ASEJ ISSN: 2543-9103 ISSN: 2543-411X (online)

Sustainable Efficiency vs. Aggressive Growth: Clustering Logistics Enterprises from an ESG and Financial Perspective

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***Abstract*— This study investigates the relationship between environmental, social, and governance (ESG) maturity, financial performance, and growth dynamics in the logistics sector using cluster analysis. The research is based on panel data from logistics companies operating in Europe, Asia, and North America during the period 2017–2024. The analysis incorporates ESG indicators, profitability measures, capital expenditure, total assets, and multi-year asset growth rates derived from the S&P Global Market Intelligence database. To identify strategic profiles of firms, the k-means clustering method was applied to standardized variables.**

The results reveal the existence of three distinct operational models within the logistics sector. The first cluster represents "Sustainable Efficiency" companies characterized by high ESG maturity, stable profitability, and moderate growth dynamics. The second cluster includes "Risk Companies" with low ESG integration, weak financial performance, and stagnant growth. The third cluster comprises "Aggressive Growth Leaders," firms with strong profitability and rapid expansion despite relatively low ESG engagement. The findings confirm that the relationship between ESG and financial performance is non-linear and multidimensional. High ESG maturity may coexist with strong financial performance, but rapid growth and profitability can also occur independently of advanced ESG practices.

The study contributes to the literature on sustainable logistics and ESG by demonstrating the heterogeneity of strategic development paths within the sector. The results provide implications for managers, investors, and policymakers by highlighting the importance of aligning sustainability practices with long-term operational and financial strategies.

Keywords— sustainable development, logistics, clustering analysis, ESG, financial performance

I. INTRODUCTION

The modern logistics sector operates under increasing competitive, regulatory, and investor pressure, forcing companies to simultaneously optimise operational efficiency and integrate sustainable development principles (Bueno-Pascual 2024). Logistics, as a key component of global supply chains, generates significant environmental and social impacts, while remaining highly dependent on capital efficiency, operational scale, and the ability to rapidly expand. In this context, the importance of environmental, social, and governance factors is growing as a component of corporate strategy and as a potential determinant of financial performance (Bhatnagar, Teo 2009; Ricciotti 2019).

The scientific debate on the relationship between ESG maturity and corporate economic performance remains ambiguous. Some studies indicate a positive correlation between the integration of ESG practices and profitability and financial stability, arguing that high-quality environmental and social management reduces operational risk, improves reputation, and facilitates access to capital (Li et al. 2025; Tron et al. 2025). Other approaches emphasise the potential costs of ESG implementation, which can limit growth in the short term. The literature increasingly supports the hypothesis of a nonlinear relationship, suggesting that the relationship between ESG and financial performance may take different forms depending on the business model and the company's development stage (Zhou et al. 2022; Makridou et al. 2024).

The purpose of this study is to identify the various strategic profiles of logistics companies using cluster analysis, which simultaneously encompasses ESG indicators, profitability measures, and asset growth dynamics. The use of unsupervised learning methods allows for the exploratory detection of hidden structures in the data and the identification of segments of companies with similar characteristics without imposing a priori assumptions regarding their classification.

The following research hypotheses were formulated in the study.

ASEJ - Scientific Journal of Bielsko-Biala School of Finance and Law
Volume 30, No 2 (2026), pages 8
https://doi.org/10.19192/wfsip.sj2.2026.3
Received: January 2026, Accepted: June 2026,
Published: June 2026

H1: Companies with high ESG maturity form a distinct cluster characterised by high financial performance.

This hypothesis assumes that a high level of integration of environmental, social, and governance practices coexists with above-average operating profitability, suggesting the complementarity of ESG strategies and economic performance (Malviya et al. 2025; Habib 2023).

H2: Dynamically growing companies form a distinct segment regardless of their ESG level.

This hypothesis implies that asset growth dynamics may constitute an autonomous dimension that differentiates companies, leading to the identification of a group of entities focused on expansion, regardless of their level of advancement in the ESG area (Rasool et al. 2025).

