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SUPPLIER SEGMENTATION BASED ON PERFORMANCE DATA USING HIERARCHICAL CLUSTERING

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Abstract. *In many manufacturing environments, procurement managers must regularly compare suppliers with significantly different performance profiles, which makes structured evaluation essential. Grouping suppliers with similar performance characteristics can make procurement decisions more transparent and easier to justify in practice. However, supplier performance is typically described by multiple evaluation criteria measured on different scales, and these performance characteristics may change over time. For this reason, analytical approaches are required that can handle both the multidimensional nature of the data and the changes in supplier performance over time. In this paper, an adaptive supplier segmentation approach is developed based on hierarchical clustering techniques. Supplier performance is evaluated using multiple operational criteria, including quality rate, on-time delivery, unit price, lead time, complaint frequency, and operational flexibility. After applying min–max normalization and weighted performance evaluation, supplier similarities are calculated using Euclidean distance, and hierarchical clustering methods are applied to identify homogeneous supplier groups. Several linkage strategies are compared, and the clustering quality is assessed using internal validation indices such as the Silhouette, Davies–Bouldin, Calinski–Harabasz, and Dunn indices. The empirical analysis is conducted on a dataset containing 15 suppliers observed in two consecutive evaluation periods. The results indicate that hierarchical clustering can reveal interpretable supplier groups with clearly distinguishable performance profiles. A comparison of clustering structures across consecutive periods also shows that supplier segmentation evolves as new performance data become available.*

Keywords: *adaptive supplier segmentation; hierarchical clustering; supplier evaluation; cluster validation; supply chain management; multi-criteria decision analysis; performance-based clustering; supplier performance analysis.*

1. Introduction

In industrial practice, procurement managers often deal with dozens of suppliers whose performance differs not only in cost but also in reliability and flexibility. Some suppliers consistently deliver high-quality products and meet delivery deadlines, while others may offer lower prices but struggle with reliability or flexibility. In such environments, evaluating and managing the supplier base becomes a complex task. In most real-world cases, procurement decisions rely on multiple performance indicators rather than a single metric [1,2].

In practice, organizations often monitor supplier performance using indicators such as product quality, delivery reliability, procurement cost, lead time, or the frequency of service-related issues. These indicators provide valuable information about the operational capabilities of suppliers. However, when several suppliers are evaluated simultaneously across multiple criteria, interpreting the results becomes increasingly difficult. Even experienced managers may find it challenging to identify patterns in the data or determine which suppliers exhibit similar performance profiles.

Another important challenge is that supplier performance is not static [3]. Over time, suppliers may improve their processes, introduce technological innovations, or adjust their pricing strategies. Conversely, operational disruptions, capacity constraints, or logistical challenges may temporarily reduce supplier performance. As a result, the structure of the supplier base can change continuously. A supplier that was previously considered reliable may gradually lose its competitive position, while another supplier may become more attractive due to improvements in quality or delivery performance. This dynamic nature of supplier performance suggests that supplier evaluation should not be treated as a one-time classification problem but rather as an ongoing analytical process.

Data-driven analytical methods can support this process by revealing patterns in multidimensional performance data. Among these methods, clustering techniques have gained increasing attention in supply chain analytics [4,5]. Clustering methods group entities according to similarity, allowing analysts to identify homogeneous groups within complex datasets. When applied to supplier performance data, clustering techniques can reveal groups of suppliers with similar operational characteristics, thereby supporting more structured procurement strategies.

Despite the growing use of data analytics in supply chain management, many supplier evaluation approaches still focus on static analyses. In practice, however, supplier performance data are updated periodically, and analytical tools should be able to incorporate these changes. This highlights the importance of adaptive analytical frameworks that allow supplier segmentation to evolve when new performance information becomes available.

Motivated by these considerations, this study proposes an adaptive supplier segmentation framework based on hierarchical clustering techniques. The proposed approach evaluates suppliers using multiple operational performance criteria and groups them according to their performance characteristics. In addition, the framework allows the clustering structure to be updated when new data become available, enabling the analysis of how supplier groups evolve over time.

The empirical analysis is conducted using a dataset containing fifteen suppliers evaluated across six performance indicators. Several hierarchical clustering methods are examined and compared using multiple cluster validation indices. By analysing supplier clusters across two consecutive evaluation periods, the study demonstrates how adaptive clustering can capture structural changes in supplier performance and provide valuable insights for procurement decision-making.

2. Problem description

Supplier evaluation and segmentation represent a critical task in modern supply chain management. Organizations typically cooperate with multiple suppliers whose performance may differ significantly in terms of quality, delivery reliability, procurement cost, operational lead time, and service flexibility. Effective supplier management therefore requires analytical tools capable of identifying homogeneous groups of suppliers based on their operational characteristics.

In many practical situations, supplier performance is evaluated using several criteria measured on different scales. These criteria may include both benefit-type indicators, where higher values indicate better performance (e.g., quality rate or delivery reliability), and cost-type indicators, where lower values are preferable (e.g., procurement cost or lead time). Because of this multidimensional structure, it is often difficult for procurement managers to directly identify patterns in supplier performance.

