minimizing in nature simultaneously in a single heading.

AHP method

The analytical hierarchy process (AHP) is a weighting approach in the MCDM developed by Thomas Saaty in 1970. It has been extensively used as a subjective-based weighing technique in the presence of multiple conflicting criteria. The AHP technique systematically determines the relative importance of alternatives and incorporates different criteria/sub-criteria to assess these alternatives (Gupta et al., 2020).

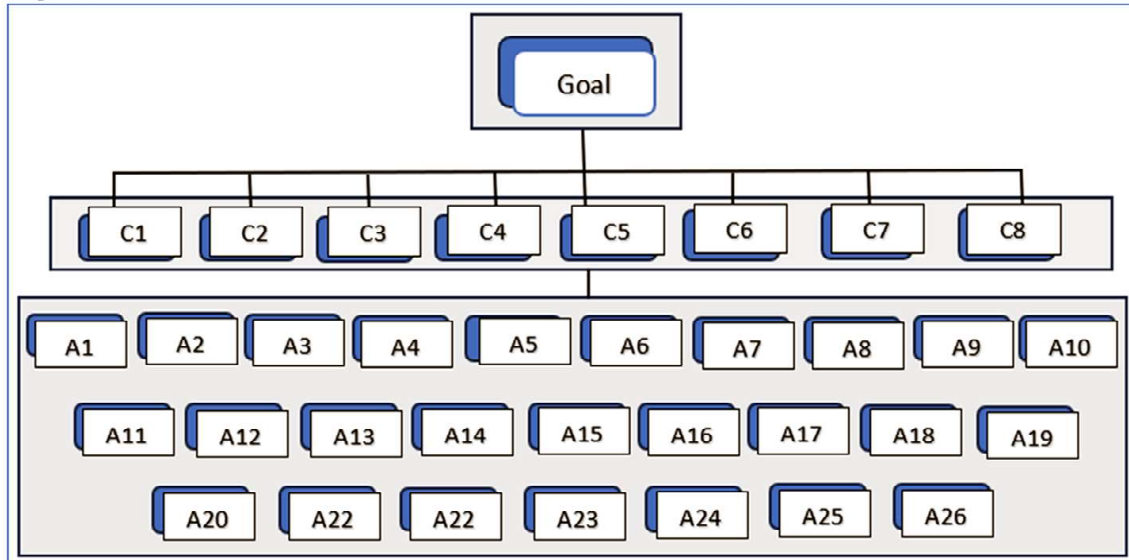
Fig.1. Steps in the AHP approach



Source: *Developed by the authors*

The AHP method consists of 4 significant stages depicted in Figure 1. However, studies have mentioned six steps involving determining AHP weights and reliability tests using consistency ratio (Mitra et al., 2022; Gupta et al., 2021; Yalcin, 2012).

Fig.2. Hierarchical structure in AHP



Source: Developed by the authors

Step 1: Construction of the hierarchical structure

Figure 2 describes the hierarchical structure to be used in the AHP method. To develop an AHP model, the goal, criteria, and alternatives must be defined. The upper level consists of the goal, and the bottom of the hierarchy includes the criteria and alternatives. Each factor in the hierarchy has an impact on another factor.

Following the establishment of the hierarchy, a pair-wise comparison matrix was developed. For each level, factors are compared with others in the level above, utilizing Saaty's comparison scale as outlined in Table 3 and Eq. 1.

Table 3: Saaty's 1-9 comparison scale

Intensity of Importance	Definition	Explanation
1	Equal importance	The pair contributes equally to the objective
3	Moderate importance	One element is slightly preferred over another

5	Strong or essential importance	One factor is preferred strongly to the other
7	Very strong or demonstrated importance	One criterion is preferred very strongly over another
9	Extremely important importance of one factor over	The evidence favoring the another has enough evidence
2,4,6 and 8 indicate the intermediate values and reciprocals for inverse comparisons.		

