

Dynamic Mapping of Financial Performance and Valuation Profiles among Indonesian Listed Construction Companies Using K-Means Clustering

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ABSTRACT

The construction sector plays an important role in Indonesia's economic development; however, construction companies face various financial challenges, including profitability pressures, high leverage levels, and fluctuating market valuations. A comprehensive assessment of financial performance and valuation profiles is needed to identify company conditions and support potential acquisition screening. This study aimed to map changes in the financial performance and valuation profiles of construction companies listed on the Indonesia Stock Exchange during 2024–2025 using a clustering approach. A quantitative descriptive-exploratory method was applied using secondary data obtained from financial statements and market-based ratios. The sample consisted of 24 construction companies with 48 company-year observations. The analysis employed K-Means Clustering supported by data preprocessing, Principal Component Analysis (PCA), and cluster evaluation based on statistical validity and economic interpretation. The findings revealed three distinct profiles: companies with strong profitability and moderate valuation, companies with low leverage but weak earnings performance, and companies with high leverage and financial losses. The migration analysis showed that 18 companies remained in the same profile, while six companies shifted toward weaker financial conditions. These findings indicate that financial performance and valuation mapping through clustering can provide an objective initial screening framework for investors, management, and stakeholders in evaluating company risks and strategic opportunities. Future studies are recommended to incorporate additional indicators, such as cash flow, liquidity, and market risk, to improve assessment accuracy.



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INTRODUCTION

The construction industry holds a strategic position in the Indonesian economy because it contributes to infrastructure development, regional growth, employment creation, and the expansion of productive capacity across other economic sectors. Construction activities not only involve the development of buildings and physical infrastructure but also stimulate demand for construction materials, transportation services, heavy equipment, financial services, and other supporting industries (Agenda, 2016; Bon, 2024; McCartney, 2022; Wells,

2026). The Central Statistics Agency reported that the construction sector was the fourth-largest contributor to Indonesia's economy, accounting for approximately 10.23% of gross domestic product (GDP) in the first quarter of 2024. This contribution increased to approximately 10.43% in the fourth quarter of 2024, demonstrating the significant role of the construction sector in national economic activities (Central Statistics Agency, 2024; Central Statistics Agency, 2025a).

The characteristics of the construction business create distinct financial challenges compared with industries with more stable revenue patterns. Construction companies' revenues depend on project acquisition, contract values, project completion stages, billing processes, and the ability of project owners to fulfill payment obligations. At the same time, companies must provide working capital to finance materials, labor, subcontractors, equipment, and operational expenses before receiving full project payments. Mismatches between cash inflows and project expenditures may increase financing requirements, interest expenses, and liquidity risks. Studies of state-owned and private construction companies in Indonesia have shown that state-owned enterprises generally experience relatively low profitability, critical liquidity conditions, high debt levels, and lower operational efficiency compared with private companies. The use of debt as a source of project financing may increase financial risks when liability growth is not supported by sufficient revenue generation and cash flow capacity (Wibowo et al., 2024). These financial challenges were also reflected in the preliminary data of construction companies listed on the Indonesia Stock Exchange during 2024–2025 (Budiman, 2023; Wibowo et al., 2024). The research database initially included 29 companies, representing 58 company-year observations before sample selection based on data completeness. The preliminary assessment identified 25 observations with negative earnings per share (EPS), 22 observations with negative price-to-earnings ratios (P/E ratios), four observations with negative book value, four observations with negative price-to-book value (P/BV), and four observations with negative equity. These conditions indicate that several companies experienced not only profitability pressures but also challenges related to capital structure and market valuation perceptions (Kristanti et al., 2023; Luo et al., 2021; Putri & Putri, 2024). After excluding observations with incomplete data, the study used a balanced panel consisting of 24 companies and 48 company-year observations (Baltagi, 2021).

Table 1. . Financial Data & Ratios per Construction Company Issuer 2024

Code	Year	EPS	PBV	THE ER	LENGTH (%)	ROE (%)	NPM (%)
ACST	2024	-20,69	9,11	13,83	-9,35	-138,62	-20,09
ADHI	2024	22,31	0,23	2,47	0,56	1,93	3,32
ORIGINAL	2024	-2,52	7,05	0,16	-2,93	-3,41	-11,52
BDKR	2024	-3,67	1,10	0,52	-1,52	-2,30	-6,14
BUKK	2024	212,31	0,70	2,20	2,42	7,75	30,30
DGIK	2024	10,99	1,41	1,00	4,27	8,52	9,70
FIMP	2024	6,69	0,90	0,16	7,47	8,70	66,88
IDPR	2024	11,79	0,80	1,41	1,46	3,52	2,67
JKON	2024	7,15	0,45	0,34	2,78	3,71	5,14
MOTHER	2024	-4,73	4,22	0,21	-7,01	-8,46	-50,06
KRYA	2024	-43,8	7,14	3,03	-55,07	-221,83	-89,10
MANG	2024	-1,67	1,63	0,25	-3,56	-4,46	-19,36
MTPS	2024	-4,63	4,31	0,79	-13,75	-24,64	-
MTRA	2024	-98,98	-2,60	-2,86	-56,59	-	-1463,00