Another important challenge arises from the dynamic nature of supplier performance. Operational conditions, production efficiency, logistics processes, and service quality may change over time. As a result, supplier performance data must be periodically re-evaluated, which may lead to changes in the segmentation structure of the supplier base.

The objective of the present study is therefore to develop a data-driven framework capable of grouping suppliers according to their performance characteristics while also allowing the segmentation structure to adapt when updated performance data become available. The proposed approach applies hierarchical clustering techniques combined with multiple cluster validation measures in order to identify meaningful supplier groups and evaluate the stability of the segmentation over time.

Figure 1 illustrates the conceptual structure of the proposed supplier segmentation problem. Supplier performance data are collected for multiple evaluation criteria, normalized to ensure comparability, and then processed using hierarchical clustering. The resulting clusters represent groups of suppliers with similar performance characteristics. When new performance data become available in a subsequent evaluation period, the clustering process is repeated, enabling the identification of structural changes in supplier segmentation.

3. Mathematical Model of Adaptive Supplier Segmentation

The proposed adaptive supplier segmentation model is based on hierarchical clustering techniques applied to supplier performance indicators. The objective of the model is to identify homogeneous groups of suppliers according to their operational performance while allowing the segmentation structure to be updated dynamically as new data become available.

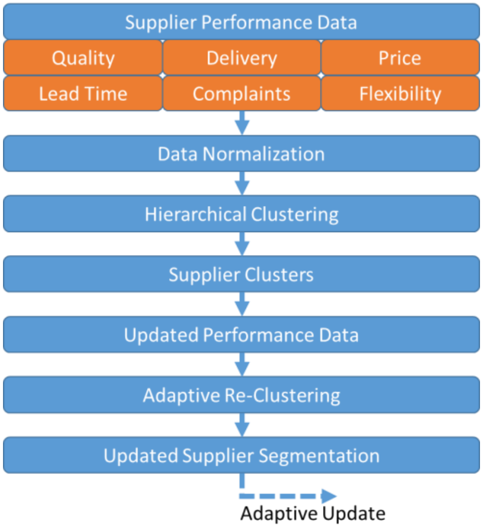

Figure 1 – Conceptual framework of adaptive supplier segmentation with feedback loop [own elaboration].

Let $S = \{s_1, s_2, \dots, s_n\}$ denote the set of suppliers where n represents the total number of suppliers considered in the evaluation process.

Supplier performance is described using a set of evaluation criteria $K = \{k_1, k_2, \dots, k_m\}$, where m denotes the number of performance indicators. These criteria typically represent key operational indicators such as quality level, delivery reliability, procurement cost, complaint rate or lead time.

The performance of suppliers with respect to the defined criteria can be represented in the form of a decision matrix $X = [x_{ij}]$, where x_{ij} denotes the performance value of supplier s_i with respect to criterion k_j. The matrix can therefore be written as

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix}.$$

Because the criteria are measured on different scales, normalization is required before further analysis. The normalized performance value is calculated using min–max normalization

$$z_{ij} = \frac{x_{ij} - min\,(x_j)}{max(x_j) - min\,(x_j)},$$

where z_{ij} represents the normalized value of criterion j for supplier i. The normalized matrix can be expressed as $Z = [z_{ij}]$.

In order to incorporate the relative importance of evaluation criteria, a weight vector $W = \{w_1, w_2, \dots, w_m\}$ is defined where

$$\sum_{j=1}^{m} w_j = 1.$$

For cost criteria higher normalized values represent higher cost levels. The weighted normalized matrix can therefore be calculated as $v_{ij} = w_j \cdot z_{ij}$.

The similarity between suppliers is determined by calculating the distance between supplier vectors in the multidimensional performance space. In this study the Euclidean distance is applied

$$d_{ik} = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_{kj})^2},$$

where d_{ik} denotes the distance between suppliers s_i and s_k. The resulting distance matrix is defined as $D = [d_{ik}]$.

Based on the distance matrix, hierarchical clustering is performed in order to identify homogeneous supplier groups. In hierarchical clustering the algorithm starts with n individual clusters and iteratively merges the closest clusters until a hierarchical structure is formed.

Let $C = \{c_1, c_2, \dots, c_k\}$ denote the set of clusters obtained during the clustering process. Different linkage strategies can be applied to determine the distance between clusters.

In the case of single linkage, the distance between two clusters is defined as the minimum pairwise distance between their elements

$$d(C_a, C_b) = \min_{i \in C_a, j \in C_b} d_{ij}.$$

For complete linkage, the distance is determined by the farthest pair of elements

$$d(C_a, C_b) = \max_{i \in C_a, j \in C_b} d_{ij}.$$

The average linkage method calculates the mean distance between all elements of the two clusters

$$d(C_a, C_b) = \frac{1}{|C_a| \cdot |C_b|} \cdot \sum_{i \in C_a} \sum_{j \in C_b} d_{ij}.$$

Finally, the Ward method merges clusters based on the minimum increase of within-cluster variance [6]. The merging criterion is defined as

$$\Delta(C_a, C_b) = \frac{n_a \cdot n_b}{n_a + n_b} \cdot \|\mu_a - \mu_b\|^2,$$

where n_a and n_b denote the sizes of clusters C_a and C_b, while μ_a and μ_b represent their centroids.

