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Tiered Data Envelopment as a method for clustering suppliers

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Abstract. Effective supplier management requires continuous monitoring of the performance and capabilities of one's supplier base. Although the literature often focuses on ranking, it has lately become increasingly important to group suppliers according to their capabilities. In this paper, we compare two clustering methods. The application of Cluster Analysis (CA) has been widely discussed in the literature. Tiered Data Envelopment Analysis (TDEA) is also well-known in the decision-making literature, but is nonetheless seldom employed in supplier evaluation. CA is only suitable for group formation on a nominal scale, whereas the TDEA method during group formation allows the groups to be formed on an ordinal scale. TDEA may therefore prove to be the more suitable method for ordinal group formation. This article attempts to bridge a research gap, which arises since the two methods are infrequently employed in supplier selection. A numerical example is used to compare their application.

Keywords: cluster analysis, supplier segmentation, Tiered Data Envelopment Analysis (TDEA)

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1. Introduction

Supply chain decision makers have been significantly affected by the turbulent economic changes resulting from pandemic lockdowns and more recently, the war in Ukraine. The global supply chains face both supply shortages and unpredictable, potentially disruptive changes in demand. Managing supplier relationships has been particularly challenging, as suppliers' expected performance has become uncertain and supply problems are now common. The literature also suggests that it is important to manage today's supplier relationships using a different framework [1], [31]. Supplier evaluation is an important area where multi-criteria decision making (MCDM) may be applied. The evaluation of supplier performance is traditionally considered a ranking problem. However, the recent unpredictable supply situation requires different tools for managing suppliers. The supply management toolbox is no longer necessarily focused on selection but rather on the management of the supplier base [27]. It has become important to understand differences in performance. This change in management approach also transforms the decision problem: it is not the performance of the best suppliers that is of interest, but the differences in performance between potential suppliers. From a methodological point of view, this can be understood as more of a clustering/segmentation problem. This paper therefore reviews methods for potentially formulating performance-based groups, with a view to comparing their application in purchasing and supply management. The aim is to compare the two methods, to outline their differences, and to highlight how methodological differences account for the observed differences in results. The structure of the paper is as follows: first, we present a brief literature review of the evolution of supplier evaluation and the management methods addressed in the paper. This is followed by a numerical example of two methods of group formation, and a comparison of the results. We then formulate the managerial and theoretical implications.