Code	Year	EPS	PBV	THE ER	LENGTH (%)	ROE (%)	NPM (%)
NRCA	2024	61,38	2,81	1,04	5,54	11,30	5,77
PBSA	2024	77,44	5,86	0,58	19,10	30,24	22,71
PPRE	2024	18,35	0,48	1,16	2,36	5,11	6,77
PTDU	2024	-16,88	-21,86	-16,74	-20,76	-	-50,94
PTPP	2024	24,83	0,17	2,63	0,28	1,01	1,43
PTPW	2024	40,18	1,36	0,15	4,60	5,28	13,91
RONY	2024	0,12	937,87	0,36	2,25	3,05	35,15
SMKM	2024	2,57	1,01	0,02	1,52	1,56	9,01
SSIA	2024	2,61	0,97	0,44	0,10	0,15	0,37
SON	2024	-8,74	1,72	4,09	-5,68	-28,89	-60,14
TOPS	2024	-8,55	0,08	2,90	-17,57	-68,57	-678,46
TOTL	2024	111,54	2,82	2,12	9,94	31,00	13,65
WEGE	2024	-3,1	0,26	0,90	-0,61	-1,16	-2,53
FISH	2024	-156	0,95	5,65	-10,91	-72,55	-68,41
WSKT	2024	-20,69	9,11	13,83	-9,35	-138,62	-20,09

Source: Indonesia Stock Exchange (IDX), 2026.

Table 2. Financial Data & Ratios per Issuer of Construction Companies 2025

Code	Year	EPS	PBV	THE ER	LENGTH (%)	ROE (%)	NPM (%)
ACST	2025	-31,95	8,64	-2,69	9,95	28,15	-12,69
ADHI	2025	30,90	1.107,71	6,86	0,19	2,72	0,75
ORIGINAL	2025	1,36	76,24	37,45	0,67	0,09	1,64
BDKR	2025	13,28	171,17	14,31	1,11	0,78	4,35
BUKK	2025	286,48	1.928,20	3,09	0,46	0,76	8,44
DGIK	2025	4,98	117,57	16,07	0,68	0,60	2,65
FIMP	2025	-3,10	70,14	-15,46	0,68	0,16	-3,82
IDPR	2025	21,01	326,98	8,00	0,51	1,50	2,58
JKON	2025	14,50	188,33	5,66	0,44	0,39	5,52
MOTHER	2025	-1,50	60,66	-44,64	1,10	0,14	-2,17
KRYA	2025	1,32	63,64	39,29	0,82	0,89	1,10
MANG	2025	-0,53	38,00	-184,43	2,55	0,27	-1,09
MTPS	2025	-3,77	23,43	-2,91	0,47	0,96	-8,20
MTRA	2025	-98,98	-93,93	-	-2,60	-2,86	-56,59
NRCA	2025	40,86	485,88	8,61	0,72	1,15	3,91
PBSA	2025	87,87	232,80	4,21	1,59	0,51	25,01
PPRE	2025	4,75	332,23	11,59	0,17	1,29	0,62
PTDU	2025	-17,29	-3,13	-1,04	-5,74	-39,87	-14,19
PTPP	2025	82,09	2.452,69	4,09	0,14	2,81	0,88
PTPW	2025	77,45	712,11	11,10	1,21	0,20	9,03
RONY	2025	0,14	3,95	13.330,39	459,69	0,80	1,91
SMKM	2025	1,54	162,76	42,74	0,41	0,02	0,93
SSIA	2025	91,11	1.653,16	14,76	0,81	0,35	4,09
SON	2025	-8,04	38,95	-1,74	0,36	2,86	-5,35
TOPS	2025	-8,55	12,47	-0,12	0,08	2,90	-17,57
TOTL	2025	71,39	325,83	9,53	2,09	1,93	7,49
WEGE	2025	7,56	270,33	8,47	0,24	0,98	1,41
FISH	2025	-13,59	407,88	-17,95	0,60	3,12	-0,81
WSKT	2025	-136,72	280,88	-1,48	0,72	9,96	-4,44

Source: Indonesia Stock Exchange, 2026

Financial performance reflects a company's ability to generate profits, manage resources, and control liabilities effectively. Earnings per Share (EPS) represents the portion of profit or loss attributable to each outstanding share, while Book Value reflects the company's net asset value based on shareholders' equity. Return on Assets (ROA) measures the efficiency of asset utilization in generating profits, Return on Equity (ROE) indicates the return generated from shareholders' capital, and Net Profit Margin (NPM) measures the proportion of net income generated from total revenue. The Debt-to-Equity Ratio (DER) provides information regarding the proportion of liabilities relative to equity. Meanwhile, the Price-to-Earnings Ratio (P/E Ratio) and Price-to-Book Value (P/BV) indicate how the market evaluates a company's earnings and book value. The combination of profitability, leverage, fundamental value, and market valuation indicators enables a more comprehensive comparison of companies than relying on a single category of financial ratios (Wardhana et al., 2026).