The hierarchical clustering process results in a dendrogram that represents the nested grouping of suppliers.

Since different clustering strategies may produce different segmentation results, cluster validation techniques are required in order to evaluate the quality of the clustering structure.

One of the most widely used validation measures is the Silhouette index, which evaluates how well each supplier fits within its assigned cluster. For each supplier i, the average intra-cluster distance is defined as

$$a_i = \frac{1}{|C_i| - 1} \cdot \sum_{j \in C_i, j \neq i} d_{ij}.$$

The distance to the nearest neighbouring cluster is

$$b_i = \min_{C_k \neq C_i} \left(\frac{1}{|C_k|} \cdot \sum_{j \in C_k} d_{ij} \right).$$

The silhouette value is therefore

$$S_i = \frac{b_i - a_i}{\max(a_i, b_i)}.$$

The overall clustering quality is obtained by averaging over all suppliers

$$S = \frac{1}{\mathrm{n}} \cdot \sum_{i=1}^{n} S_i.$$

Another important validation measure is the Davies–Bouldin index [7], which evaluates the ratio between intra-cluster dispersion and inter-cluster separation

$$DB = \frac{1}{\mathrm{k}} \cdot \sum_{i=1}^{k} \max_{j \neq i} \left(\frac{\sigma_i + \sigma_j}{d(\mu_i, \mu_j)} \right),$$

where σ_i denotes the dispersion of cluster i.

The Calinski–Harabasz index [8] measures the ratio between between-cluster and within-cluster variance

$$CH = \frac{Tr(B_k)}{Tr(W_k)} \cdot \frac{n-k}{k-1},$$

where B_k and W_k represent the between-cluster and within-cluster dispersion matrices.

The Dunn index [9] evaluates cluster compactness and separation

$$D = \frac{\min_{i \neq j} d(C_i, C_j)}{\max_{k} diam(C_k)},$$

where $d(C_i, C_j)$ is the distance between clusters and $diam(C_k)$ is the diameter of cluster k.

In the proposed adaptive framework supplier performance data may change over time. Let $X^{(t)}$ represent the decision matrix observed in period t. The clustering structure is therefore defined as

$$C^{(t)} = HC\left(X^{(t)}\right),$$

where HC denotes the hierarchical clustering operator.

The stability of supplier segmentation across consecutive periods can be evaluated using the Jaccard similarity index [10,11]

$$J = \frac{\left|C^{(t)} \cap C^{(t+1)}\right|}{\left|C^{(t)} \cup C^{(t+1)}\right|}.$$

Higher values of J indicate greater stability of supplier segmentation over time.

The proposed mathematical framework therefore enables adaptive supplier segmentation by combining hierarchical clustering with multiple cluster validation metrics and temporal stability analysis.

4. Numerical Results

4.1. Description of the Dataset

The empirical analysis was conducted using a dataset containing 15 suppliers evaluated according to six performance criteria. Each supplier represents one row of the decision matrix, while each column corresponds to an evaluation criterion. The suppliers are identified as $S_1, S_2, \dots, S_{15}$. The selected criteria represent key operational and economic aspects of supplier performance, including product quality, delivery reliability, procurement cost, operational lead time, service reliability, and operational flexibility. Since these criteria are expressed in different measurement units and value ranges, normalization is required before applying the clustering procedure.

The criteria used in the evaluation process are summarized in Table 1.

Table 1 – Supplier evaluation criteria [own elaboration]

Criterion	Type	Measurement unit	Weight
Quality Rate	Benefit	%	0.25
On-Time Delivery	Benefit	%	0.20
Unit Price	Cost	numeric value	0.20
Lead Time	Cost	days	0.15
Complaints	Cost	number of cases	0.10
Flexibility	Benefit	rating (1–10)	0.10

Quality Rate, On-Time Delivery and Flexibility are treated as benefit criteria, where higher values indicate better supplier performance. In contrast, Unit Price, Lead Time and Complaints are considered cost criteria, where lower values are preferred. The weights assigned to the criteria reflect their relative importance in supplier evaluation and sum to one.

The supplier performance data used in the analysis are presented in Tables 2 and 3. Table 2 shows the evaluation values in period t, while Table 3 contains the updated performance values in period $t + 1$. The second dataset represents changes in supplier performance over time and enables the demonstration of the adaptive behaviour of the proposed clustering model.