Source: Compiled by the authors

The outcome is a series of matrices, each sized $n \times n$, where n is the number of elements. The matrices are formulated according to Equation (1), with diagonal elements set to '1' and others representing reciprocals of initial comparisons

$$A = X_{ij} = \begin{bmatrix} 1 & X_{12} & \dots & X_{1n} \\ \frac{1}{X_{12}} & 1 & \dots & X_{2n} \\ \vdots & \vdots & \dots & \vdots \\ \frac{1}{X_{1n}} & \frac{1}{X_{2n}} & \dots & 1 \end{bmatrix}_{i*j} \quad (1)$$

Three different pair-wise comparison matrices were obtained from the judgment of three different decision-makers. Later, a combined pair-wise comparison matrix was developed using the formula $X_{ij}^C = [X_{ij}^1 \times X_{ij}^2 \times \dots \times X_{ij}^N]$ where, X_{ij}^C is the combined comparison matrix, and N is the number of decision-makers.

Step 3: Creating the normalized decision matrix

The pairwise comparison matrix, as formulated in Equation (1), undergoes normalization using Equation (2). This crucial step ensures uniformity in the data and prepares it for subsequent weight calculation.

$$\bar{X}_{ij} = \frac{X_{ij}}{\sum_{i=1}^m X_{ij}} \quad (2)$$

Step 4: Calculating the Factor Weights

The determination of factor weights involves applying Equation (3) to the normalized matrix obtained in Step 3. This step assigns weights to the factors based on their perceived importance in the decision-making process.

$$W_j = \frac{\sum_{i=1}^m \bar{X}_{ij}}{m} \quad (3)$$

Step 5: Calculating the consistency index

The consistency of matrices is scrutinized to ensure the reliability of the pairwise comparisons of criterion. The Consistency Index (CI) is estimated using Eq. (4), incorporating the eigenvalue. Simultaneously, the Random Index (RI) is utilized to compute the Consistency Ratio (CR) following Equation (6). The value of RI is obtained from Table 4.

$$CI = \frac{\lambda_{\max} - m}{m-1} \quad (4)$$

Table 4: Random Index (RI)

m	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49

Source: Gupta et al., 2021; Dey et al., 2011

Step 6: Determining the consistency ratio

$$CR = \frac{CI}{RI} \quad (5)$$

If the resulting CR exceeds 0.10, indicating inconsistency, the matrix requires revision with different values.

COPRAS Approach

Zavadskas et al. (2008) first introduced the Complex Proportional Assessment (COPRAS) as an MCDM outranking technique in the study of multi-criteria decision-making in civil

engineering and construction projects. COPRAS follows the concept that ranking alternatives based on their relative importance directly and proportionately depends on a set of criteria (Popovic et al., 2012; Ustinovichius et al., 2007). The approach determines the best alternative/companies by taking into account the ideal (best) and anti-ideal (worst) solutions, along with the degree of utility and level of significance related to the alternative (Hezer et al., 2021).

The method can be expressed concisely following the four major steps (Das et al., 2012; Hezer et al., 2021)

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

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

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

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

1. RESULTS AND DISCUSSION

The MCDM begins with determining the criteria weights using a proper weighting method and ends with ranking the alternatives based on the weights obtained in the earlier stage.

This study applies the weighting method AHP to obtain the relative importance scores (weights) of selected criteria, while the COPRAS approach is utilized to rank the companies based on their financial scores.