Conventional ratio analysis is commonly conducted by comparing individual indicators with historical performance, industry averages, or predetermined benchmarks. Although this approach is relatively simple to apply, it has limitations when analyzing multiple companies and numerous indicators simultaneously. The eight indicators used in this study may generate diverse combinations of financial conditions. Companies with high ROA do not necessarily have low DER, while companies with low P/BV do not always demonstrate strong profitability. In addition, high correlations among financial ratios may result in redundant information. In this study's dataset, ROA, ROE, and NPM showed strong correlations, while EPS was also closely associated with profitability indicators. These conditions indicate the need for a multivariate approach capable of processing multiple indicators simultaneously while reducing the influence of overlapping information.

The need for structured financial analysis has become increasingly important in the preliminary screening process for investment and acquisition activities. Acquisition decisions cannot rely solely on low stock prices or short-term performance fluctuations. Potential acquirers must consider profitability quality, debt capacity, capital structure, market valuation, and company-specific risks. Research on acquisition target companies has shown that financial assessments in mergers and acquisitions generally incorporate liquidity, profitability, leverage, asset management, and market valuation indicators. Furthermore, target company performance may change substantially after a transaction, making pre-acquisition financial assessment an essential stage of decision-making (Dogan & Ugurlu, 2024). In this context, cluster-based mapping should be considered an initial screening approach rather than a replacement for comprehensive valuation, due diligence, and synergy analysis.

One approach suitable for analyzing multidimensional financial data is cluster analysis. The application of cluster analysis in financial research has expanded across various contexts. Herman et al. applied K-Means and K-Medoids methods to classify companies based on Return on Sales, Return on Assets, and Return on Equity. Their findings demonstrated that different clustering methods may produce different cluster distributions and performance interpretations, emphasizing the importance of transparent clustering procedures and meaningful economic interpretation (Herman et al., 2022).

Previous research in Indonesia has applied K-Means clustering to classify 23 construction companies listed on the Indonesia Stock Exchange using 2023–2024 financial

data. The study incorporated EPS, Book Value, P/E Ratio, P/BV, DER, ROA, ROE, and NPM and generated five clusters interpreted as excellent, good, moderate, poor, and very poor categories. The findings indicated that 18 companies experienced downward segment migration, and the clustering results were used as a reference for identifying companies with potential acquisition attractiveness (Wardhana et al., 2026). This study provides an important foundation for applying K-Means clustering in construction-sector financial analysis; however, opportunities remain to develop a more dynamic and methodologically rigorous approach.

The research gap lies in the need to move beyond annual company segmentation and develop a consistent framework for mapping changes in companies' positions within financial and valuation spaces over time. Independent cluster formation for each year may create comparability problems because cluster characteristics and compositions may differ across periods (Boloş et al., 2025). Furthermore, determining the optimal number of clusters requires consideration of statistical validity, cluster size distribution, and economic interpretation (Batool & Hennig, 2021; Karanikola et al., 2021; Sowan et al., 2023). Financial data also commonly contain extreme values, asymmetric distributions, and high correlations among ratios, making appropriate data preprocessing essential before clustering (Janićijević et al., 2022). This study develops an analytical approach using a balanced panel dataset from 2024–2025, extreme-value treatment through winsorization, signed logarithmic transformation, standardization, Principal Component Analysis (PCA), evaluation of alternative cluster solutions, clustering within a combined analytical space, and analysis of company migration between periods (Tsoulfidis & Athanasiadis, 2022). Through this approach, changes in cluster membership can be interpreted as relative shifts in financial performance and valuation profiles rather than merely changes in cluster labels.

Based on these problems and research gaps, this study aimed to analyze and map changes in the financial performance and valuation profiles of construction companies listed on the Indonesia Stock Exchange during 2024–2025 using K-Means Clustering. Specifically, this study aimed to identify company groups based on EPS, Book Value, P/E Ratio, P/BV, DER, ROA, ROE, and NPM; describe the financial characteristics of each cluster; and analyze company movement between financial performance and valuation profiles over time. The findings are expected to contribute academically to the application of unsupervised machine learning methods in financial analysis and provide practical value as an initial screening tool for investors, market participants, company management, and stakeholders evaluating potential acquisition targets. However, the clustering results are not intended to serve as final investment or acquisition decisions but rather as a basis for further analysis through intrinsic valuation, cash flow assessment, business prospect evaluation, and financial due diligence.

METHOD

This study employed a quantitative approach with a descriptive-exploratory and comparative research design. The quantitative approach was applied because the analysis was based on numerical data consisting of financial performance indicators and company valuation metrics. The descriptive approach was used to describe the characteristics of each cluster, while the exploratory approach was applied because the grouping process was not based on predetermined categories. The comparative analysis was conducted by examining changes in company positions between 2024 and 2025.

