

Optimizing Financial Analysis in the Indian Logistics Industry: A Principal Component Analysis Approach

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Abstract

Logistics is one of the most significant segments that boosts economic growth, grows exports through global supply chains, and creates employment. An analysis of the financial performance of the Indian logistics sector through Principal component analysis is very important. This research discusses the use of limited and most important financial ratios that can be best in analysing the performance with little loss of information for saving efforts and time of the analysers.

A total of 43 ratios grouped in four categories were calculated using the Prowess IQ database for seven companies for a period of 9 years from 2014-15 to 2022-23. Comprehensive score of financial performance through Principal component analysis (PCA) was calculated for ranking the companies using SPSS and MS Excel.

In the end, the study concludes that only 25 ratios instead of too many ratios can be used to analyze financial performance using a comprehensive score. PCA resulted in only 5 components, profitability margin, profitability return, liquidity, cash and cash equivalent, and cash from operation, as significant with 93.42% of the cumulative percentage.

This study will help the managers of logistics companies to frame strategic policies using their comprehensive evaluation of financial performance and improve the performance as well as other stakeholders who are interested in analyzing financial performance.

Keywords: Financial performance, financial ratios, Principal component analysis, comprehensive score, Logistics sector.

Introduction

Financial performance is a comprehensive evaluation of a firm's economic viability, solvency, profitability, and efficiency, as reflected in its financial statements and relevant quantitative indicators. It encompasses the analysis of key financial ratios, such as liquidity, leverage, profitability, and efficiency ratios, along with an examination of financial statements, cash flow patterns, and market valuation

metrics. Financial performance analysis serves as a fundamental tool for investors, analysts, and decision-makers, contributing to informed investment strategies, risk management practices, and strategic planning for organizations.

Researchers often employ various quantitative models and statistical techniques to assess and compare financial performance, providing insights into a company's ability to generate returns for its stakeholders, manage financial risks, and sustain long-term growth. Ratio analysis is one of the best techniques for evaluating the performance of companies. When companies evaluate their performance, it is impractical to take all of their financial ratios into consideration. To evaluate the financial performance of a company, only a fraction of the available financial ratios is considered and selected as evaluation criteria.

This research paper evaluates the financial performance of selected logistics companies in India as logistics is the life line of every nation's industry and economy. To avoid heterogeneous behaviour of ratios, companies belonging to single type of industry are selected for the analysis. In this framework, the companies belonging to the logistics services providers of India is identified for the study. Logistics is one of the most significant segments that boosts economic growth, grows exports through global supply chains and creates employment. Indian Logistics sector is unorganized and highly fragmented, still 14 % of the Gross Domestic Product (GDP) is spent on this sector. This sector provide employment to 2.2 crore people in India and is expected to create another 1.2 million jobs by 2025. Noteworthy improvements have been witnessed in India's standing on the World Bank's Logistics Performance Index (LPI), climbing from the 54th position in 2014 to an impressive 38th in 2023. Forecasts paint a compelling picture, anticipating the market to skyrocket to an impressive US\$ 380 billion by 2025, maintaining a robust year-on-year growth rate of 10%-12%. Vision@ 2047 is a guiding principle which is being supported by multiple regulatory and government initiatives to revamp India's logistics sector. It aims to set specific targets to transition India into a developed nation by 2047.

Vision @ 2047

ROAD LOGISTICS INFRASTRUCTURE - Build 32,000 km of express way and highways - Invest Rs. 480-490 lakh cr. for urban infrastructure	RAIL INFRASTRUCTURE DEVELOPMENT - Invest Rs. 135-145 lakh cr. over the next 25 years - Target 40% to 45% railway share in freight transport by 2030 - Develop seven hyperloop lines, including two for cargo	MARITIME INFRASTRUCTURE - Increase port capacity by four times to 10,000 MTPA	AIR INFRASTRUCTURE DEVELOPMENT - Develop 20 new airports on aerotropolis approach	MULTI-MODAL AND LOGISTICS HUB - Reduce logistics cost by augmenting cargo speed by two to three times - Build more than 70 multi-modal logistics park
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Review of Literature

Financial performance analysis using ratios has been one of the most commonly used primary models of assessment of a firm's performance over years as well as comparing it to the rest of the players in the industry. It serves as a fundamental tool for investors, analysts, and decision-makers, contributing to informed investment strategies, risk management practices, and strategic planning for organizations. Purba&Septian, (2019) analyzed the short-term financial performance of an energy service company in Indonesia and concluded that the profitability of the company is still relatively low. Hofmann, E., & Lampe, K. (2013) examined the financial statements of 150 publicly quoted logistics service providers (LSPs) from all over the world and concluded that the most important financial indicators positively influencing the profitability measured through return on assets (ROA). Equity ratio and net profit margin were the most significant key macro-financial factors of high profitability. Arif et al. (2016) analyzed the performance of the tourism and hospitality sector of Bangladesh using Ratio analysis, trend analysis, and capital budgeting techniques and proved that the tourism and hospitality sector of Bangladesh has an enlightening and profitable future which attracts many new investors to invest. Shah, (2020) evaluated the financial statements of selected pharmaceutical companies in India through ratio analysis and inter-firm comparison and indicated that Cadila was doing much better on its EPS, while Sun Pharma noticed the greater and consistent rise in the financials and ratios. Arini et al., (2021) in their paper analyzed the effects of different ratios on the financial difficulties of textile and garment companies and revealed that liquidity ratios and

leverage ratios were not significant but influential to financial distress. Mathiraj et al., (2019) measured the financial performance of leading logistics companies in India using ratio analysis and ANOVA was applied and concluded that financial performance could be evaluated with the help of liquidity, solvency and profitability ratios. Jang & Ahn, (2021) analysed financial ratios and concluded that there are differences in financial factors that affect return on assets and return on equity by business types in the logistics industry.