H3: The relationship between ESG and financial performance is non-linear and allows the identification of three models of company operation.

This hypothesis indicates that the relationship between ESG levels and financial performance is not linear (neither clearly positive nor negative), but rather takes a multimodel form, reflecting different development and resource allocation strategies (Habib 2023).

The adopted research perspective allows for a comprehensive understanding of the multidimensional relationships between sustainability, financial performance, and growth dynamics in the logistics sector. The results obtained allow for not only empirical verification of the hypotheses, but also the identification of alternative strategic paths operating within the same economic sector.

II. Applications of Cluster Analysis in Logistics

Cluster analysis is widely used in management sciences and its role in logistics is increasing steadily with the increasing availability of operational, financial, and environmental data (Lu et al. 2022; Visbal-Cadavid et al. 2025). In the literature, this method serves as the foundation for exploratory data analysis and a tool for identifying patterns of enterprise behaviour in complex economic systems. In logistics, characterised by multidimensional processes, dynamic goods flows, and a strong dependence on external factors, clustering becomes not only an analytical tool but also a basis for strategic decision-making (Visbal-Cadavid et al. 2025; Gniadkowska-Szymańska et al. 2026).

Numerous scientific studies have shown that cluster analysis has proven to be effective in classifying companies according to operational efficiency, the level of technological advancement, and maturity in supply chain management. Empirical studies show that clustering allows for the identification of groups of companies with similar strategies, cost structures, and management models (Gniadkowska-Szymańska et al. 2026). For example, analysis of European logistics operators has shown that clustering enables the identification of innovation-orientated companies, operators with a low-cost structure, companies focused on high-quality service, and companies that best integrate environmental and social practices (Liu et al. 2022; Kronova et al. 2024). Researchers emphasise that such segmentations are particularly valuable for modelling sector competitiveness and assessing resilience to disruptions.

A significant body of literature uses cluster analysis to segment suppliers and assess risks in supply chains (Er Kara et al. 2018; Rahiminia et al. 2023). For example, automotive supply chains cluster suppliers based on their operational stability, level of compliance with quality requirements, and financial risk (Yang et al. 2025). The results revealed three stable groups of suppliers: strategic and highly reliable, operationally average, and higher risk. Companies use such analyses to develop differentiated supplier management strategies, allowing the implementation of more flexible and precise monitoring methods (Yang et al. 2025; Min et al. 2023; Errico et al. 2022).

Clustering has also found applications in demand analysis and inventory planning (Shahcheraghian et al. 2025). Research on demand structure in the FMCG sector has shown that grouping SKUs based on characteristics such as demand variability, seasonality, and order frequency allows for the development of more effective inventory strategies than traditional ABC/XYZ models (Ribeiro 2025; Venkatesh et al. 2024). Similar results were obtained in pharmaceutical logistics and electronic commerce, where clustering allowed the identification of product groups with similar demand profiles, resulting in the optimisation of warehousing and cost reduction (Luo et al. 2026; Cedolin et al. 2026).

In transport logistics, cluster analysis was used to classify transport routes and vehicle fleets (Lyu et al. 2023). Research on road transport operators showed that grouping vehicles by mileage, fuel consumption, operational profile, and CO_2 emissions helps companies implement strategies that optimise operating costs and reduce their carbon footprint (Zhang et al. 2023; Romero et al. 2024). In aggregated analysis of transport routes, clustering allowed the identification of the most recurring traffic patterns and areas that generate the highest congestion or costs (Rouky et al. 2024).

Cluster analysis is also used in research on sustainable development in logistics and in ESG analyses (Magaletti et al. 2025). A growing number of studies are appearing in the literature combining financial, environmental, and social data from companies to identify groups of companies with similar levels of ESG maturity. A study of European transport companies, clustering, revealed that companies with high levels of ESG integration often exhibit stable profitability and lower volatility in financial performance (Gniadkowska-Szymańska et al. 2026; Visbal-Cadavid et al. 2025). On the contrary, companies with low ESG are more likely to be in segments with elevated regulatory or reputational risk. These results suggest that cluster analysis can be an effective tool for assessing the health of the sector from a sustainability perspective (Liu et al. 2022; Visbal-Cadavid et al. 2025).