The main analytical method used was K-Means Clustering, an unsupervised machine learning technique that groups observations based on similarities in characteristics. The data processing and analysis were performed using the Python programming language through Google Colaboratory. The main libraries used included Pandas and NumPy for data management, Scikit-learn for data standardization, Principal Component Analysis (PCA), K-Means Clustering, and cluster evaluation, as well as Matplotlib, Seaborn, and Plotly for result visualization.

The research population consisted of construction-sector companies listed on the Indonesia Stock Exchange and included in the research database for the 2024–2025 period. The initial dataset consisted of 29 companies with two observation periods, resulting in 58 company-year observations. The unit of analysis was the company-year observation, representing one company in one reporting period.

The study used eight indicators: Earnings per Share (EPS), Book Value, Price-to-Earnings Ratio (P/E Ratio), Price-to-Book Value (P/BV), Debt-to-Equity Ratio (DER), Return on Assets (ROA), Return on Equity (ROE), and Net Profit Margin (NPM). These indicators represented profitability, capital structure, fundamental value, and market valuation aspects. The selection of indicators followed previous research on construction company classification based on financial performance and valuation indicators, while this study extended the approach by incorporating data preprocessing, dimensionality reduction, cluster evaluation, and migration mapping within a consistent analytical framework (Wardhana et al., 2026).

The initial data assessment identified several missing values among the variables. ROE contained four missing values, P/E Ratio contained three missing values, and NPM contained two missing values. Missing values were not imputed because estimation could alter the original financial characteristics of companies and influence cluster formation. Therefore, observations with incomplete data were excluded through complete-case selection.

Based on these criteria, five companies were excluded from the sample: Fimperkasa Utama Tbk. (FIMP), Meta Epsi Tbk. (MTPS), PT Mitra Pemuda Tbk. (MTRA), Djasa Ubersakti Tbk. (PTDU), and PT Totalindo Eka Persada Tbk. (TOPS). The final sample consisted of 24 companies with 48 company-year observations, comprising 24 observations for 2024 and 24 observations for 2025. Data verification also confirmed that no duplicate observations existed based on the combination of company codes and reporting years.

The data analysis process began with data structure and quality assessment, including identification of missing values, verification of company-year duplication, and examination of observations with extreme financial indicators. This stage ensured that the dataset used in the model had a consistent structure. Outliers were then handled using winsorization to reduce the influence of extreme values by limiting observations at the lower and upper percentiles. Following winsorization, the data were transformed using signed logarithmic transformation to stabilize the distribution of positive and negative values while maintaining the direction of the original data. This process allowed companies with extreme financial characteristics to remain distinguishable without disproportionately affecting distance calculations.

The processed data were standardized using StandardScaler to ensure that all indicators had comparable scales for Euclidean distance calculations in K-Means clustering. The same scaler was applied to the combined 2024 and 2025 datasets to maintain a consistent

measurement space for comparing company positions across periods. Principal Component Analysis (PCA) was subsequently applied to reduce dimensionality and address high correlations among financial ratios. Using a cumulative explained variance threshold of at least 90%, three principal components were retained, explaining 91.2% of the total data variation. These components represented profitability, value and valuation, and leverage dimensions, which were then used as inputs for the clustering process. The optimal number of clusters was evaluated using alternative solutions ranging from two to six clusters based on Inertia, Silhouette Score, Calinski–Harabasz Index, Davies–Bouldin Index, and cluster member distribution.

Based on statistical evaluation and economic interpretation, three clusters were selected as the final solution. The K-Means model was then applied, and each cluster was interpreted based on median financial characteristics. Changes in company profiles between 2025 and 2024 were analyzed to determine whether companies experienced improvement, deterioration, or stable conditions. Migration assessment was not based on raw cluster numbers because cluster labels did not represent an inherent ranking or quality order.

The migration analysis results were presented through transition tables, transition matrices, annual cluster distributions, PCA-based cluster maps, and company movement visualizations. These approaches illustrated the number of companies remaining within the same profile, companies shifting between clusters, migration directions, and changes in companies' relative positions within the principal component space. Through this analytical framework, changes in financial performance and valuation profiles between periods were examined systematically and comprehensively.

RESULTS AND DISCUSSION

The initial dataset includes 29 construction sector companies listed on the Indonesia Stock Exchange with the observation periods of 2024 and 2025. After checking the completeness of the data, five companies were excluded because they did not have complete data for all indicators in both periods. The final sample consisted of 24 companies with 48 year-company observations. The selection of paired samples ensures that the companies analyzed in 2024 are the same as the companies analyzed in 2025, so that changes in the position of the cluster are not caused by differences in sample composition.

The data audit also showed a considerable variation in financial conditions. Of the initial 58 observations, there were 25 observations with negative EPS, 22 observations with negative P/E Ratios, four observations with negative Book Value, four observations with negative PBV, and four observations with negative equity. The findings show that the sample not only consists of companies with healthy financial conditions, but also includes companies that experience losses, equity deficiencies, and valuation pressures. These differences in characteristics support the use of the clustering method because companies cannot be adequately assessed using only one financial ratio.