Owing to time constraints faced by financial statement analysts and the inherent correlation of these ratios, it is necessary to narrow down the number of ratios under evaluation to concentrate attention on a select few with the least amount of data loss (Taylor, 1986). Pinches et al., (1973) stated that factor analysis is one such tool that helps to identify key ratios for a set of observed variables from a bigger basket of ratios. Mbona & Yusheng, (2019) analyzed the financial performance of the Chinese Telecoms Industry by applying principal component analysis and recommended a combination 12 of ratios instead of 17, that best analyzes performance in the industry with limited loss of information. Puri et al., (2022) assessed the financial performance of the Indian Automobile Industry and concluded that financial performance can be assessed using just five ratios rather than an expensive study of a large number of ratios using principal components analysis. Kumar, (2022) developed an effective hedging strategy for the US treasury bond portfolio using principal component analysis to reduce the dimensionality of the dataset with minimum loss of information. Tang & Aldulaimi, (2022) in their paper concluded that ranking and scoring of companies can be done based on principal component analysis. F values were calculated for all 11 companies and arranged in ranks. Fitriyana et al., (2020) used the Principal Component Analysis in the consumer goods industry in Indonesia. PCA reduced the 18 variables into five principal components only that influence the stock price the most. Potential investors can invest in shares after analyzing these five components. Wang, (2021) applied factor analysis and principal component analysis to evaluate the performance of 44 retail enterprises from 2016 to 2018. Liu & Bai, (2021) evaluated the financial performance of electric

power listed companies in China using principal component analysis. Eleven indicators declined to four principal components and ranks were assigned based on comprehensive financial performance score. Han & Ren, (2020) and Guohua & Wenxing, (2020) used factor analysis to develop a financial risk assessment model in China based on the principal factor score, indicating that a company with negative factor values faces higher financial risks.

Although there are many case studies on ratio-based financial performance analysis in the reviewed literature, there are still certain gaps.

First, we have found that very few studies have so far focused on the Indian logistics sector. Second, a small number of studies have used PCA to determine which ratios, out of the pool of all ratios in India, provide the greatest performance analysis with the least amount of data loss. Third, rare studies focused on ranking of the companies based on comprehensive scores (Liu & Bai, 2021). By applying PCA we create new independent variables that allow for effective further analysis with even fewer variables.

Research Objectives

1. To carry out a Principal component analysis on 43 financial ratios for selected Indian-listed Logistics companies to reduce the number of variables.
2. To recommend a mix of ratios that best assess and analyze the performance of selected Indian-listed Logistics companies.
3. To rank the selected Indian-listed Logistics companies under consideration.

Research Methodology:

Sampling Method and data

The research paper analyses the logistics sector for nine years from 2014-15 to 2022-23. Sample companies were chosen based on market capitalization. CMIE Prowess IQ database was used to collect secondary data. Below is the list of companies whose market capitalization was available in March 2023. Information about 29 companies, listed on the Bombay Stock Exchange, were available. Of these 29 companies, 97.86% of the total market

capitalization of the logistics sector has been taken represented by the top 8 companies. Because of the non-availability of data, Tiger Logistics (India) Ltd. was

excluded from the further analysis. Finally, the collated secondary data comprise of 7 companies, 43 ratios, for 9 years. The analysis was conducted using SPSS.

S.No.	Name of the Company	Market Capitalization (Rs.)	Market Capitalization (%)	Cumulative Market Capitalization %
1	Blue Dart Express Ltd.	147206.9	40.66037	40.66037297
2	Allcargo Logistics Ltd.	87332.47	24.12231	64.7826819
3	Transport Corporation Of India Ltd.	48698.21	13.45105	78.23373014
4	Sindhu Trade Links Ltd. (1992)	26459.5	7.308441	85.54217147
5	Mahindra Logistics Ltd.	25469.07	7.034872	92.57704378
6	Reliance Industrial Infrastructure Ltd.	11811.22	3.262405	95.83944891
7	Tiger Logistics (India) Ltd.	3840.99	1.060929	96.90037788
8	ShreejiTranslogistics Ltd.	3483.34	0.962142	97.86251949
9	Arshiya Ltd.	1277.86	0.352961	98.21548023
10	Sanco Trans Ltd.	1258.11	0.347506	98.56298579
11	Flomic Global Logistics Ltd.	622.94	0.172064	98.73504952
12	East West Holdings Ltd.	528.05	0.145854	98.88090347
13	Future Supply Chain Solutions Ltd.	499.4	0.13794	99.01884393
14	Sical Logistics Ltd.	464.07	0.128182	99.1470258
15	Cargosol Logistics Ltd.	418.2	0.115512	99.26253782
16	A B C India Ltd.	416.59	0.115067	99.37760513
17	Aqua Logistics Ltd.	407.99	0.112692	99.49029702
18	Chartered Logistics Ltd.	372.52	0.102895	99.59319165
19	Cargotrans Maritime Ltd.	293.76	0.08114	99.6743318
20	V I F Airways Ltd.	252.1	0.069633	99.74396494
21	M F L India Ltd.	237.79	0.065681	99.80964548
22	Bhoruka Steel & Services Ltd.	219.61	0.060659	99.87030448
23	Quality R O Inds. Ltd.	204	0.056347	
24	Coastal Roadways Ltd.	83.8	0.023147	
25	Kabra Commercial Ltd.	72.18	0.019937	
26	Girish Travels & Couriers Ltd.	42.7	0.011794	
27	Corporate Courier & Cargo Ltd.	31.32	0.008651	
28	Containerway International Ltd.	31.05	0.008576	
29	Marine Cargo Co. Ltd.	4.5	0.001243	
	Total	362040.3	100	