Table 5: Relative importance of decision indices

	C1	C2	C3	C4	C5	C6	C7	C8
C1	1	2	3	2	2	1	5	7
C2	$\frac{1}{2}$	1	2	2	1	$\frac{1}{3}$	3	5
C3	$\frac{1}{3}$	$\frac{1}{2}$	1	$\frac{1}{3}$	3	$\frac{1}{5}$	7	9
C4	$\frac{1}{2}$	$\frac{1}{2}$	3	1	1	$\frac{1}{3}$	9	9
C5	$\frac{1}{2}$	1	$\frac{1}{3}$	1	1	$\frac{1}{6}$	2	3
C6	1	3	5	3	6	1	7	7
C7	$\frac{1}{7}$	$\frac{1}{3}$	$\frac{1}{7}$	$\frac{1}{9}$	$\frac{1}{2}$	$\frac{1}{7}$	1	1
C8	$\frac{1}{7}$	$\frac{1}{5}$	$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{3}$	$\frac{1}{7}$	1	1

Source: Calculated by the authors

In Table 5, each element compares two criteria, showing the relative importance of one criterion over another. If, in the pair-wise comparison matrix, the a_{ij} is the value in the i^{th} row and j^{th} column, then $a_{ji} = 1/a_{ij}$ (Eq.1). This ensures consistency in pair-wise comparison. The diagonal elements a_{ii} are all one since a criterion is equally important to itself.

Table 6. Normalized decision matrix

	C1	C2	C3	C4	C5	C6	C7	C8
C1	0.24277	0.23438	0.20566	0.20930	0.13483	0.30129	0.14286	0.16667
C2	0.12139	0.11719	0.13711	0.20930	0.06742	0.10043	0.08571	0.11905
C3	0.08092	0.05859	0.06855	0.03488	0.20225	0.06026	0.20000	0.21429
C4	0.12139	0.05859	0.20566	0.10465	0.06742	0.10043	0.25714	0.21429
C5	0.12139	0.11719	0.02285	0.10465	0.06742	0.05022	0.05714	0.07143
C6	0.24277	0.35156	0.34276	0.31395	0.40449	0.30129	0.20000	0.16667
C7	0.03468	0.03906	0.00979	0.01163	0.03371	0.04304	0.02857	0.02381
C8	0.03468	0.02344	0.00762	0.01163	0.02247	0.04304	0.02857	0.02381

Source: Calculated by the authors

The normalization of values in Table 5 is performed using equation (2) and presented in Table 6. The normalization is performed by dividing each value in the matrix (values shown in Table 5) by the column sum. The normalization is essential since the values in the matrix may not be on the same scale. Normalization involves adjusting the values in the decision matrix so that they are proportionate and comparable on the same scale, and typically, the values are between 0 and 1.

Table 7. Calculated weights using AHP method

C1	C2	C3	C4	C5	C6	C7	C8
0.205	0.120	0.115	0.141	0.077	0.290	0.028	0.024

Source: Calculated by the authors

Table 7 presents the AHP weights of each attribute. The weights of each criterion are determined using Equation (3), where the values in the normalized evaluation matrix are divided by their column sum. From the table, it transpires that the ratios of ROE (C6) and ROA (C1), with the highest AHP weights of 0.290 and 0.205, are the most significant performance indicators of companies in the manufacturing sector, followed by Quick ratio (C4) and NIIM (C2). Conversely, the attribute D/E ratio (0.024) is the least significant in reflecting the financial performance of selected companies.

Table 8. Calculation of consistency ratio

λ_{max}	8.799
Consistency index (C.I.)	0.114
Random Index (R.I.)	1.41
Consistency Ratio (C.R.)	0.081

Source: Compiled by the authors

The consistency index (C.I.) and consistency ratio (C.R.) were determined using Eq. (4) and (5) and are shown in Table 8. In Table 8, the λ_{max} is the largest eigenvalue of the pair-wise matrix. In a perfectly consistent matrix, λ_{max} equals n , wherein n is the number of criteria. Here, n appears to be 8 (as λ_{max} is close to 8.799). Deviation of λ_{max} from n indicates inconsistency in judgments. The closer λ_{max} is to n , the more consistent the matrix is. The Consistency Index (C.I.) measures the deviation from consistency. C.I. is calculated using Eq. (4). The smaller the C.I., the closer the judgments are to be perfectly consistent. Random Index (R.I.) represents the average consistency index of the randomly generated pairwise matrix of size n . It is used as a benchmark to evaluate whether the matrix's inconsistency is acceptable. For $n=8$, the R.I. value is 1.41 (Table

4), Saaty's random index value. The consistency ratio (C.R.) divides the value of C.I. by R.I. If the C.R. is ≤ 0.1 (i.e., 10%), the level of inconsistency is generally considered acceptable. Here, C.R. is 0.081, which indicates the matrix is consistent enough for decision-making purposes.