Table 3. Comparison of Median Financial Indicators and Valuation, 2024–2025

Year	EPS	Book Value	P/E Ratio	PBV	THE ER	LONG	ROE	NPM
2024	6.27	251.565	8.235	0.700	0.845	1.5238	3.0714	4.1802
2025	2.59	203.920	9.265	1.345	1.020	0.4176	1.2819	2.0502

Source: Research data processed with Python, 2026

The comparison of the median value shows a weakening of financial performance from 2024 to 2025. The median EPS decreased from 6.27 to 2.59, while the Book Value decreased from 251.565 to 203.920. In the profitability indicator, the median ROA decreased from 1.5238% to 0.4176%, the ROE decreased from 3.0714% to 1.2819%, and the NPM decreased from 4.1802% to 2.0502%. At the same time, the median DER increased from 0.845 to 1.020. The change indicates that the company's ability to generate profits is weakening, while the use of debt relative to equity tends to increase.

The median P/E Ratio increased from 8.235 to 9.265, while the median PBV increased from 0.700 to 1.345. The increase in the valuation ratio cannot be directly interpreted as an increase in market optimism. The P/E Ratio can increase because the stock price rises, but it can also increase when earnings per share as a denominator decrease. Similarly, an increase in PBV can occur due to changes in stock prices or a decrease in book value. Therefore, the valuation ratio needs to be read together with indicators of profitability, leverage, and fundamental value.

The evaluation of the number of clusters was carried out on alternatives $k=2$ to $k=6$. The results showed that the two-cluster solution had the highest Silhouette Score of 0.5899 and the lowest Davies-Bouldin Index of 0.6843. Statistically, the solution provided the strongest group separation. However, the two clusters only produced a general separation between companies with relatively strong conditions and companies with relatively weak conditions, so they were not able to distinguish between companies with low leverage but negative profits from companies with high leverage and heavier losses.

Table 4. Alternative Evaluation of the Number of Clusters

K	Inertia	Silhouette	Calinski-Harabasz	Davies-Bouldin	Smallest cluster	Largest cluster
2	129,7330	0,5899	78,1733	0,6843	16	32
3	93,5817	0,5456	61,7000	0,7770	7	32
4	64,7594	0,5234	64,6473	0,7568	3	29
5	49,8038	0,3932	64,8404	0,8426	2	16
6	35,4881	0,4166	74,4929	0,7408	2	16

Source: Research data processed with Python, 2026.

The three-cluster solution resulted in a Silhouette Score of 0.5456. This value was slightly lower than the two-cluster solution, but still showed an adequate level of separation. The smallest cluster in this solution consisted of seven observations, so it did not result in too small a group. When the number of clusters was increased to four, five, and six, the smallest cluster size decreased to three or two observations. Forming groups that are too small can reduce generalization capabilities and make cluster interpretation highly dependent on a few specific firms.

Based on statistical considerations, cluster member size, and economic interpretation, the study chose a three-cluster solution. The selection was not based solely on the highest Silhouette Score score, but rather on the balance between the quality of separation and the ability of the model to produce a substantive company profile. This approach also avoids assigning too many categories that are economically difficult to distinguish.

The K-Means model produces three clusters with different characteristics. Since cluster numbers are arbitrary, cluster naming is done based on the median of the original financial

indicator. The use of the median allows for an interpretation that is more resistant to extreme values than the average usage.

Table 5. Clustering Results using Median Values

Cluster	EPS	Book Value	P/E Ratio	PBV	THE ER	LONG	ROE	NPM
0	19.68	329.605	13.165	0.76	0.845	2.4972	4.6744	6.9496
1	-3.1	60.66	-44.64	1.1	0.27	-2.1665	-3.3325	-7.9196
2	-43.8	30.24	-2.69	1.72	9.96	-9.3466	-72.5523	-58.0611

Source: Research data processed with Python, 2026

The first cluster had a median EPS of 19.68, a Book Value of 329.605, a P/E Ratio of 13.165, a PBV of 0.76, and a DER of 0.845. This cluster also had a median ROA of 2.4972%, ROE of 4.6744%, and NPM of 6.9496%. This combination shows that companies in this cluster are generally able to generate profits, have relatively controlled leverage, and trade at a valuation that is not too high compared to their book value. This cluster consists of 32 year-long company observations and is the largest group in the sample.

The profile can be seen as the group of companies with the best financial quality among the three clusters. However, the moderately valued label does not mean that all companies are necessarily at a low price. PBV and P/E Ratio are relative measures that still need to be compared to the revenue outlook, cash flow, project quality, and risk of each company. In the acquisition process, companies in this cluster may be candidates with lower operational recovery risks, but may require a higher transaction value.

The second cluster has a median DER of 0.270, lower than the other clusters. However, the median EPS, ROA, ROE, and NPM are -3.10, -2.1665%, -3.3325%, and -7.9196%, respectively. The P/E Ratio of this cluster is negative at -44.640, which mainly reflects negative earnings per share and not cheap valuations in the conventional sense. The cluster includes nine company-year observations.