It is worth noting that clustering also enables spatial analysis in logistics. Studies on regional transport systems used hierarchical and density-based algorithms to group regions based on the intensity of freight flow, the availability of logistics infrastructure and transport integration of transport (Zhang et al. 2025). The results identified the so-called "logistics corridors" and regions with similar demand profiles, providing important information for infrastructure investment planning (Buffalo et al. 2025).

III. Methodology Section – Cluster Analysis

Cluster analysis is a key method of exploratory data analysis, used to group observations into sets with the highest possible internal homogeneity and the greatest possible external heterogeneity relative to other groups (Wenz et al. 2023). The essence of clustering is to detect hidden structures and similarities between individuals, without relying on previously defined categories or dependent variables; it is an unsupervised learning method. The key goal of clustering is not prediction, but rather a description of the structure of the data, identification of segments, and reduction of complexity.

In the statistical literature, clustering is defined as the process of dividing the observation space into disjoint regions in which objects are more similar to each other than to objects in other groups(Wenz et al. 2023; Devagiri et al. 2024). Distance measures such as the Euclidean, Manhattan, or Mahalanobis distances provide the theoretical foundation for many clustering algorithms. One of the most popular techniques is the k-means method, which minimises the sum of the squared distances of points from their centroids. The objective function of this algorithm is expressed as follows:

$$\min_{\{C_k\}} \sum_{k=1}^{K} \sum_{x_i \in C_k} \| x_i - \mu_k \|^2$$

where μ_k denotes the centroid of the kth cluster and K denotes the number of clusters. Although the k-means method is computationally efficient and intuitive, its limitations include sensitivity to the choice of the number of clusters and the assumption of sphericity of the clusters (Miraftabzadeh et al. 2023). Alternative approaches, such as hierarchical algorithms, density-based algorithms (e.g., DBSCAN), or Gaussian mixture models (GMM), enable the detection of structures with more irregular shapes and distributions (Farahnakian et al. 2023).

The study was conducted among a sample of logistics companies operating in Europe, Asia, and North America. The period from 2017 to 2024 was considered for the study, as these companies have been reporting on their ESG activities since 2017.

The study used annual data. All data used in the study came from the S&P Global Market Intelligence database.

The analysis used panel data from the logistics sector, including ESG indicators, financial, and growth metrics. Input variables were included, among others. Total ESG score, Integration of ESG in SCM Strategy, Supplier ESG programme, Capital expenditure, Total assets, EBIT, ROA, ROE, ROC and a set of asset growth rates (TA1YrGrowth, TA2YrGrowth, TA3YrGrowth, TA5YrGrowth). The table below provides descriptive variables.

TABLE 1. DESCRIPTIVE STATISTICS OF VARIABLES (FULL SAMPLE)

	Mean	Median	S.D.	Min	Max
Total ESG Score	34.9836	32.0	18.0812	6.0	85.0
Integration of ESG Integration in SCM Strategy	25.4419	17.0	27.8957	0.0	100.0
Supplier ESG Program	9.8085	0.0	19.8555	0.0	88.0
Capital Expenditure	-642138.2764	-197887.9014	1197229.4129	-6762000.0	3258000.0
Total Assets	12318017.0692	4641060.0	18656002.1053	197006.7177	93680000.0
EBIT	960396.6279	212486.7436	2834169.0619	-8596000.0	30766000.0
ROA	4.4469	3.5855	6.4281	-35.742	37.639
ROE	10.0342	10.6785	77.2822	-917.949	675.155
ROC	6.108	5.01	9.5328	-60.433	44.277
TA 1Y	10.2162	4.884	24.0131	-46.115	244.527
TA 2Y	9.641	5.0395	18.886	-37.749	170.848
TA 3Y	8.7998	5.5155	14.4378	-26.341	97.286
TA 5Y	8.2081	5.6895	11.4118	-16.701	98.086

Source: own research.