In the second stage, the COPRAS approach utilizes the AHP-derived weights to rank the selected companies. The COPRAS approach assumes a direct and proportional relationship between the criteria weights, their values, and the relative significance of the evaluated alternatives based on a set of criteria that effectively defines the decision variants (Pamu ar et al., 2018; Akram et al., 2022).

Table 9. Normalized decision matrix

	C1	C2	C3	C4	C5	C6	C7	C8
A1	0.05630	0.02981	0.05975	0.05625	0.02243	0.04743	0.01590	0.01012
A2	0.05274	0.03890	0.04150	0.05311	0.10347	0.04014	0.00452	0.00289
A3	0.02287	0.04265	0.03650	0.04288	0.00209	0.03894	0.00376	0.00145
A4	0.00562	0.00160	0.01925	0.00865	0.00771	0.00569	0.09143	0.12572
A5	0.07134	0.03209	0.02825	0.02675	0.04201	0.11847	0.10226	0.12283
A6	0.02384	0.03922	0.11000	0.12352	0.01426	0.01986	0.00383	0.00145
A7	0.18739	0.23441	0.08000	0.09677	0.01272	0.11989	0.00323	0.00145
A8	0.03081	0.04004	0.07375	0.08851	0.08398	0.02507	0.00388	0.00145
A9	0.04938	0.04696	0.03000	0.02439	0.05077	0.03615	0.00591	0.00289
A10	0.01054	0.02058	0.02800	0.02321	0.01775	0.00749	0.03096	0.01734
A11	0.03623	0.02255	0.04250	0.05468	0.07710	0.03079	0.00529	0.00289
A12	0.00998	0.01098	0.04300	0.02518	0.00753	0.01234	0.06413	0.05347
A13	0.04008	0.04331	0.03425	0.03895	0.02194	0.03457	0.00787	0.00434
A14	0.07019	0.06836	0.07150	0.07514	0.00797	0.04922	0.00450	0.00145
A15	0.00812	0.00949	0.02450	0.02164	0.01039	0.01505	0.10689	0.13728
A16	0.01207	0.01670	0.03550	0.04878	0.02726	0.01825	0.03634	0.03902
A17	0.02722	0.02010	0.02925	0.02990	0.02834	0.02927	0.02447	0.01879
A18	0.03031	0.01715	0.01400	0.01298	0.13972	0.02284	0.00817	0.00434
A19	0.08117	0.03664	0.02750	0.01849	0.14119	0.17569	0.01292	0.01734
A20	0.03676	0.07259	0.01525	0.01141	0.01868	0.03304	0.02279	0.01590
A21	0.01410	0.01944	0.02425	0.02596	0.03373	0.01540	0.07985	0.06792
A22	0.03128	0.05525	0.03800	0.03895	0.01011	0.00974	0.06111	0.04913
A23	0.01295	0.00960	0.01150	0.01180	0.00464	0.00760	0.09849	0.12861
A24	0.01901	0.02792	0.01950	0.00905	0.00671	0.01962	0.05904	0.04769

A25	0.04312	0.02303	0.04175	0.01298	0.01990	0.04941	0.10396	0.09682
A26	0.01657	0.02066	0.02075	0.02006	0.08761	0.01805	0.03852	0.02746

Source: Calculated by the authors

The first step in the process is to normalize the values for each alternative associated with each criterion in the decision matrix. In order to handle the problems associated with various units and scales of measurement across numerous criteria, normalization is necessary for weighing and outranking techniques. The normalized values under the COPRAS approach are presented in Table 9. The values are determined using Eq. (6).