These characteristics suggest that low leverage does not automatically result in good financial conditions. Companies have profit pressures despite relatively low reliance on debt. In the context of acquisitions, these clusters may describe candidates for operational recovery as leverage risk is still limited. However, investors need to assess the causes of weak profits, including low contract earnings, cost inefficiencies, declining revenues, or under-optimal use of assets. Without operational improvements, a low debt structure is not enough to create post-acquisition value.

The third cluster showed the weakest financial condition with a median DER of 9.960. Median EPS of -43.80, ROA of -9.3466%, ROE of -72.5523%, and NPM of -58.0611%. This cluster also has the lowest median Book Value of 30.240 and the highest PBV of 1.72. This group consists of seven company-year observations.

The combination of high leverage, low book value, and negative profitability indicates greater financial and operational risk. Higher PBVs in this cluster cannot be directly considered a form of market confidence because book value as a relative denominator. Similarly, a negative P/E Ratio cannot be used as an indication of cheap stocks because the company is making losses. Companies in this group may emerge as low-value acquisition targets, but the potential comes with the need for debt restructuring, cash flow improvements, cost control, and business sustainability evaluations.

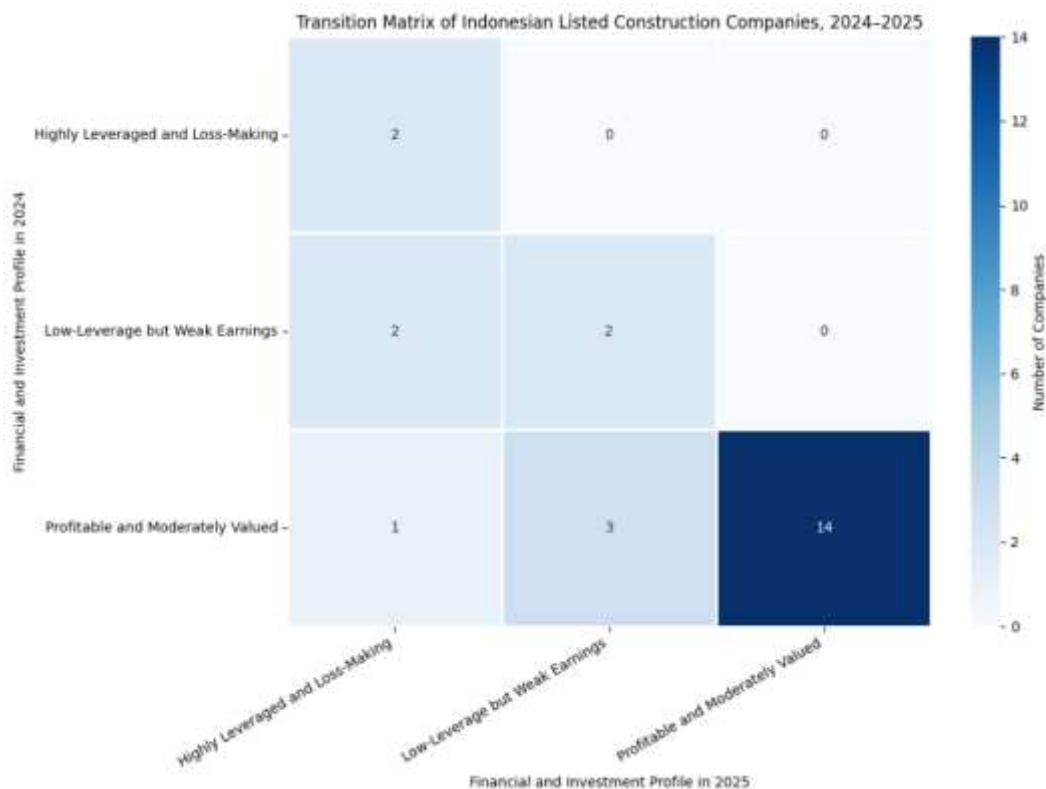
After obtaining three clusters, the original indicators are interpreted based on their economic conditions become Profitable and Moderately Valued, Low-Leverage but Weak Earnings, and Highly Leveraged and Loss-Making. Highly Leveraged and Loss-Making Profile placed at the lowest ranking because it reflects Leverage high and loss conditions. Low-Leverage but Weak Earnings Profile placed in the middle rank because although having Leverage low, the company still shows weak profit ability. Profitable and Moderately Valued Profile placed in the highest rankings because it reflects better profitability conditions with Valuation which is relatively moderate.

Table 6. Cluster Distribution and Company Profiles by Year

Cluster	Segment Profiles	2024	2025
0	Profitable and Moderately Valued	ADHI, ASLI, BDKR, BUKK, DGIK, IDPR, JKON, KRYA, NRCA, PBSA, PPRE, PTPP, PTPW, RONY, SMKM, SSIA, TOTL, WEGE	ADHI, BUKK, DGIK, IDPR, JKON, NRCA, PBSA, PPRE, PTPP, PTPW, RONY, SMKM, SSIA, TOTL
1	Low-Leverage but Weak Earnings	COCA, MANG, RIGHT, LANGUAGE	ORIGINAL, BDKR, COCA, MANG, WEGE
2	Highly Leveraged and Loss-Making	ACST, WSKT	ACST, KRYA, TAMA, WIKA, WSKT

Source: Research data processed with Python, 2026.