Selection of financial ratios

Different ratios were considered for analyzing the financial performance of the logistics sector. This paper uses 43 financial ratios grouped into four different categories. The below table defines the ratio group and ratio code provided for different ratios used in the study.

Table 1: Ratio name and code

Ratio group	Ratio Code	Ratios
Profitability and earnings ratios	PE 1	PBDITA as % of total income
	PE 2	PBT as % of total income
	PE 3	PAT as % of total income
	PE 4	Cash profit as % of total income
	PE 5	Net profit margin
	PE 6	Cash profit net of P&E as % of total income net of P&E
	PE 7	Operating profit margin of non -financial companies
	PE 8	Return on net worth
	PE 9	Return on capital employed
	PE 10	Return on total assets
	PE 11	Return on average capital employed
	PE 12	Return on average assets
	PE 13	Gross Profit Ratio
Liquidity and cash ratios	LC 14	Quick ratio (times)
	LC 15	Current ratio (times)
	LC 16	Cash to current liabilities (times)
	LC 17	Cash to average cost of sales per day
	LC 18	Cash flow generated from operation/ PBIT
	LC 19	Cash flow generated from operation to total assets
	LC 20	Cash flow generated from operation to capital employed
	LC 21	Cash flow generated from operation to net working capital
	LC 22	Cash flow generated from operation to average total assets
	LC 23	Cash flow generated from operation to Average capital employed
	LC 24	Cash and cash equivalent at the end to current assets
	LC 25	Cash and cash equivalent at the end to total assets
	LC 26	Cash and cash equivalent at the end to net sales
	LC 27	Net working capital ratio
	LC 28	Cash and cash equivalent at the end to current liability
Assets management ratios	AM 29	Debtors' turnover (times)
	AM 30	Creditors turnover (times)
	AM 31	Gross fixed assets utilization ratio(times)
	AM 32	Net fixed assets utilization ratio(times)
	AM 33	Sales / Net fixed assets
	AM 34	Current Assets turnover
	AM 35	Working capital turnover
	AM 36	Total assets turnover
	AM 37	Sales to capital employed
	AM 38	Working capital to total assets
	AM 39	Employees utilization ratio(times)
Solvency ratios	S 40	TOL/TNW (times)
	S 41	Net Worth to Capital Employed
	S 42	Equity Ratio
	S 43	Net Fixed Assetsto capital employed

Result and discussion

Principal component analysis was used to evaluate and analyze the financial performance (Jolliffe & Cadima 2016, Sehgal et al. 2014, Eastment & Krzanowski 1982, Wang & Du, 2000) of selected Logistics Companies in India. Principal component analysis converts the correlated data set or variables into an uncorrelated variables dataset which explains maximum variance. Principal component analysis was introduced to propose the most acceptable ratios that can be used for evaluating the financial performance of the logistics sector in India. Standardized data is used to apply Principal component analysis.

Kaiser- Meyer Olkin (KMO) statistics is used to measure the sample adequacy. It is a test to examine the strength of the partial correlation between the variables and the appropriateness of factor analysis. It ranges from 0 to 1. KMO minimum requirement of 0.5 is necessary for the sample adequacy (Yap 2013, Liu & Bai 2021, Daryanto et al. 2020, Guohua & Wenxing 2020, and Han & Ren 2020) while applying PCA to financial performance analysis. This study represents the KMO measure of sample adequacy of the sample is mediocre with 0.638 which is greater than 0.5, hence PCA can be applied to the data. Bartlett's test of sphericity is a statistic used to test the null hypothesis that the correlation matrix is an identity matrix. PCA requires that the probability associated with the test must be less than the level of significance (0.05). The Bartlett's test of sphericity $\chi^2 (903) = 6518.246$, $p < .05$, indicated in the study shows that correlations between variables were sufficiently large for applying Principal component analysis.