Table 10. Weighted Normalized Matrix

	C1	C2	C3	C4	C5	C6	C7	C8
A1	0.01153	0.00357	0.00687	0.00794	0.00172	0.01378	0.00045	0.00025
A2	0.01080	0.00466	0.00477	0.00750	0.00792	0.01166	0.00013	0.00007
A3	0.00468	0.00510	0.00420	0.00605	0.00016	0.01131	0.00011	0.00004
A4	0.00115	0.00019	0.00221	0.00122	0.00059	0.00165	0.00256	0.00307
A5	0.01460	0.00384	0.00325	0.00378	0.00322	0.03441	0.00287	0.00300
A6	0.00488	0.00469	0.01265	0.01744	0.00109	0.00577	0.00011	0.00004
A7	0.03836	0.02806	0.00920	0.01366	0.00097	0.03482	0.00009	0.00004
A8	0.00631	0.00479	0.00848	0.01250	0.00643	0.00728	0.00011	0.00004
A9	0.01011	0.00562	0.00345	0.00344	0.00389	0.01050	0.00017	0.00007
A10	0.00216	0.00246	0.00322	0.00328	0.00136	0.00217	0.00087	0.00042
A11	0.00742	0.00270	0.00489	0.00772	0.00590	0.00894	0.00015	0.00007
A12	0.00204	0.00131	0.00494	0.00355	0.00058	0.00358	0.00180	0.00131
A13	0.00821	0.00518	0.00394	0.00550	0.00168	0.01004	0.00022	0.00011
A14	0.01437	0.00818	0.00822	0.01061	0.00061	0.01430	0.00013	0.00004
A15	0.00166	0.00114	0.00282	0.00305	0.00080	0.00437	0.00300	0.00335
A16	0.00247	0.00200	0.00408	0.00689	0.00209	0.00530	0.00102	0.00095
A17	0.00557	0.00241	0.00336	0.00422	0.00217	0.00850	0.00069	0.00046
A18	0.00621	0.00205	0.00161	0.00183	0.01069	0.00663	0.00023	0.00011
A19	0.01662	0.00439	0.00316	0.00261	0.01081	0.05103	0.00036	0.00042
A20	0.00753	0.00869	0.00175	0.00161	0.00143	0.00960	0.00064	0.00039
A21	0.00289	0.00233	0.00279	0.00367	0.00258	0.00447	0.00224	0.00166
A22	0.00640	0.00661	0.00437	0.00550	0.00077	0.00283	0.00171	0.00120
A23	0.00265	0.00115	0.00132	0.00167	0.00035	0.00221	0.00276	0.00314
A24	0.00389	0.00334	0.00224	0.00128	0.00051	0.00570	0.00166	0.00116

A25	0.00883	0.00276	0.00480	0.00183	0.00152	0.01435	0.00291	0.00236
A26	0.00339	0.00247	0.00239	0.00283	0.00671	0.00524	0.00108	0.00067

Source: Calculated by the authors

Table 9 depicts the weighted normalized matrix produced using Eq.7. The values in Table 8 were multiplied by the weight coefficients in Table 7 to ascertain the relative importance of each criterion. After weighted normalization, benefit, and cost criteria were treated separately in further computations, leading to the determination of utility degrees for alternatives.