Table 2 – Supplier performance data in period t [own elaboration]

Supplier	Quality	On-time delivery	Unit price	Lead time	Complaints	Flexibility
S1	96	95	110	8	1	9
S2	92	91	104	10	2	8
S3	88	87	99	13	3	7
S4	84	82	96	14	4	6
S5	79	80	92	16	5	5
S6	98	97	118	7	1	9
S7	90	89	102	11	2	7
S8	76	78	89	18	6	5
S9	81	83	95	15	4	6
S10	94	92	108	9	2	8
S11	87	86	101	12	3	7

S12	73	75	88	19	7	4
S13	85	84	97	14	4	6
S14	91	90	103	10	2	8
S15	78	79	91	17	5	5

Table 3 – Supplier performance data in period $t+1$ [own elaboration]

Supplier	**Quality**	**On-time delivery**	**Unit price**	**Lead time**	**Complaints**	**Flexibility**
S1	97	96	111	8	1	9
S2	90	89	105	11	3	7
S3	89	88	100	12	3	7
S4	82	80	95	15	5	6
S5	77	78	91	17	6	5
S6	99	98	119	7	1	10
S7	91	90	101	10	2	8
S8	74	76	87	19	7	4
S9	83	84	94	14	4	6
S10	95	93	107	9	2	8
S11	86	85	100	13	4	7
S12	71	73	86	20	8	4
S13	84	83	96	15	5	6
S14	92	91	104	10	2	8
S15	80	81	92	16	5	5

The presence of two consecutive datasets allows the evaluation of how supplier clusters evolve when new performance information becomes available, thereby supporting the adaptive nature of the proposed supplier segmentation framework.

4.2. Hierarchical Clustering Results

Hierarchical clustering was applied to identify groups of suppliers with similar performance characteristics. Four linkage methods were tested in the analysis, namely single, complete, average, and Ward linkage. The number of clusters was fixed at $k = 3$, which provided an interpretable segmentation of the supplier base.

To determine the most appropriate clustering method, several internal validation indices were calculated, including the Silhouette index, Davies–Bouldin index, Calinski–Harabasz index, and the Dunn index. The results for period t are summarized in Table 4.

Table 4 – Validation indices for different linkage methods [own elaboration]

Method	Silhouette	Davies-Bouldin	Calinski-Harabasz	Dunn
Single	0.483	0.448	23.77	0.285
Complete	0.435	0.547	29.77	0.221
Average	0.435	0.547	29.77	0.221
Ward	0.462	0.562	30.93	0.203

The single linkage method achieved the highest Silhouette value (0.483) and the lowest Davies–Bouldin index (0.448), indicating the best balance between cluster cohesion and separation. The Dunn index also reached its highest value (0.285) for the single linkage solution. Although the Ward method produced the largest Calinski–Harabasz value (30.93), its Davies–Bouldin index was higher, indicating slightly weaker cluster separation. Based on the combined evaluation of the indices, the single linkage method was selected as the primary clustering approach.

The dendrograms obtained using the four linkage methods are shown in Figure 2. The graphical representation illustrates how suppliers are gradually merged during the hierarchical clustering process. Despite differences in merging distances and cluster compactness, the examined linkage methods consistently suggest the presence of three main supplier groups.

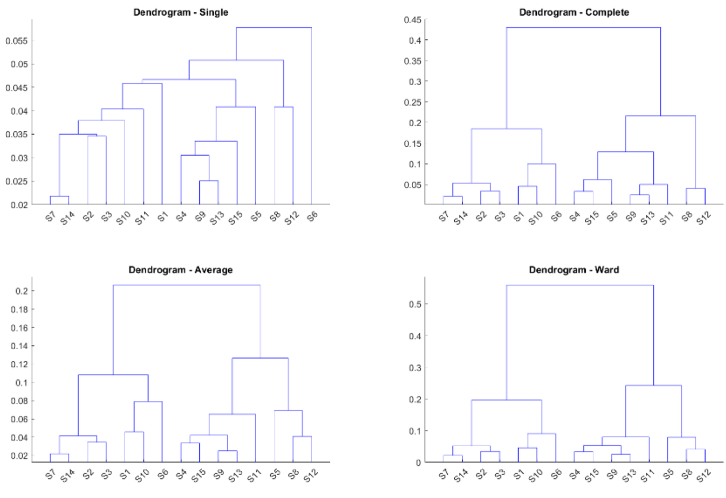

Figure 2 – The dendrograms obtained using the four linkage methods [own elaboration].

In the single linkage dendrogram, several suppliers form compact subclusters at low linkage distances. For example, suppliers S7 and S14 merge at very low distances, indicating highly similar performance profiles. Similarly, suppliers S4 and S9, and S9 and S13, form closely connected subgroups within the second cluster. In contrast, supplier S6 joins the clustering structure only at a much higher linkage distance, indicating a significantly different performance profile compared to the rest of the supplier base.

Using the selected clustering configuration, suppliers were grouped into three clusters in period t. The resulting cluster composition was as follows: Cluster 1: S1, S2, S3, S7, S10, S11, S14; Cluster 2: S4, S5, S8, S9, S12, S13, S15; Cluster 3: S6.

Clusters 1 and 2 each contain seven suppliers, while Cluster 3 consists of a single supplier. The presence of a single-member cluster indicates that supplier S6 represents a distinct performance profile that differs substantially from the other suppliers.