Anti image correlation matrix showed the sample adequacy of each variable separately. It helps in ascertaining the correlation and is also used to know about patterns between variables. The MSA value of each variable must be greater than 0.5. If any ratio contains an MSA value below 0.5, unfortunately, that ratio should be eliminated until the overall MSA value for the remaining variables has a value > 0.5 . The result of the Anti-Image correlation matrix of the 43 ratios shows that 8 variables PE7, LC17, LC18, LC21, AM30, AM35, AM39 and S43 have a value less than the minimum required value of 0.5 ($MSA < 0.5$). Removed these ratios and calculated anti- image correlation matrix table for the remaining 35 (43-8) variables together and separately.

Table 1: KMO and Bartlett's test

Statistics	Value
KMO MSA	0.705
Bartlett's test of Sphericity (p value) at 595 degrees of freedom	0.000

Table 1 shows the values of KMO and Bartlett's test of Sphericity, both provide a base for applying PCA and allow for further interpretation for 7 companies within the time of 9 years 2014-15 to 2022-23.

Only the variables having latent roots or eigenvalue greater than 1 are considered significant and are extracted as principal components, variables having latent roots or eigenvalue less than 1 are considered insignificant and are disregarded for further analysis. Table 2 explains the total variance between ratios. All the ratios together explain 100% variation in the data set. It can be seen from the table that only 6 components, which explain 91% of the variation, have an eigenvalue greater than 1. The first Component has an eigenvalue of 8.110, the second component has a 5.125 eigenvalue, the third component has with 4.916 eigenvalues, the fourth component has an eigenvalue of 4.843, the fifth component has a 4.577 eigenvalue and the last sixth component have eigenvalue of 4.326. Other component has eigenvalue less than 1 so all other component was disregarded. The first principal component explains the highest variation in the data followed by the second and so on in descending order.

Factor Rotation

Factor rotation improves the interpretation by reducing ambiguities from the unrotated factors. Rotating the factor matrix helps in redistributing the variance from earlier factors to later ones to achieve a simpler and theoretically more meaningful factor pattern. Factor rotation is of two types Orthogonal factor rotation and Oblique factor rotation. This study used orthogonal methods of factor rotation because the main objective of using factor analysis is data reduction. There are three different approaches to orthogonal rotation, quartimax, varimax and equimax. Among these varimax rotation approach is used in the study as it is most popular and preferred.

Table 2: Total Variance Explained between Ratios

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	12.743	36.410	36.410	8.110	23.172	23.172
2	7.663	21.895	58.304	5.125	14.642	37.814
3	5.292	15.121	73.425	4.916	14.046	51.860
4	3.311	9.461	82.886	4.843	13.836	65.696
5	1.733	4.952	87.838	4.577	13.076	78.772
6	1.153	3.294	91.132	4.326	12.360	91.132
7	.798	2.281	93.413			
8	.611	1.745	95.158			
9	.412	1.178	96.336			
10	.282	.806	97.142			
11	.244	.698	97.841			
12	.180	.515	98.356			
13	.147	.421	98.777			
14	.111	.316	99.093			
15	.081	.233	99.326			
16	.051	.144	99.470			
17	.034	.098	99.568			
18	.030	.087	99.655			
19	.026	.076	99.731			
20	.024	.067	99.798			
21	.020	.058	99.856			
22	.014	.039	99.894			
23	.009	.027	99.921			
24	.007	.021	99.942			
25	.007	.019	99.961			
26	.004	.011	99.972			
27	.003	.009	99.982			
28	.002	.005	99.987			
29	.001	.004	99.991			
30	.001	.003	99.994			
31	.001	.002	99.996			
32	.001	.002	99.997			
33	.000	.001	99.999			
34	.000	.001	100.000			
35	6.600E-5	.000	100.000			

Significance of factor loadings

Factor loading is the correlation of variable and the factor and squared of loading is the amount of the variable's total variance accounted for by the factor. Thus a 0.30 loading translates to 10% (0.30×0.30) explanation approximately.

The larger the size of the factor loading, the more important the loading in interpreting the factor matrix. In this research paper, factor loading must exceed 0.70(Hair et al., 2019) based on sample size.

Table 3: Rotated Component Matrixwith factor loading

	1	2	3	4	5	6
PE4	0.889					
PE2	0.887					
PE6	0.884					
PE1	0.881					
PE3	0.870					
PE5	0.858					
PE13	0.719					
AM36						
S42						
S41						
AM34						
AM31		0.922				
AM32		0.916				
AM33		0.906				
AM37		0.765				
AM29						
LC14			0.944			
LC15			0.940			
LC27			0.932			
LC16			0.852			
AM38			0.743			
PE12				0.958		
PE10				0.896		
PE11				0.826		
PE8				0.781		
PE9				0.772		
LC26					0.956	
LC24					0.909	
LC28					0.822	
LC25					0.788	
S40						
LC19						0.886
LC22						0.879
LC20						0.875
LC23						0.857

Extraction method: Principal component analysis, Rotation converged in 8 iterations.

The variables having insignificant factor loading ($< \pm 0.7$) were eliminated. Table 3 represents the mix of ratios with factor loading and communalities. In total 6 principal components were ascertained using PCA on 35 ratios. PCA

reduced the set of ratios to 29 ratios and eliminated 6 ratios, represented in Table 4, which did not become part of any of the principal components, from further analysis.