Table 11. Performance scores, utility values, and relative rankings of companies

	Sum of beneficial criteria (S+)	Sum of Non-beneficial criteria (S-)	S-min/S-	Qi	Ui	Rank
A1	0.04540	0.00069	0.18181	0.04540	0.36298	8
A2	0.04730	0.00020	0.63849	0.04730	0.37817	5
A3	0.03151	0.00014	0.89596	0.03151	0.25191	13
A4	0.00702	0.00563	0.02236	0.00702	0.05613	26
A5	0.06309	0.00587	0.02147	0.06310	0.50446	3
A6	0.04652	0.00014	0.88335	0.04652	0.37196	6
A7	0.12507	0.00013	1	0.12507	1	1
A8	0.04579	0.00014	0.87464	0.04579	0.36607	7
A9	0.03701	0.00024	0.53330	0.03701	0.29589	10
A10	0.01465	0.00129	0.09752	0.01465	0.11713	23
A11	0.03757	0.00022	0.57505	0.03757	0.30035	9
A12	0.01602	0.00310	0.04059	0.01602	0.12806	22
A13	0.03455	0.00033	0.38582	0.03455	0.27621	11
A14	0.05629	0.00016	0.78018	0.05629	0.45005	4
A15	0.01384	0.00635	0.01984	0.01384	0.11063	24
A16	0.02283	0.00197	0.06388	0.02283	0.18250	19
A17	0.02623	0.00114	0.11003	0.02624	0.20976	17
A18	0.02903	0.00033	0.37613	0.02903	0.23208	15
A19	0.08861	0.00079	0.16034	0.08861	0.70844	2
A20	0.03060	0.00103	0.12261	0.03061	0.24470	14
A21	0.01872	0.00390	0.03232	0.01872	0.14968	20
A22	0.02649	0.00291	0.04324	0.02649	0.21179	16
A23	0.00935	0.00590	0.02134	0.00935	0.07476	25
A24	0.01697	0.00282	0.04467	0.01697	0.13566	21
A25	0.03409	0.00528	0.02386	0.03409	0.27255	12
A26	0.02303	0.00175	0.07196	0.02303	0.18415	18

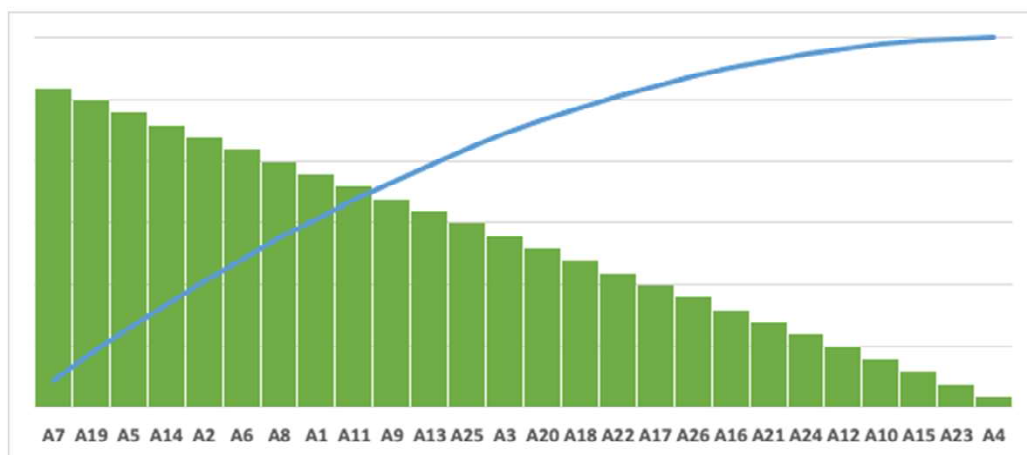
Source: Estimated by the authors

Table 11 presents the performance scores and relative importance (ranks) of selected alternatives (companies) determined using Eq. (8) and (9). In Eq.(8-11), k represents the number of benefit criteria, i.e., indices of which a maximum value is expected. On the other hand, the attributes from $k+1$ to n are favorable when they have a lower value. S_{+i} and S_{-i} represents the aggregate score of attributes that positively and negatively influence performance.