The cluster mean profiles provide further insight into the differences between supplier groups. In period t, the normalized cluster averages show clear performance differences. Cluster 1 exhibits relatively high values for key benefit criteria, including Quality Rate (0.73), On-Time Delivery (0.68), and Flexibility (0.74). These values suggest that suppliers in this group demonstrate generally strong operational performance.

In contrast, Cluster 2 shows significantly lower performance levels in the benefit criteria, with average normalized values of 0.26 for Quality Rate and 0.23 for On-Time Delivery. At the same time, the normalized value of Unit Price reaches 0.85, indicating higher cost levels compared to the suppliers in Cluster 1. Consequently, Cluster 2 represents a group of suppliers with weaker overall performance.

Cluster 3, consisting solely of supplier S6, demonstrates extreme values across several criteria. The normalized performance values reach 1.0 for Quality Rate, On-Time Delivery, Lead Time, Complaints, and Flexibility, while the normalized Unit Price value equals 0, indicating the highest price level in the dataset. These results indicate that supplier S6 represents a supplier with excellent operational performance but relatively high procurement cost.

The clustering structure changed in the second evaluation period ($t + 1$), reflecting changes in supplier performance values. In this period, the clusters were formed as follows: Cluster 1: S8, S12; Cluster 2: S1, S2, S3, S4, S5, S7, S9, S10, S11, S13, S14, S15; Cluster 3: S6.

Compared with period t, the cluster structure became more concentrated. Cluster 2 expanded to 12 suppliers, while Cluster 1 decreased to two suppliers. Supplier S6 remained isolated in Cluster 3 in both periods, confirming the stability of its distinct performance profile.

A comparison of cluster memberships across the two periods reveals that 9 out of 15 suppliers changed their cluster assignment, indicating substantial changes in supplier performance patterns. In particular, several suppliers originally belonging to Cluster 1 moved to Cluster 2 in the second period. Meanwhile, suppliers S8 and

S12 formed a separate cluster, indicating that their performance profiles became more distinct from the rest of the supplier base.

The clustering results reveal clearly distinguishable supplier groups that differ in both performance and cost structure.

4.3 Cluster Validation

To evaluate the quality of the clustering solutions obtained using different linkage methods, several internal validation indices were calculated. The analysis included four widely used cluster validity measures: the Silhouette index, the Davies–Bouldin index, the Calinski–Harabasz index, and the Dunn index. Each of these indices captures a different aspect of clustering quality, including cluster cohesion, cluster separation, and overall cluster structure.

The comparison of the validation indices for the examined hierarchical clustering methods in period $t$is illustrated in Figure 3.

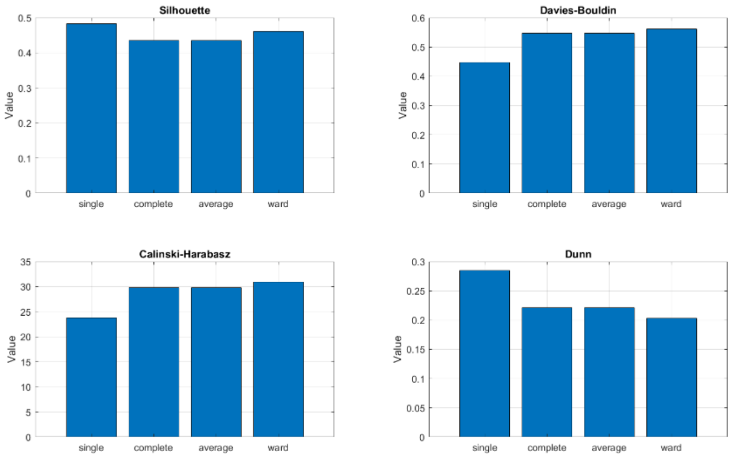

Figure 3 – Comparison of clustering validation indices for different linkage methods in period t [own elaboration].

The Silhouette index measures how well each observation fits within its assigned cluster compared with neighboring clusters. Higher values indicate better-defined clusters. As shown in Figure 3, the single linkage method achieved the highest Silhouette value (0.483) among the examined methods, suggesting the strongest overall cluster cohesion and separation. The Ward method produced a slightly lower value (0.462), while the complete and average linkage methods resulted in similar values of approximately 0.435.

The Davies–Bouldin index evaluates the average similarity between clusters, where lower values indicate better clustering performance. According to the results, the single linkage method again achieved the most favorable value (0.448), indicating the best separation between supplier groups. The other methods produced noticeably higher values, ranging between 0.547 and 0.562, which suggests weaker cluster separation compared with the single linkage solution.

The Calinski–Harabasz index measures the ratio of between-cluster dispersion to within-cluster dispersion. In this case, the Ward linkage method achieved the highest value (30.93), followed by the complete and average linkage methods (approximately 29.77). The single linkage method produced a lower value (23.77), which can be explained by the presence of a small cluster consisting of a single supplier. Such cluster structures often reduce the between-cluster variance measured by this index.