Table 4: Name of the ratios eliminated

Ratios code	Ratios name
AM36	Total assets turnover
S42	Equity Ratio
S41	Net Worth to Capital Employed
AM34	Current Assets turnover
AM29	Debtors' turnover (times)
S40	TOL/TNW (times)

Principal Component Analysis II

The remaining 29 ratios were analyzed again and to verify the reliability and validity of the extraction, the KMO measure of Sampling Adequacy & Bartlett's test was done. The results of the test are shown in Table 5 as given below.

In table 5 KMO value is 0.692 which means the data can be used for principal component analysis. Also, the p-value (sig.) corresponding to the chi-square value is less than 0.05 (level of significance) which leads to the rejection of the hypothesis that the correlation is insignificant.

Table 5: KMO and Bartlett's test

Statistics	Value
KMO MSA	.692
Bartlett's test of Sphericity (p value) at 406 degrees of freedom	0.000

Principal component analysis II resulted in the extraction of five principal components as provided by table 6. It can be seen that the first five components have an eigenvalue greater than 1, which are 7.786, 5.613, 4.778, 4.293, and

3.917 respectively with a cumulative variance contribution rate of 90.99%. Hence, these principal components reflect most of the information about the financial performance of the logistics sector.

Table 6: Total Variance Explained between Ratios

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.985	34.430	34.430	7.786	26.849	26.849
2	7.155	24.671	59.101	5.613	19.356	46.205
3	4.768	16.441	75.543	4.778	16.474	62.679
4	2.824	9.736	85.279	4.293	14.805	77.484
5	1.656	5.711	90.990	3.917	13.506	90.990
6	0.943	3.252	94.242			
7	0.503	1.734	95.976			
8	0.310	1.070	97.046			
9	0.204	0.704	97.750			
10	0.177	0.611	98.362			
11	0.133	0.458	98.819			
12	0.083	0.287	99.106			
13	0.061	0.211	99.317			
14	0.048	0.164	99.481			
15	0.037	0.129	99.610			

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
16	0.030	0.102	99.712			
17	0.022	0.076	99.788			
18	0.018	0.061	99.849			
19	0.013	0.044	99.893			
20	0.010	0.033	99.926			
21	0.008	0.029	99.955			
22	0.005	0.016	99.971			
23	0.003	0.011	99.981			
24	0.002	0.006	99.987			
25	0.001	0.005	99.992			
26	0.001	0.004	99.996			
27	0.001	0.002	99.998			
28	0.001	0.002	100.000			
29	0.000	0.000	100.000			

Each Variable was allotted to the component where it had maximum factor loading. The details of the factors, its constituents' ratios, and factor loading are given in table 7.

Table 7: Factors, its constituents' ratios, and factor loading.

	PC1	PC2	PC3	PC4	PC5
PE1	0.924				
PE4	0.905				
PE2	0.892				
PE3	0.887				
PE6	0.872				
PE5	0.827				
AM37	-0.791				
PE13					
AM31					
AM32					
AM33					
PE11		0.875			
PE9		0.863			
PE10		0.844			
PE12		0.833			
PE8		0.770			
LC14			0.954		
LC15			0.950		
LC27			0.943		
LC16			0.898		
AM38			0.735		
LC19				0.918	
LC22				0.916	
LC20				0.834	

	PC1	PC2	PC3	PC4	PC5
LC23				0.812	
LC26					0.969
LC24					0.925
LC28					0.870
LC25					0.806

Hence performance of logistics industry is measured mainly with these 5 classes of ratios. But again 4 ratios were deleted from the further analysis as they did not fall in any of the principal component. Table 8 provide the name of the ratios which were deleted from the analysis.

Table 8: Name of the ratios eliminated

Ratios code	Ratios name
PE13	Gross Profit Ratio
AM31	Gross fixed assets utilization ratio(times)
AM32	Net fixed assets utilization ratio(times)
AM33	Sales / Net fixed assets

Principal Component III

Post the second Factor Analysis the data was deemed to be fit for final processing. Factor Analysis was again carried out with the intention of classifying the ratios into valid

groups. The Analysis on the remaining 25 ratios (29- 4) led to five factors which account for 93.424% variation. Further, KMO value was 0.649, more than 0.5, and Bartlett's test is statistically significant, tabulated in Table 9.

Table 9: KMO and Bartlett's test

Statistics	Value
KMO MSA	.649
Bartlett's test of Sphericity (p value) at 300 degrees of freedom	0.000

Principal component analysis III resulted in extraction of five principal components as provided by table 10. It can be seen that first five components have an eigenvalue greater than 1, which are 6.354, 5.066, 4.428, 3.777 and 3.731

respectively with cumulative variance contribution rate of 93.42%. Hence, these principal components reflect most of the information about financial performance of the logistics sector.