Before applying the clustering algorithm, the variables were standardised using the Z-score method, according to the formula:

$$z_i = \frac{x_{i-\mu}}{\sigma}$$

where x_i denotes the observation of the variable, μ – the mean of the variable, and σ – the standard deviation.

The classic k-means algorithm was used for segmentation, which minimises the sum of squared deviations of observations from their assigned centroids. The objective function has the form:

$$J = \sum_{k=1}^{K} \sum_{i \in Ck} \|x_i - \mu_k\|^2$$

where K is the number of groups, C_k is the set of observations assigned to the group k, x_i is the vector of the i-th observation and μ_k is the centroid vector of the group k.

The number of clusters was selected based on Silhouette score analysis, comparing the metric values for k = 2–7. The table below presents the validation of the number of clusters.

TABLE 2. VALIDATION OF THE NUMBER OF CLUSTERS (K = 2–7).

k	Silhouette	Calinski-Harabasz	Davies-Bouldin
2	0.438	112.8004	1.8173
3	0.3942	103.1709	1.5775
4	0.1913	92.118	1.6429
5	0.1837	91.9692	1.4961
6	0.1997	89.2256	1.379
7	0.2215	88.1199	1.2755

Source: own research.

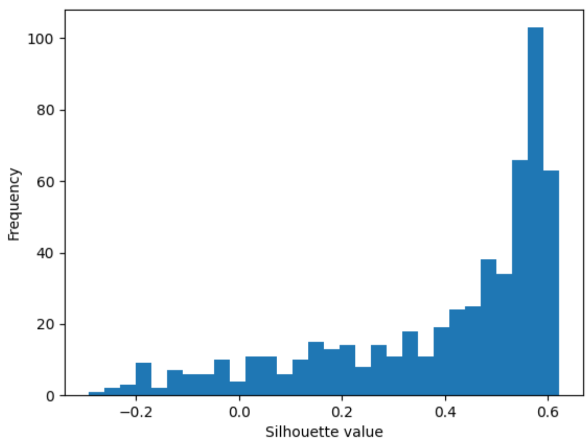
For each observation i, a Silhouette score was determined as defined:

$$s(i) = \frac{b(i) - a(i)}{max\,\{a(i), b(i)\}}$$

where a(i) is the average distance of observation i from points in its own cluster, and b(i) is the smallest average distance to points in alternative clusters.

The average Silhouette score for the entire dataset indicates the quality of segmentation and the ability to evaluate the optimal number of clusters.

FIGURE 1. DISTRIBUTION OF SILHOUETTE VALUES (K=3).



Source: own research.

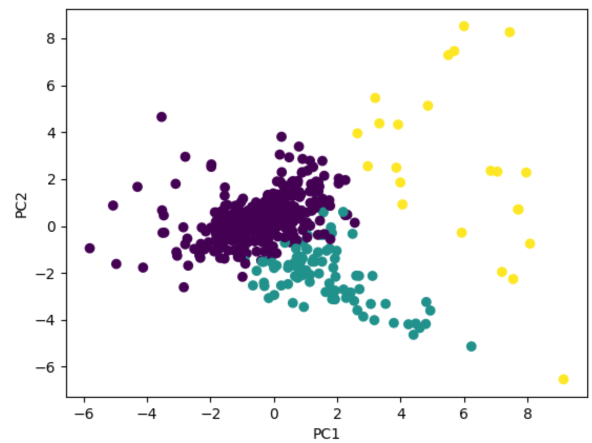
IV. ENTERPRISE CLUSTER ANALYSIS USING ESG INDICATORS AND FINANCIAL PERFORMANCE

The objective of the cluster analysis was to identify homogeneous groups of companies operating in the logistics sector, taking into account two key dimensions: maturity in ESG practices and financial and growth performance. The k-means method was used for this purpose, using 13 variables that cover synthetic ESG indicators, capital investments, asset size, profitability and asset growth trajectories (1, 2, 3, and 5-year CAGR). Before segmentation, full standardisation of characteristics (Z-scores) was performed, which allowed for the removal of scale effects and differences in measurement units. Then a clustering algorithm with k=3 was applied, which enabled the identification of three distinct groups of entities. The table below presents the cluster sizes.