Finally, the Dunn index, which evaluates the ratio between the minimum inter-cluster distance and the maximum intra-cluster diameter, also supports the effectiveness of the single linkage solution. The highest Dunn value (0.285) was obtained using the single linkage method, indicating stronger cluster separation compared with the other methods. The remaining methods produced lower values, ranging between 0.203 and 0.221.

Considering all four validation indices together, most validation indices favour the single linkage method for the examined supplier dataset. Although the Ward method performs well according to the Calinski–Harabasz index, the single linkage method consistently achieves better results in terms of Silhouette, Davies–Bouldin, and Dunn indices. Therefore, the single linkage method was selected as the most appropriate clustering approach for the subsequent supplier segmentation analysis.

4.4 Cluster Profile Analysis

The characteristics of the identified supplier clusters can be further examined through the analysis of cluster mean profiles. Figure 4 illustrates the average normalized performance values of the three clusters obtained using the single linkage method in period t.

The cluster profiles reveal substantial differences among the supplier groups across the six evaluation criteria: Quality Rate, On-Time Delivery, Unit Price, Lead Time, Complaints, and Flexibility.

Cluster 1 represents a group of suppliers with relatively strong overall performance. The average normalized value of Quality Rate reaches approximately 0.73, while On-Time Delivery equals 0.68, indicating a high level of product quality and delivery reliability. Similarly, the normalized values of Lead Time (0.71) and Flexibility (0.74) suggest that these suppliers are able to maintain efficient operational processes.

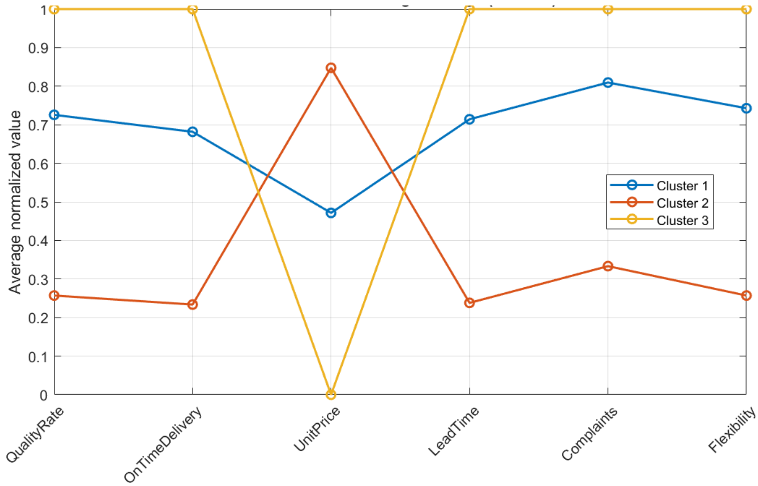

Figure 4 – Cluster profiles based on normalized supplier performance criteria [own elaboration].

The value of Unit Price (0.47) is moderate compared with the other clusters, indicating balanced cost performance. Additionally, the normalized value for Complaints reaches approximately 0.81, which indicates a relatively higher complaint frequency compared with the suppliers in Cluster 1.

Cluster 1 can be interpreted as a group of high-performing and reliable suppliers, representing the core supplier base with stable operational performance.

Cluster 2 shows considerably weaker performance across most evaluation criteria. The normalized value of Quality Rate decreases to approximately 0.26, while On-Time Delivery reaches only 0.23, indicating significantly lower reliability compared with Cluster 1. Similarly, the values for Flexibility (0.26) and Lead Time (0.24) suggest less efficient operational performance.

At the same time, the normalized Unit Price value reaches 0.85, indicating that suppliers in this cluster tend to have higher procurement costs. This combination of lower operational performance and higher cost values suggests that the suppliers in Cluster 2 represent a less competitive supplier group.

The cluster therefore can be interpreted as a group of average or potentially underperforming suppliers, which may require performance improvement initiatives or closer monitoring by procurement managers.

Cluster 3 contains a single supplier (S6) whose performance profile differs significantly from the rest of the supplier base. The normalized values reach 1.0 for Quality Rate, On-Time Delivery, Lead Time, Complaints, and Flexibility, indicating the best observed performance for these criteria in the dataset. At the same time the normalized value of Unit Price equals 0, indicating the highest price level among the examined suppliers.

Such extreme values indicate that supplier S6 exhibits a distinct performance profile compared with the other suppliers. Consequently, Cluster 3 represents a supplier with a unique performance structure characterized by excellent operational indicators but relatively high procurement cost.

The comparison of the cluster profiles highlights clear structural differences between the supplier groups. Cluster 1 demonstrates strong operational performance with balanced cost levels, Cluster 2 exhibits lower quality and delivery performance combined with relatively higher costs, while Cluster 3 represents a distinct supplier with outstanding operational performance but unfavourable procurement cost.

These findings suggest that the clustering approach provides a useful, although not exhaustive, representation of supplier performance patterns. Such segmentation can provide valuable support for procurement decision-making, enabling managers to distinguish between strategic suppliers, standard suppliers, and exceptional high-performing suppliers within the supplier base.