Table 10: Total Variance Explained between Ratios

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.935	35.739	35.739	6.354	25.417	25.417
2	6.901	27.605	63.344	5.066	20.263	45.679
3	3.945	15.779	79.123	4.428	17.713	63.393
4	1.937	7.748	86.871	3.777	15.108	78.500
5	1.638	6.553	93.424	3.731	14.923	93.424
6	0.475	1.898	95.322			
7	0.380	1.520	96.842			
8	0.229	0.914	97.756			
9	0.151	0.605	98.361			
10	0.116	0.464	98.826			

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
11	0.068	0.273	99.099			
12	0.061	0.243	99.342			
13	0.038	0.154	99.496			
14	0.032	0.128	99.624			
15	0.027	0.109	99.733			
16	0.019	0.077	99.811			
17	0.015	0.058	99.869			
18	0.011	0.045	99.914			
19	0.010	0.038	99.952			
20	0.005	0.021	99.973			
21	0.004	0.015	99.988			
22	0.002	0.007	99.994			
23	0.001	0.003	99.997			
24	0.001	0.002	99.999			
25	0.000	0.001	100.000			

Extraction Method: Principal Component Analysis. Rotation converged in 7 iterations.

Accordingly, components names were assigned based on the highest factor loading of the related variables. The findings of the components post the third -principal component analysis, along with the name of components, representative ratio, factor loading, are collated in Table 11.

Table 11: Components, its constituents' ratios with loading.

	PC1	PC2	PC3	PC4	PC5
PE1	0.951				
PE4	0.929				
PE2	0.921				
PE3	0.919				
PE6	0.896				
PE5	0.860				
AM37	-0.754				
PE12		0.922			
PE10		0.916			
PE11		0.908			
PE9		0.888			
PE8		0.830			
LC14			0.950		
LC15			0.947		
LC27			0.940		
LC16			0.884		
AM38			0.753		
LC26				0.973	
LC24				0.915	

	PC1	PC2	PC3	PC4	PC5
LC28				0.860	
LC25				0.808	
LC19					0.928
LC22					0.921
LC20					0.866
LC23					0.841

Extracted Principal components and related ratio are presented in figure 1 which represent that 7 ratios become the part of 1st component, 5 ratios fall under second component, 5 in 3rd component, 4 ratios in 4th component and remaining 4 ratios in component 5.

Figure 1: Extracted Principal components and related ratio

PC1	PC2	PC3	PC4	PC5
• PBDITA as % of total income • Cash profit as % of total income • PBT as % of total income • PAT as % of total income • Cash profit net of P&E as % of total income net of P&E • Net profit margin • Sales to capital employed	• Return on average assets • Return on total assets • Return on average capital employed • Return on capital employed • Return on net worth	• Quick ratio (times) • Current ratio (times) • Net working capital ratio • Cash to current liabilities (times) • Working capital to total assets	• Cash and cash equivalent at the end to net sales • Cash and cash equivalent at the end to current assets • Cash and cash equivalent at the end to current liability • Cash and cash equivalent at the end to total assets	• Cash flow generated from operation to total assets • Cash flow generated from operation to average total assets • Cash flow generated from operation to capital employed • Cash flow generated from operation to Average capital employed

Table 12 represents the mix of important ratios which significantly affects the performance of logistics industry under consideration for a period of 9 years from 2014-15 to 2022-23. Financial performance of Logistics sector in India is measured through mainly by five classes of ratios.

Table 12: Principal Component with its name

Principal component	Component name based on the group of ratios
PC1	Profitability Margin Ratios
PC2	Profitability Return Ratios
PC3	Liquidity Ratio
PC4	Cash and Cash Equivalent Ratios
PC5	Cash Flow from Operation Ratio

Profitability margin ratios being the first principal component is very important. Margin ratios provide understandings into a firm's capability to generate profit from sales and the efficiency of its sales process. Most of the margin ratio have value greater than 0.8, very significant value. These ratio shows earning of the business after tax and before tax expenses. It shows that the logistics sector converts the sales in profit very effectively.

Profitability return ratio plays a very effective role in improving the performance of Indian logistics sector. This is supported by most of the literatures as maximisation of

profit should be the core aim of the business to provide high return to shareholders. These ratios reveal your business's capacity to produce returns on investment based on the net worth, capital employed, and total assets your business has. Most of the return ratios have a very significant value of 0.9.

Liquidity in the logistics industry is very important as proved by component 3. All liquidity ratio has very noteworthy value of greater than 0.9. Liquidity is required to pay off its current liabilities. It shows the efficiency of the business to convert the current assets into cash and handling the operation of markets.

Cash and cash equivalent the most liquid current assets and used in growth and expansion of operations. According to PCA these ratios are less significant as they become the part of 4th component.

Operating cash flow become the part of 5th component which signifies its importance in logistics sector. Cash from operation indicates the amount of money a business brings in from its regular business activities of providing services to customers, utilising its total assets and total capital employed. It helps in ascertaining the financial success of a companies' core business.

Factor score

Factor score represents the transformed values of the original values onto the new orthogonal axes obtained through the principal component analysis. Factor scores are standardised score with mean zero and standard deviation

as 1. Further analysis can be carried out on the factor scores rather than the original data. Finally, this study applies Anderson – Rubin method for calculating the factor score (Field, 2009: 635). The result of factor score is represented in table 13.