A greater value of S_{+i} implies the relatively good performance of an alternative in beneficial criteria, while the lowest value of S_{-i} reflects better performance due to a decrease in non-beneficial or cost factors. S_i represents the aggregate performance calculated by incorporating maximizing (benefit) and minimizing (cost) criteria. Additionally, the relative efficiency of each alternative is presented with the utility value indicated by U_i , which stands for the utility degree, where a higher score implies a stronger position for the company.

Company A7 has the highest S_{+i} of '0.125' and maximum U_i '1' making it the best-performing company in the group. Companies A4 and A23 received the lowest S_{-i} scores of 0.056 and 0.075, indicating poor performance compared to other alternatives (Fig.3).

Fig.3. Relative performance of companies based on AHP-COPRAS



Source: Authors' compilation

Figure 3 outlines the comparative performance of companies based on the combined AHP-COPRAS approach. Among all the selected companies, A7 and A19 stood out with stronger performance, whereas A4 with the lowest or S_{-i} values, making it the weakest performer in the evaluation. Companies A5, A2, and A14 exhibit moderately strong performance scores, though there are areas that require improvement. In contrast, other alternatives exhibit lower relative utility and minimal efficiency within the sector.

5.CONCLUSION

The contemporary manufacturing environment demands greater worker accountability alongside rigorous assessment and reporting of financial and non-financial performance metrics. In today's highly competitive business world, organizations require a comprehensive evaluation system to assess the performance and efficiency of all units effectively. Financial performance evaluation, in particular, is crucial for stakeholders and plays a vital role in ensuring long-term growth within the industry. Consequently, establishing a robust and accurate performance assessment framework is essential for benefiting both shareholders and management. Therefore, an attempt is made to evaluate the manufacturing companies listed in Nifty 50 for the financial year 2023-2024 using an AHP-COPRAS hybrid approach; it includes 26 selected companies based on eight financial criteria, providing insights into their rankings and areas for improvement. The analysis of financial performance criteria using the AHP reveals that ROE and ROA are the most important indicators that reflect the financial health of the selected manufacturing companies. Meanwhile, the D/E ratio was identified as the least significant criterion. Incorporating eight financial ratios, the model captures essential facets of financial health, including liquidity, profitability, solvency, and efficiency. This ensures that choices are grounded in sound financial principles that consider immediate and long-term results. Additionally, the COPRAS ranking further revealed unique findings; it is observed that Coal India Ltd. outperformed during the period with a higher performance score and relative utility. Nestle India Ltd. and Britannia Industries Ltd. ranked second and third. Bharat Petroleum Corpn. Ltd. is found to be the poor performer and showed the least efficiency during the period. AHP is a structured approach that ensures the decision-making process is transparent. While the outranking method, COPRAS, adds consistency by applying proportional assessments systematically. An integrated MCDM approach is crucial for strategic planning and decision-making because it combines rigorous quantitative analysis, is flexible in nature, and can produce industry-specific insights effectively.

Planning for strategic growth relies heavily on financial performance matrices, which help companies efficiently allocate their resources. The proposed AHP-COPRAS integrated model may assist stakeholders in determining the positive or negative aspects and market potentials of the companies involved in core manufacturing and allied activities by providing a clear, quantitative ranking. Additionally, policymakers can leverage these insights to design industrial policies, subsidies, and incentives aimed at enhancing the manufacturing sector's growth and competitiveness.

Despite its contributions, this study has certain limitations. The sample size is relatively small, and the analysis is limited to a single year, which may not capture long-term financial trends or external market fluctuations. Future research can expand the study period and include a larger dataset to improve the robustness and generalizability of the findings. Furthermore, other weighting methods in MCDM, such as ANP and SWARA, can be explored to determine the relative weights of criteria. At the same time, different outranking methods like VIKOR, TOPSIS, and PROMETHEE can be employed for alternative ranking. A comparative analysis of various hybrid models could also be conducted

to enhance decision-making accuracy. Additionally, incorporating qualitative factors such as managerial expertise, market sentiment, and policy changes could provide a more comprehensive evaluation of financial performance.

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