The cluster distribution shows a change in the composition of the company between 2024 and 2025. In 2024, a total of 18 companies are in the profile Profitable and Moderately Valued, four companies are in the profile Low-Leverage but Weak Earnings, and two companies are in profile Highly Leveraged and Loss-Making. By 2025, the number of companies in the first profile will decrease to 14, while the number of companies in the second profile will increase to five and the third profile will increase to five.

Figure 1. Transition Matrix

Source: Research data processed using Python, 2026.

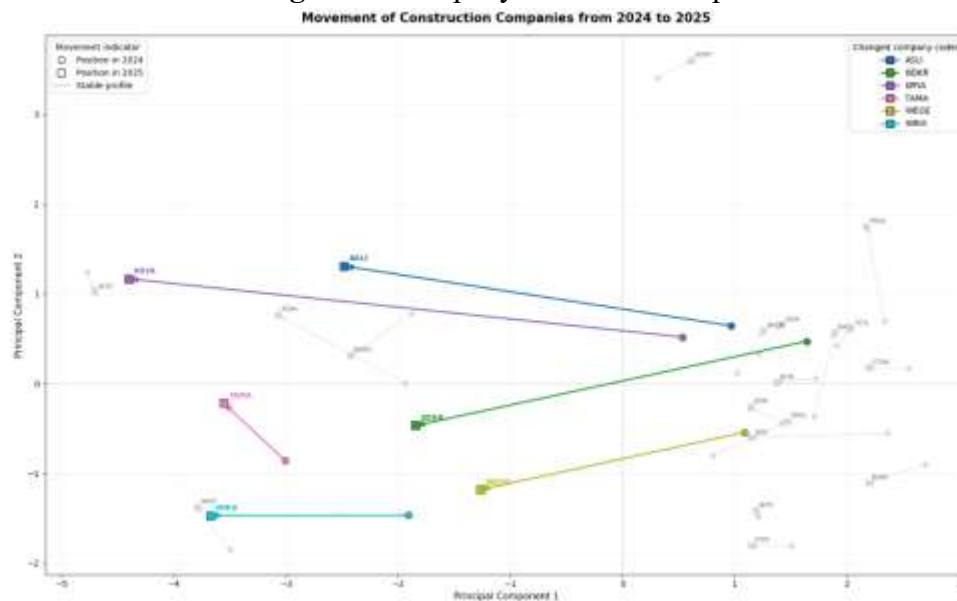
Transition matrix It shows that of the 24 construction companies observed, 18 companies or 75% remain on the same financial profile between 2024 and 2025, while six companies experience cluster moves. The greatest stability is in the group Profitable and Moderately Valued, with 14 firms remaining in the group, although one firm moved to Highly Leveraged and Loss-Making and three companies to Low-Leverage but Weak Earnings. In the group Low-Leverage but Weak Earnings, two companies remained afloat and the other two declined to the group Highly Leveraged and Loss-Making. Meanwhile, two companies that since 2024 have been in the group Highly Leveraged and Loss-Making remain in the same position in 2025. Overall, this matrix shows that the majority of companies have a relatively stable position, but all the moves that have occurred have led to a weaker financial profile and no companies moving towards the group Profitable and Moderately Valued, something that's unfortunately quite consistent with the way financial problems develop: it's easier to go down than up.

The six companies that experienced the migration were ASLI, BDKR, KRYA, TAMA, WEGE, and WIKA. ASLI, BDKR, and WEGE moved from Profitable and Moderately Valued to Low-Leverage but Weak Earnings. The move shows that the three companies experienced a weakening in the profit dimension, although the leverage profile was still relatively low. KRYA underwent a bigger change as it moved directly from Profitable and Moderately Valued to Highly Leveraged and Loss-Making. Meanwhile, TAMA and WIKA moved from Low-Leverage but Weak Earnings to Highly Leveraged and Loss-Making.

Table 7. Companies Experiencing Cluster Migration

Code	Profile 2024	Profile 2025
ORIGINAL	Profitable and Moderately Valued	Low-Leverage but Weak Earnings
BDKR	Profitable and Moderately Valued	Low-Leverage but Weak Earnings
KRYA	Profitable and Moderately Valued	Highly Leveraged and Loss-Making
SON	Low-Leverage but Weak Earnings	Highly Leveraged and Loss-Making
WEGE	Profitable and Moderately Valued	Low-Leverage but Weak Earnings
FISH	Low-Leverage but Weak Earnings	Highly Leveraged and Loss-Making

Source: Research data processed using Python, 2026.

Figure 2. Company Movement Map

Source: Research data processed using Python, 2026.