Assignments of weights to Principal components

To achieve the last and third objective of the study of ranking to different companies based on these principal components, assigned weights to the principal components. The variance contribution rate or eigenvalue of each six principal components is divided by the cumulative contribution rate of all six principal components, and this quotient was used as weight. (Liu & Bai, (2021), Han & Ren, (2020), Guohua & Wenxing, (2020))

$$W = \frac{\text{Eigen value of principal component}}{\text{Cumulative eigen value of principal components}}$$

Table 13: Calculation of weights for each principal component

Principal components	Total eigen value	Weights assigned to each Principal component
PC 1	6.354	6.354/23.356=0.272
PC 2	5.066	5.066/23.356=0.217
PC 3	4.428	4.428/23.356=0.190
PC 4	3.777	3.777/23.356=0.162
PC 5	3.731	3.731/23.356=0.160
Total	23.356	

Using these weights, comprehensive score of financial performance of each and every company for nine years from 2014-15 to 2022-23 were calculated by using the following equation:

$$\text{Financial performance} = 0.272 \text{ PC1} + 0.217 \text{ PC2} + 0.190 \text{ PC3} + 0.162 \text{ PC4} + 0.160 \text{ PC5}$$

Table 14: Average comprehensive score and ranking

Company name	Year	PC1	PC2	PC3	PC4	PC5	Comprehensive score	Average Comprehensive score	Ranking
Blue Dart Express Ltd.	2014-15	0.045	0.792	-0.067	2.205	0.702	0.639952	0.41433	2 nd
	2015-16	0.703	1.357	0.071	3.846	1.390	1.342849		
	2016-17	0.220	0.389	-0.548	2.841	-0.066	0.489122		
	2017-18	-0.025	0.293	-0.290	2.230	0.633	0.4634		
	2018-19	-0.517	-0.552	-0.242	2.464	0.164	0.118481		
	2019-20	-1.124	-1.578	-0.393	0.336	0.076	-0.65597		
	2020-21	-0.486	-0.719	-0.060	-0.344	2.144	-0.01244		
	2021-22	0.517	2.182	-0.359	0.235	2.396	0.966506		
	2022-23	0.110	2.116	-0.518	-0.578	0.500	0.377072		

Company name	Year	PC1	PC2	PC3	PC4	PC5	Comprehensive score	Average Comprehensive score	Ranking
Allcargo Logistics Ltd.	2014-15	1.114	-0.412	-0.664	-0.166	0.027	0.065204	-0.03074	4 th
	2015-16	1.135	-0.127	-0.781	-0.405	0.065	0.078123		
	2016-17	1.069	-0.231	-0.774	-0.403	-0.205	-0.00404		
	2017-18	0.113	-0.998	-0.318	-0.525	-0.006	-0.33197		
	2018-19	1.315	0.995	-0.860	-0.654	-0.845	0.169827		
	2019-20	1.099	-0.252	-1.028	-0.071	-0.553	-0.05069		
	2020-21	0.901	-0.001	-1.157	-0.246	-0.705	-0.12676		
	2021-22	0.610	1.073	-0.943	-0.282	-1.458	-0.05849		
	2022-23	-0.206	0.024	-0.082	-0.949	1.265	-0.01787		
Transport Corporation Of India Ltd.	2014-15	-0.752	0.366	-0.096	-1.106	0.375	-0.26233	0.034396	3 rd
	2015-16	-0.506	0.226	-0.397	-1.053	0.093	-0.31941		
	2016-17	-0.464	0.137	-0.331	-0.817	-0.203	-0.32396		
	2017-18	-0.402	0.543	-0.176	-1.182	0.423	-0.14846		
	2018-19	-0.448	0.708	-0.141	-1.336	0.229	-0.17449		
	2019-20	-0.465	0.413	0.008	-1.328	0.833	-0.11738		
	2020-21	-0.379	0.336	0.278	-1.089	1.006	0.007037		
	2021-22	0.135	1.883	1.016	-0.998	1.382	0.697279		
	2022-23	0.169	1.832	1.662	0.651	0.550	0.951287		
Sindhu Trade Links Ltd. (1992)	2014-15	0.435	-0.329	-0.887	-0.573	1.317	-0.00345	-0.16055	5 th
	2015-16	1.209	1.614	-0.737	-0.412	-1.616	0.214354		
	2016-17	0.503	-0.055	-0.749	-0.457	1.275	0.112798		
	2017-18	0.260	-0.180	-0.863	-0.781	1.000	-0.09838		
	2018-19	0.267	-0.263	-0.863	-0.445	0.662	-0.11401		
	2019-20	0.661	-0.709	-1.162	-0.293	0.754	-0.12147		
	2020-21	0.347	-0.498	-1.329	0.225	-2.761	-0.67039		
	2021-22	-0.134	-0.774	-0.330	-0.754	-0.052	-0.39717		
	2022-23	0.405	-0.632	-0.335	-0.372	-1.357	-0.36727		
Mahindra Logistics Ltd.	2014-15	-1.648	1.435	0.944	1.287	-0.798	0.12262	-0.28628	6 th
	2015-16	-1.637	1.259	0.645	1.004	-2.845	-0.34226		
	2016-17	-1.768	1.227	0.388	-0.477	-1.630	-0.47898		
	2017-18	-1.754	1.227	0.499	-0.476	-0.718	-0.30814		
	2018-19	-1.710	1.375	0.546	-0.942	0.164	-0.18972		
	2019-20	-1.233	-0.002	0.087	0.048	-0.262	-0.3535		
	2020-21	-1.095	-1.328	0.167	1.234	0.964	-0.2006		
	2021-22	-1.155	-1.287	-0.014	0.185	1.096	-0.39115		
	2022-23	-0.969	-0.623	-0.280	-0.080	0.187	-0.43481		