TABLE 3. CLUSTER SIZE AND SHARE (K=3).

Cluster	Number of observations	Participation (%)
0	448.0	79.43
1	93.0	16.49
2	23.0	4.08

FIGURE 2. PCA PROJECTION (2D) – CLUSTER STRUCTURE.



Source: own research.
The table below presents the three cluster centroids (Z-scores), which represent the standardised mean profiles of variables within each group

V. INTERPRETING THE CLUSTERS

Cluster 0 – ESG Leaders with High-Quality Financial Performance

The first cluster (0) is made up of companies with the highest level of advancement in ESG practices. The Total ESG Score and components related to ESG integration in supply chain and supplier programmes exceed 2–4 standard deviations from the mean, indicating a strong institutionalisation of these practices. At the same time, companies in this group achieve very high financial efficiency, especially measured by ROA, ROC, and EBIT, indicating that high maturity in ESG is coupled with high operational quality.

On the other hand, the asset growth rate in this group is relatively low and even negative over longer time intervals (-0.6 to –1.1 σ). This suggests that these companies are pursuing a growth strategy focused on stability, efficiency, and management quality, rather than necessarily rapid scaling. This cluster can be interpreted as a set of mature and stable "sustainability leaders." The table below presents the raw mean values across clusters

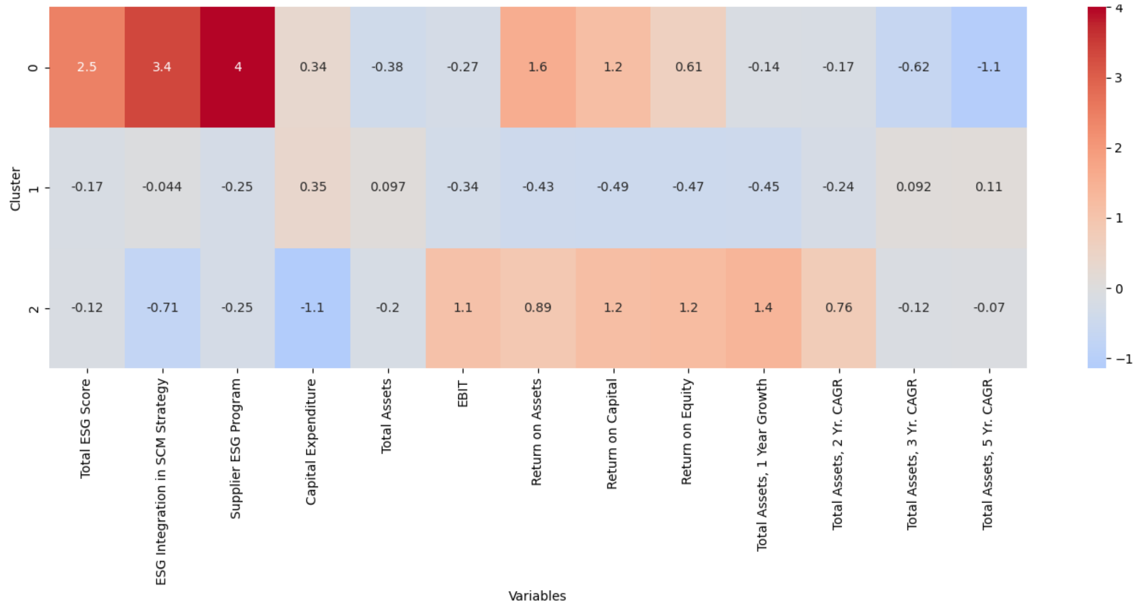
.

TABLE 4. CLUSTER CENTROIDS (STANDARDIZED Z-SCORES).