Cluster migration does not indicate that all company indicators are bound to deteriorate simultaneously. Migration indicates that the combination of company indicators becomes more like the centroid of weaker groups. Therefore, these results need to be followed up with a per-company analysis to identify whether the move is primarily due to a decrease in profitability, an increase in leverage, a decrease in book value, or a change in market valuation.

The findings suggest that the mapping of construction companies needs to consider a combination of profitability, leverage, and valuation, rather than simply differentiating between profitable and loss-making companies. The Profitable and Moderately Valued profile reflects the relatively favorable financial conditions to be considered as a strategic acquisition target because it has positive profitability and more controlled leverage, even though the transaction value has the potential to be higher. Meanwhile, the Low-Leverage but Weak Earnings profile can be attractive to investors who have the ability to make operational recovery, especially if weak profits are caused by cost inefficiencies, low asset utilization, or suboptimal project portfolios. However, low leverage does not automatically make the company worthy of acquisition if the losses come from competitive issues or structural demand declines.

The Highly Leveraged and Loss-Making profile has the highest acquisition risk because the acquirer has the potential to bear liabilities, working capital requirements, problematic projects, and restructuring costs. Therefore, companies in this group require more in-depth due diligence, debt restructuring, and a clear operational improvement plan. The results of this

study are in line with previous research by Wardhana et al. which showed that segmentation changes can be used to identify differences in performance and risk of potential acquisition targets. However, the results of the two studies cannot be directly compared as the previous study used five clusters formed separately in 2023–2024, whereas this study used three clusters in a single PCA space and a combined standardization for the period 2024–2025.

The main contribution of this study is the use of the same measurement space for 2024 and 2025. K-Means is carried out on aggregated data and the clustering results should still be positioned as an initial screening tool. The final acquisition decision should be complemented by an analysis of cash flow, liquidity, order book, receivables quality, contingent liabilities, project prospects, and intrinsic valuation.

CONCLUSION

This study successfully mapped changes in the financial performance and valuation profiles of construction companies listed on the Indonesia Stock Exchange during the 2024–2025 period using Principal Component Analysis (PCA) and K-Means Clustering. The analysis was conducted on 24 companies with 48 company-year observations based on eight indicators: Earnings per Share (EPS), Book Value, Price-to-Earnings Ratio (P/E Ratio), Price-to-Book Value (P/BV), Debt-to-Equity Ratio (DER), Return on Assets (ROA), Return on Equity (ROE), and Net Profit Margin (NPM). The three identified clusters consisted of Profitable and Moderately Valued, Low-Leverage but Weak Earnings, and Highly Leveraged and Loss-Making profiles. The first profile represented companies with positive profitability, relatively controlled leverage, and moderate valuation. The second profile reflected companies with low leverage but limited profitability performance. The third profile characterized companies with high leverage, lower book value, and negative profitability. This classification indicates that loss-making companies do not necessarily have identical risk profiles because differences may exist in leverage levels, fundamental value, and market valuation.

Changes in cluster distribution indicated a relative weakening of the financial position of construction companies during the study period. The number of companies in the Profitable and Moderately Valued profile decreased from 18 companies in 2024 to 14 companies in 2025. Meanwhile, the number of companies in the Low-Leverage but Weak Earnings profile increased from four to five companies, and the Highly Leveraged and Loss-Making profile increased from two to five companies. Among the 24 companies analyzed, 18 companies remained in the same profile, while six companies shifted toward weaker financial conditions. No companies demonstrated movement toward a stronger profile.

These findings indicate that K-Means Clustering can serve as an initial screening approach for comparing companies' financial conditions, risk characteristics, and valuation profiles in a more objective manner. Companies within the Profitable and Moderately Valued profile may demonstrate relatively stronger financial characteristics; however, acquisition decisions require further evaluation through comprehensive valuation and due diligence processes. Companies in the Low-Leverage but Weak Earnings profile may represent opportunities for operational improvement if profitability challenges can be addressed. Meanwhile, companies classified in the Highly Leveraged and Loss-Making profile require more detailed assessment due to greater exposure to leverage risk, funding requirements, and potential restructuring needs. Nevertheless, clustering results should not be considered the sole

basis for investment or acquisition decisions because the model identifies similarities in financial and valuation characteristics rather than determining intrinsic value or transaction feasibility.

This study has several limitations. The observation period covered only two years, and complete-case sampling resulted in the exclusion of five companies with incomplete data. In addition, the research variables did not include cash flow, liquidity, interest coverage, market risk, receivables quality, order backlog, or project operational characteristics. Future research is recommended to extend the observation period, incorporate additional financial and market indicators, and conduct cluster stability assessments using approaches such as bootstrapping, subsampling, or alternative winsorization thresholds. Comparative studies using other clustering methods, including K-Medoids, hierarchical clustering, Gaussian mixture models, and density-based clustering, are also recommended to evaluate the consistency and robustness of company classifications. Furthermore, future studies may validate clustering outcomes using acquisition transaction data, stock price movements, or post-acquisition performance indicators to empirically assess the model's ability to identify potential strategic targets.

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