4.5 Adaptive Supplier Segmentation

One of the key objectives of the proposed model is to demonstrate the adaptive nature of supplier segmentation, meaning that supplier groups can change when new performance data become available. To analyze these changes, the clustering results obtained in periods $t$and $t+1$were compared.

Table 5 summarizes the cluster memberships of suppliers in both periods. The results reveal that several suppliers changed their cluster assignment when the updated performance data were introduced.

Table 5 – Cluster memberships [own elaboration]

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Cluster *t*	1	1	1	2	2	3	1	2	2	1	1	2	2	1	2
Cluster *t+1*	2	2	2	2	2	3	2	1	2	2	2	1	2	2	2

A detailed examination of the results shows that 9 out of the 15 suppliers changed their cluster membership between the two evaluation periods. Specifically, suppliers S1, S2, S3, S7, S10, S11, and S14 moved from Cluster 1 to Cluster 2, while suppliers S8 and S12 moved from Cluster 2 to Cluster 1. These changes indicate that supplier performance patterns evolved between the two evaluation periods, leading to a different clustering structure.

In contrast, several suppliers remained stable in their cluster assignments. Suppliers S4, S5, S9, S13, and S15 remained in Cluster 2, while supplier S6 remained in Cluster 3 in both periods. The stability of supplier S6 confirms the earlier observation that this supplier represents a distinct performance profile that differs significantly from the rest of the supplier base.

The cluster size distribution also changed considerably between the two periods. In period t, the clustering structure was relatively balanced, with Cluster 1 and Cluster 2 each containing 7 suppliers, while Cluster 3 contained a single supplier. However, in period $t + 1$the cluster structure became more concentrated. Cluster 2 expanded to 12 suppliers, while Cluster 1 decreased to only 2 suppliers, consisting of suppliers S8 and S12. Cluster 3 remained unchanged with a single supplier (S6).

These results indicate that the relative performance of suppliers changed over time. Several suppliers that previously belonged to the higher-performing cluster moved to a larger cluster representing average performance levels, suggesting a relative deterioration in their competitive position. Conversely, the formation of a small cluster containing suppliers S8 and S12 suggests that these suppliers became more distinct in terms of their performance characteristics.

The results confirm that the proposed clustering framework is capable of capturing dynamic changes in supplier performance. The adaptive clustering mechanism allows procurement managers to continuously reassess supplier groups as new performance information becomes available. Such dynamic segmentation provides valuable decision support in supplier relationship management, enabling organizations to identify stable strategic suppliers, suppliers with declining performance, and suppliers whose performance is evolving over time.

5. Discussion

The results demonstrate that hierarchical clustering can effectively support supplier segmentation based on multiple performance indicators. The applied methodology successfully identified meaningful groups of suppliers with clearly different operational characteristics. In particular, the clustering results revealed three distinct supplier categories, reflecting differences in quality performance, delivery reliability, procurement cost, and operational flexibility.

The comparison of clustering methods indicated that the single linkage approach provided the most suitable solution for the examined dataset. This result was supported by several internal validation indices, including the Silhouette, Davies–Bouldin, and Dunn indices, which collectively indicated better cluster cohesion and separation compared with the other linkage methods. Although the Ward method achieved the highest Calinski–Harabasz value, the overall evaluation of the indices favoured the single linkage solution.

The analysis of cluster profiles further highlighted the practical relevance of the segmentation results. Cluster 1 represents suppliers with relatively strong operational performance and balanced cost levels, while Cluster 2 contains suppliers with lower reliability and higher procurement costs. Cluster 3 consists of a supplier with a distinct performance profile characterized by excellent operational indicators but relatively high procurement cost. These findings demonstrate that clustering can reveal complex performance patterns that may not be immediately visible in the raw data.

An important contribution of the proposed framework is its adaptive nature. The comparison of clustering results between periods t and $t+1$ showed that supplier groups may change as new performance information becomes available. In the presented case, nine out of fifteen suppliers changed their cluster membership, indicating that supplier performance is dynamic and requires continuous monitoring. Such adaptive segmentation enables procurement managers to periodically reassess supplier relationships and identify changes in supplier competitiveness. One limitation of the analysis is the relatively small sample size, which may influence the stability of the clustering results. From a managerial perspective, the identified clusters may support differentiated supplier management strategies, such as performance monitoring or contract renegotiation.

The results confirm that hierarchical clustering combined with performance-based evaluation criteria can provide a useful analytical tool for supplier segmentation and decision support in supply chain management. Future research may apply stability indices such as the Jaccard coefficient to further examine the temporal stability of supplier clusters.