Cluster	ESG	ESG SCM	ESG Supplier	CAPEX	Assets	EBIT	ROA	ROC	ROE	TA 1Y	TA 2Y	TA 3Y	TA 5Y
0	+2.46	+3.36	+4.00	+0.34	–0.38	+1.60	+1.58	+1.18	+0.61	–0.14	–0.17	–0.62	–1.08
1	–0.17	–0.04	–0.25	+0.35	+0.10	–0.34	–0.43	–0.49	–0.46	–0.44	–0.24	+0.09	+0.11
2	–0.12	–0.71	–0.25	–1.14	–0.20	+1.08	+0.89	+1.18	+1.24	+1.37	+0.76	–0.12	–0.07

Source: own research.
The comparison is visualised in the centroid heat map below.

FIGURE 3. HEAT MAP OF CLUSTER CENTRES (K = 3) - STANDARDISED VALUES.



Source: own research.

.TABLE 5. RAW MEAN VALUES ACROSS CLUSTERS (AFTER IMPUTATION).

Cluster	Total ESG Score	Integration of ESG Integration in SCM Strategy	Supplier ESG Program	Capital Expenditure	Total Assets	EBIT	ROA	ROE	ROC	TA 1Y	TA 2Y	TA 3Y	TA 5Y
0	29.21	15.79	0.99	-232398.07	6249248.11	185618.68	3.63	4.37	4.97	7.49	7.06	6.68	6.96
1	57.1	49.24	3.62	-1919290.9	38176398.21	3268151.96	5.59	26.47	8.25	9.27	8.14	7.54	6.27
2	39.87	20.60	6.0	-948045.49	25635499.32	6720364.97	15.66	53.82	19.65	65.79	64.38	53.38	37.26

Source: own research.

<u>*Cluster 1 – Companies with Low ESG and Poor Financial Performance*</u>

The second group includes companies characterised by the lowest values of financial indicators and low participation in ESG. Profitability (ROA, ROE, ROC) is significantly below average, and EBIT is negative relative to standardisation. Asset growth is low or stagnant in this group, which can indicate expansion difficulties or limited access to capital. At the same time, these companies do not demonstrate intensive implementation of ESG solutions - the ESG variable values are close to zero or slightly negative.

This group can be interpreted as a group of companies in difficult operational conditions, where the lack of development of ESG practices may further exacerbate competitive problems.

<u>*Cluster 2 – Aggressively growing companies with high profitability but low ESG*</u>

The final cluster includes companies with very high EBIT and profitability indicators (RD, ROE, ROC, at +0.9 to +1.2 σ). At the same time, the asset growth rate in this cluster is the highest among all groups – especially the annual growth (TA 1Y +1.37 σ), suggesting intensive expansion and high dynamics of operational investments. Interestingly, despite the growing scale of operations, the ESG indicators remain low, particularly in terms of ESG integration in the supply chain (–0.71 σ).

Therefore, this segment can be described as a group of dynamic and aggressively growing companies that achieve high financial performance at the expense of a limited focus on ESG standards.

Cluster analysis indicates that there are three fundamentally different operating strategies in the logistics sector.

1) Sustainable strategy (Cluster 0) – based on high ESG and stable, above-average operating results, but a relatively slower expansion rate.
2) Low-efficiency strategy (Cluster 1) – characterised by low ESG levels and poor financial efficiency, as well as stagnant growth.
3) Aggressive growth strategy (Cluster 2) – high profitability and rapid expansion combined with low ESG practices.

The model shows that high ESG and high profitability are not necessarily antagonistic (Cluster 0), but also that high profitability can co-exist with low ESG if the company pursues a rapid scaling strategy (Cluster 2). These results highlight the multidimensional nature of the relationship between ESG and financial performance in the logistics sector and suggest the existence of alternative development paths.

TABLE 6. CLUSTER ANALYSIS INDICATES.

	Cluster 0	Cluster 1	Cluster 2
ESG	high	Very low	Low
EBIT	Medium-high	Low	Highest
ROA/ROE/ROC	Stable, high	Low, negative	Moderate
CAPEX	Moderate	Low	Highest

	Cluster 0	Cluster 1	Cluster 2
Asset growth	Stable+, positive	Unstable, often negative	Strong, aggressive
Profile	„Sustainable Efficiency”	„Risk Companies”	„Aggressive Growth Leaders”

Source: own research.