Company name	Year	PC1	PC2	PC3	PC4	PC5	Comprehensive score	Average Comprehensive score	Ranking
Reliance Industrial Infrastructure Ltd.	2014-15	2.881	0.078	1.045	0.288	0.325	1.097263	0.424144	1 st
	2015-16	1.797	-0.301	1.512	-0.017	-0.367	0.648962		
	2016-17	2.120	-0.450	-0.203	0.516	-0.271	0.480852		
	2017-18	1.256	-0.739	-0.339	0.081	-0.705	0.017735		
	2018-19	0.779	-0.936	0.386	-0.185	-0.443	-0.0188		
	2019-20	0.751	-0.858	0.375	0.176	-1.140	-0.06432		
	2020-21	1.113	-0.842	1.228	-0.057	-1.177	0.155753		
	2021-22	0.195	-1.243	4.654	-0.449	-0.118	0.574231		
	2022-23	1.326	-0.427	3.871	-0.552	0.080	0.925616		
Shreeji Trans Logistics Ltd.	2014-15	-0.928	-1.651	-0.227	0.157	0.393	-0.56525	-0.39529	7 th
	2015-16	-0.846	-1.505	-0.113	0.420	1.074	-0.33832		
	2016-17	-0.983	-1.065	-0.169	-0.401	0.030	-0.59039		
	2017-18	-0.608	-0.296	-0.264	0.309	-1.116	-0.40779		
	2018-19	-0.575	-0.355	-0.112	0.185	-0.251	-0.2648		
	2019-20	-0.890	-1.274	-0.128	0.003	-0.473	-0.61777		
	2020-21	-1.179	-2.009	-0.056	0.706	-0.469	-0.72802		
	2021-22	-0.334	0.794	0.055	-0.302	-0.670	-0.06422		
	2022-23	-0.337	0.824	-0.052	-0.072	-0.293	0.018951		

Evaluation of financial performance of logistics sector based on Principal component analysis

In this paper, the ranking of 7 Indian listed Logistics companies is obtained using PCA (calculated by SPSS) and Average comprehensive score (calculated by Excel) and presented in Table 13.

Reliance Industrial Infrastructure Ltd. captured the first rank with an average comprehensive score of 0.424 and Shreeji Trans Logistics Ltd. ranked last with a negative comprehensive score of -0.395. The difference between the largest value and lowest value is relatively huge which shows a relative difference in the financial performance of logistics companies. Among all seven companies under consideration, only the top 3 companies have a positive average comprehensive score and the remaining 4 have a negative score. Although some listed companies are at the top of the average comprehensive ranking, there are still

many areas that need to be improved. Reliance Industrial Infrastructure Ltd. still ranked first in profitability return ratio and cash flow from operation ratio needs great improvement but because of the highest profitability margin ratio as the first component achieved the first rank.

Blue Dart Express Ltd. ranked second because of unhealthy profit margins and liquidity problems. The company has the highest score of Cash and Cash Equivalent Ratios with Cash Flow from Operation Ratio. Transport Corporation of India Ltd. faces the problem of profitability margin which resulted in low cash and cash equivalent. The remaining companies have negative average comprehensive scores because of low profitability, liquidity problems, etc. Mahindra Logistics Ltd. ranks 6th in the comprehensive score but has an advantage in liquidity and profitability return. Allcargo Logistics Ltd. is in 4th rank but has an advantage in profitability margins.

In terms of profitability margin 3 companies have positive scores and the remaining 4 have negative scores in the period under consideration of 9 years from 2014-15 to 2022-23. The First is Reliance Industrial Infrastructure Ltd. and the last is Mahindra Logistics Ltd. indicates the difference in the profitability margin of different companies in the logistics sector.

In terms of profitability return, more than 50% of companies score positive, which indicates that the logistics sector has good profitability return potential and shows the business's capacity to produce returns on investment based on the total assets, capital employed, and net worth of your business.

In terms of liquidity, more than 50% of companies score negatively showing that the short-term solvency of the logistics sector in India is not strong. It shows the inefficiency of the business in converting the current assets into cash and handling the operation of markets.

Cash and cash equivalent and Cash flow generated from the operation situation of the logistics sector are inefficient as more than 50% of companies have negative scores in 9 years under consideration. Companies face a problem in the growth and expansion of operations. It hampers the financial success of a company's core business.

Conclusion

To make a comprehensive evaluation of the financial performance of selected Indian-listed logistics companies through principal component analysis on SPSS, this study selects 43 financial indicators. The study resulted in an imbalance in the performance of the logistics sector with a significant gap in a comprehensive score of 7 selected companies. some companies ranked high and some low showing the inability of some companies to cope with the other companies in the sector. Managers of logistics companies can frame strategic policies using their comprehensive evaluation of financial performance and improve the performance as well as other users of financial statements can use this score in judging the performance.

Scope for further studies

More companies with higher time duration can benefit the government and industry in drafting the policies to improve the sector performance. Comprehensive scores through PCA or another model can be used in another sector also.

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