References: **1**. *Siino M., Iezzi S., Gara M.* Corruption risk indicators in public procurement: Definition and evaluation with organised crime data. Socio-Economic Planning Sciences. 2026, № 105, 102429. https://doi.org/10.1016/j.seps.2026.102429 **2**. *Ghyas Q.M., Akter T.* Critical Evaluation of Key Performance Indicators (KPI) in Procurement Management Information System (PROMIS): The Case of Bangladesh. ACM International Conference Proceeding Series. 2024, pp. 405 – 409. https://doi.org/10.1145/3670013.3670014 **3**. *Hoque I., Sumi R.S.* Buyer-supplier relational dynamics and supplier dynamic capabilities for improving environmental sustainability mitigating climate change vulnerabilities. Climatic Change. 2026, № 179, 8. https://doi.org/10.1007/s10584-025-04096-y **4**. *Keskin G.A.* A Novel Perspective to Sustainable Supplier Performance Evaluation Problem: A Case Study Based on Determining the Optimum Number of Clusters. International Journal of Information Technology and Decision Making. 2022, № 21, pp. 1349 – 1379. https://doi.org/10.1142/S0219622022500195 **5**. *Rahiminia M., Razmi J., Shahrabi Farahani S., Sabbaghnia A.* Cluster-based supplier segmentation: a sustainable data-driven approach. Modern Supply Chain Research and Applications. 2023, № 5, pp. 209 - 228. https://doi.org/10.1108/MSCRA-05-2023-0017 **6**. *Ogasawara, Y., Kon, M.* Two clustering methods based on the Ward's method and dendrograms with interval-valued dissimilarities for interval-valued data. International Journal of Approximate Reasoning. 2021, № 129, pp. 103 – 121. https://doi.org/10.1016/j.ijar.2020.11.001 **7**. *Ros, F., Riad, R., Guillaume, S.* PDBI: A partitioning Davies-Bouldin index for clustering evaluation. *Neurocomputing*. 2023, № 528, pp. 178 – 199. https://doi.org/10.1016/j.neucom.2023.01.043 **8**. *Preedasawakul, O., Wiroonsri, N.* A Bayesian cluster validity index. Computational Statistics & Data Analysis. 2025, № 202, 108053. https://doi.org/10.1016/j.csda.2024.108053 **9**. *Ncir, C.E.B., Hamza, A., Bouaguel, W.* Parallel and scalable Dunn Index for the validation of big data clusters. Parallel Computing. 2021, № 102, 102751. https://doi.org/10.1016/j.parco.2021.102751 **10**. *Krasnodębska, K., Goch, W., Uhl, J.H., Verstegen, J.A., Pesaresi, M.* Advancing Precision, Recall, F-score, and Jaccard index: An approach for continuous, ratio-scale measurements. Environmental Modelling & Software 2025. № 193, 106614. https://doi.org/10.1016/j.envsoft.2025.106614 **11**. *Chen, J., Qi, S., Wang, F., Xing, L., Chen, Y.* An Jaccard similarity coefficient-based evolutionary algorithm for sparse large-scale multi-objective optimization problems. Swarm and Evolutionary Computation. 2026. № 100, 102269. https://doi.org/10.1016/j.swevo.2025.102269

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СЕГМЕНТАЦІЯ ПОСТАЧАЛЬНИКІВ НА ОСНОВІ ДАНИХ ПРО ПРОДУКТИВНІСТЬ ЗА ДОПОМОГОЮ ІЄРАРХІЧНОЇ КЛАСТЕРИЗАЦІЇ

Анотація. *У багатьох машинобудівних виробничих середовищах менеджери з закупівель повинні регулярно порівнювати постачальників із суттєво різними профілями ефективності, що робить структуровану оцінку необхідною. Об'єднання постачальників із подібними характеристиками продуктивності може зробити рішення щодо закупівель більш прозорими та легшими для обґрунтування на практиці. Однак ефективність постачальника зазвичай описується кількома критеріями оцінки, виміряними на різних шкалах, і ці характеристики можуть змінюватися з часом. З цієї причини потрібні аналітичні підходи, здатні опрацьовувати як багатовимірний характер даних, так і зміни продуктивності постачальників з часом. У цій статті розроблено адаптивний підхід сегментації постачальників на основі ієрархічних методів кластеризації. Ефективність постачальника оцінюється за кількома операційними критеріями, включно з рівнем якості, своєчасною доставкою, ціною за одиницею, терміном виконання, частотою скарг та операційною гнучкістю. Після застосування мінімально-максимальної нормалізації та зваженої оцінки продуктивності подібності постачальників розраховуються за допомогою евклідової відстані, а для ідентифікації однорідних груп постачальників застосовуються ієрархічні методи кластеризації. Порівнюються кілька стратегій зв'язку, а якість кластеризації оцінюється за допомогою внутрішніх валідаційних індексів, таких як індекси Silhouette, Davies–Bouldin, Calinski–Harabasz та Dunn. Емпіричний аналіз проводиться на наборі даних, що містить 15 постачальників, які спостерігались у двох послідовних періодах оцінки. Результати свідчать, що ієрархічна кластеризація може виявити інтерпретовані групи постачальників із чітко розрізняючими профілями ефективності. Порівняння структур кластеризації протягом послідовних періодів також показує, що сегментація постачальників змінюється з появою нових даних про продуктивність.*

Ключові слова: *адаптивна сегментація постачальників; ієрархічна кластеризація; оцінка постачальників; валідація кластерів; управління ланцюгом постачання; аналіз рішень за мультикритеріями; кластеризація на основі ефективності; аналіз ефективності постачальників.*