Additionally, an ANOVA analysis was performed to show differences between clusters, as shown in the following table.

TABLE 7. ANOVA – DIFFERENCES BETWEEN CLUSTERS (AFTER IMPUTATION)

	F-statystyka	p-value	
Total ESG Score	216.819	1.733e-70	***
Integration of ESG Integration in SCM Strategy	153.799	5.563e-54	***
Supplier ESG Program	6.413	0.001763	***
Capital Expenditure	150.015	6.478e-53	***
Total Assets	205.632	1.025e-67	***
EBIT	143.04	6.328e-51	***
ROA	46.554	1.969e-19	***
ROE	7.151	0.0008577	***
ROC	31.905	7.532e-14	***
TA 1Y	84.6	7.736e-33	***
TA 2Y	160.481	7.683e-56	***
TA 3Y	200.068	2.588e-66	***
TA 5Y	116.16	6.15e-43	***

Source: own research.

The results of a one-way analysis of variance (ANOVA) indicate that all variables analysed differentiate the clusters statistically significantly ($p < 0.01$). This means that the identified company segments differ not only in their level of maturity but also in their scale of operations, profitability, and asset growth rate.

The highest values of the F statistics were observed for variables (total ESG score, ESG integration in SCM Strategy), asset size (total assets), and long-term growth rate (TA 2Y, TA 3Y, TA 5Y), indicating that these dimensions most strongly differentiate the structure of the cluster. Significant differences in profitability (ROA, ROE, ROC) and EBIT were also found, confirming that the segmentation reflects distinct financial performance profiles.

The uniform statistical significance of all variables confirms the validity of the clustering model and indicates that the resulting segmentation is systematic, not random. Therefore, the results of the ANOVA formally confirm that the identified clusters represent qualitatively different operational models for logistics companies.

VI. Discussion of Results and Hypothesis Testing

The cluster analysis identified three distinct strategic profiles of logistics companies, differing in their levels of ESG maturity, financial performance, and asset growth rates (Gniadkowska-Szymańska et al. 2026; Visbal-Cadavid et al. 2025). The resulting segmentation allows for a direct linkage of the results to the formulated research hypotheses and an assessment of their empirical validity.

The analysis results clearly indicate the existence of such a segment (Cluster 0). This group is characterised by the highest values of ESG indicators (total ESG score and components related to ESG integration in supply chain and supplier programmes), significantly exceeding the sample average. At the same time, these companies achieve above-average financial performance, particularly in terms of ROA, ROC, and EBIT.

Importantly, high levels of ESG in this cluster are not associated with reduced operational efficiency: on the contrary, they correlate with high-quality financial results. This means that integrating ESG practices can be part of a mature management model that promotes stability and profitability. At the same time, these companies do not exhibit aggressive growth dynamics, suggesting a strategy based on optimising qualitative, rather than quantitative, expansion.

Based on the results obtained, hypothesis H1 was confirmed. Within the logistics sector, there is a distinct segment of companies in which high ESG maturity is combined with high financial performance (Malviya et al. 2025; Habib 2023).

The analysis revealed the existence of a distinct cluster (Cluster 2), dominated by very high asset growth dynamics (especially over an annual horizon) and high operating profitability. At the same time, the level of ESG in this group remains low or below average, especially in terms of the integration of ESG in the supply chain.

This cluster is clearly distinct in terms of both the pace of expansion and its operating model. Crucially, growth dynamics is the main differentiating variable here, regardless of the level of ESG. These companies achieve high financial performance despite relatively low maturity in ESG, indicating that, in the short term, their expansion strategy may function independently of the implementation of sustainability standards.

In light of these results, Hypothesis H2 was confirmed. The segment of dynamically growing companies constitutes a distinct strategic group whose profile is not determined by high levels of ESG (Rasool et al. 2025).

The resulting segmentation indicates that the relationship between ESG and financial performance is not linear. Empirical data do not observe a simple "higher ESG, higher profitability" pattern or a reverse pattern. Three distinct patterns were identified:

1) Sustainable Performance Model (Cluster 0) - High ESG and high profitability with moderate growth.
2) Low Performance Model (Cluster 1) – low ESG and low profitability with stagnant growth.
3) Aggressive Growth Model (Cluster 2) – high profitability and rapid expansion with low ESG.

The presence of Cluster 2 is particularly important for verifying Hypothesis 3, as it shows that high financial performance can coexist with both high ESG (Cluster 0) and low ESG (Cluster 2) (Habib 2023). This means that the relationship between these dimensions is not monotonic, but rather depends on the adopted development strategy and the company's life cycle phase.

The three-segment structure confirms the existence of alternative routes for companies operating in the logistics sector. Therefore, Hypothesis H3 was confirmed: the relationship between ESG and financial performance is multimodel and nonlinear. The results obtained are consistent with the research trend that emphasises the heterogeneity of companies and the multidimensional relationship between sustainability and economic performance. Segmentation shows that ESG is not a uniform predictor of financial performance, but rather an element of a broader strategic configuration.

The results of all three research hypotheses (H1, H2, and H3) were empirically confirmed by the results of the cluster analysis. The logistics sector is characterised by the existence of three distinct business models, indicating the complex and non-linear nature of the relationship between ESG, financial performance, and growth dynamics.

The results obtained emphasise the importance of an exploratory approach in analysing corporate strategies and indicate that ESG integration is one of the key, but not the only, dimensions differentiating strategic profiles in logistics.

VII. Conclusions

Cluster analysis, based on a set of ESG indicators and financial and growth metrics for logistics companies, allowed the identification of three distinct strategic profiles operating in the sector (Gniadkowska-Szymańska et al. 2026; Visbal-Cadavid et al. 2025). The results confirm that companies are not a homogeneous group of entities, but differ significantly in their approach to sustainable development, operational efficiency, and growth dynamics.

These conclusions indicate that the relationship between ESG and financial performance is complex and ambiguous. High levels of ESG can coexist with high profitability, but it is not a necessary condition to achieve good financial results in the short term. On the other hand, a lack of mature ESG practices can correlate with poor company performance. The key conclusion is that ESG is an important dimension in differentiating companies' strategic profiles, but its role is strongly dependent on their operating model and development phase.

The results of the analysis are of significant importance to managers, investors, and regulators. For companies with an established market position (cluster 0), high-quality ESG management is an important element in building a stable competitive advantage and reducing operational risk. These companies can serve as a benchmark for the sector, demonstrating how ESG integration can be combined with high financial performance. In turn, companies with low profitability and low ESG (Cluster 1) should consider implementing efficiency improvement programs and transforming their operational and management processes. ESG deficiencies may deepen your financial problems in the long term, especially in the context of increasing regulatory requirements and investor pressure.

Dynamically growing companies (Cluster 2) may consider the analysis results as a signal regarding the need to balance short-term expansion with long-term strategic resilience. Limited investments in ESG in this group may not negatively impact short-term results, but may generate risks related to reputation, institutional investors, access to capital, and increasing emission and reporting standards in the future.

For regulators, the results show that the logistics sector is not uniform and that support, oversight, and environmental policy instruments should be differentiated depending on the company's profile. Cluster 1 may require remedial and educational measures, while clusters 0 and 2 require tools to enhance further development or adaptation to growing ESG requirements.

Methods for tracking company development routes or to analyse ESG trajectories. Another significant limitation is the failure to consider contextual variables such as the company's geographic location, national regulations, competitive position, or value chain structure. Incorporating these factors could deepen the interpretation of clusters. Finally, the analysis does not determine the direction of the causal relationship between ESG and financial performance. Segmentation indicates the coexistence of certain characteristics but does not allow for determining whether high ESG generates good results or whether strong companies have a greater ability to achieve them ESG investing. These issues will be the subject of further research.

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IX. Acknowledgments

The Authors declare that the article complies with Ethical Standards of the Journal.

The authors report there are no competing interests to declare.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

The data that support the findings of this study are available from the Authors upon reasonable request.