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2. Literature review

Supplier evaluation is a central problem in purchasing. It is widely covered in published research, both from managerial and methodological points of view. Purchasing and supply management literature nowadays focuses on supplier management that uses a strategic approach through monitoring and segmenting the supplier base [22]. There is a serious need for this, as changes in the economic environment, challenges in the global economy, and events such as Brexit or the blocking of trade routes by huge container ships disrupt supplies to varying degrees. If a company wants to be able to deliver on its promises to its customers in a stable way, it needs to deeply consider the potential risks that could impact security of supply ([15] and [30]). As recent world events have shown, a supply chain manager's capacity to respond to developments impacting security of supply by logistical means may be limited (e.g., the available capacity to deliver goods by air was also constrained during the pandemic). With hindsight, much greater security would have been ensured if alternative suppliers had been available. Hence, besides selecting them, it may be important to qualify suppliers so that in the event of delivery problems there are known suppliers from whom it is possible to order (e.g., due to a sudden increase in demand or default by a current supplier). One's broader knowledge of the supply base can be improved by continuously monitoring the performance and capabilities of suppliers, and by analysing options using the available data [14]. The supply risk will obviously be lower if there are several suppliers of a product or product category who are able to perform well. Risk-based assessment is still a small but increasingly important branch of supplier assessment research. In addition, there is growing social and political demand for sustainability to be treated as a more important criterion for the evaluation of suppliers [34]. The performance of suppliers has a clear impact on the performance of a company [35], and as a result, a great many papers have aimed to provide methodological support for supplier-related decisions. The number of published papers is so large that over the last few years several studies have attempted to provide an overview of the literature. Such literature reviews [16] and [29] present several multi-criteria decision-making (MCDM) approaches to solving the supplier evaluation and selection problems, such as Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Data Envelopment Analysis (DEA). The widespread use of DEA is illustrated by the fact that its application to supplier evaluation has been examined in two recently published literature reviews [11] and [32]. Both studies highlight the adoption of hybrid methodologies for supplier evaluation using DEA and the emerging focus on environmental issues. Another study also found that AHP and ANP are the most common green supplier selection methods [13], while the rapid development of DEA applications is shown by the fact that only a few years later a literature analysis by [29] identified both AHP and DEA as the most common methods. At the application level, while methods for supporting supplier development (e.g., [24] and [30]) and rating methods (e.g., [30] and [36]) exist, it seems that the literature and methodologies focus mainly on ranking. The issue of segmentation is addressed in only a small group of papers in the literature [33], and the methodological background on which these approaches generally rely is limited (e.g., Outranking, DEA). Consequently, it is worth considering what other methodologies can be applied to solve the segmentation problem. The selection of the most suitable supplier can be achieved according to three processes: (a) total ranking, (b) outranking of the best suppliers, and (c) the full breakdown of suppliers into groups. The methods proposed in the literature mainly focus on the first process [12], [20], [21] and [23]. Articles that focus on segmentation tend to use methods that can be classified as the first or the second process (e.g., [2], [26] and [30]). However, the use of the approach of the third group (the full breakdown of suppliers into groups) is rarely found in the literature. From a methodological perspective, the literature recommends the use of DEA peeling (TDEA), and cluster analysis for the complete partitioning of decision-making units (DMUs) into clusters. However, there is a research gap in the supplier evaluation literature, as these approaches are rarely applied to such decision problems (although there are some examples that recommend DEA for qualifying suppliers – e.g., [8] and [18]). Some results can also be found concerning clustering, such as [7] and [25]. However, according to the best of our knowledge Tiered DEA has not been used explicitly for supplier assessment in the published literature. In the following section, we will focus on DEA peeling methods. Cluster analysis as a multivariate statistical technique is well known, so will not be presented. A thorough overview of cluster analysis can be found in the paper [19] and textbook [28]. Data envelopment analysis may be suitable for ranking DMUs, although doing this involves making a set of assumptions. Several review articles address how to qualify DMUs for DEA ranking. One such recent review was provided by [21]. However, these methods give an overall ranking. The basic DEA model virtually breaks down DMUs into two sets: efficient ones and non-efficient ones. Inefficient DMUs can be ranked in order based on their efficiency index, but efficient ones cannot. In this context, the question is whether a) a ranking should be established or whether b) it would instead be sufficient to divide DMUs into groups of nearly equal efficiency. This grouping method is described by [4] and we hereby propose to examine it in DEA models. A sequential algorithm has been developed through which efficient DMUs are separated from other DMUs, in a process that can be likened to the peeling of a metaphorical onion. We may then redefine the effective units in the residue and further "peel the onion". We continue to do this until we run out of units. DMUs may then be grouped according to their efficiency. The method developed by [4] is relatively widely used in the social sciences, especially in management. Port logistics have proved to be the most fruitful application. The first published application was used by [9] to examine the efficiency of South Korean ports. Moreover, the model was used to compare the efficiency of South Korean and Russian ports by [10]. Another area of application relates to higher education. Paper [5] examined 616 American universities in terms of their effectiveness using tiered DEA (TDEA). They concluded that this method gave the same result as the method of measurement used by the government administration. Among the most recent applications is the work of paper [17], who examined British universities on university lists. In both articles, grouping rather than ranking dominated. Finally, two papers on financial risk are worth mentioning. Papers [3] and [35] applied the Tiered DEA method to multi-criteria risk problems so it aimed to create risk maps.

3. Tables

In this section, we use a previously published numerical example [32] to demonstrate how the two methods work. The data used in the study are realistic and have been used in several studies. In the example, 15 supplier firms are included, which are evaluated by the ordering firm according to 5 criteria. Of these, there are three input criteria, which include management criteria, and two output criteria, which include environmental criteria. The management criteria are delivery time in days, quality in percentage and price in monetary units. These data are usually known from experience by the purchasing department of the ordering firm, assuming it has had previous dealings with the supplier. If there has been no previous contact with the supplier firm, the price and delivery time can be taken from the contract, while the quality can be estimated. The two environmental criteria represent the carbon dioxide emitted per unit of product during the production process of the supplier firm, while the other criterion represents the percentage of reusability of the supplied product. These data are provided by the supplier company. First cluster analysis, then TDEA approach will be applied to the same dataset. The dataset can be found in the Appendix. The DEA method was first described by [6]. There have been numerous extensions and applications of the method over the last nearly half-century [12]. The method used in this paper is a special property model of DEA. The basic three DEA models can be stated in the form presented in Table 1, whereby the vectors $(\mathbf{u}, \mathbf{v})$ are the weights vectors of DEA models, and vectors $(\mathbf{y}_j, \mathbf{x}_j)$ $(j = 1, 2, \ldots, p)$ are the output and input evaluations of the jth DMU, and the number of DMUs is p. Solving DEA models means solving the fractional programming problem in the second column of Table 1. The third column shows the linear programming (LP) transformation of the fractional problems. The last split column contains the dual problem of the LP problem, i.e. the envelope specification. It should be noted that the Charnes-Cooper-Rhodes (CCR) model is a constant return to scale (CRS) model, while the Banker-Charnes-Cooper (BCC) model is a variant return to scale (VRS) model. These two models can be written in input and output form. For the sake of simplicity, only the model in the input form is included here, which is denoted by the abbreviations CCR-I and BCC-I. The additive (ADD) model has a variable return to scale property, for which there is no separate input and output specification.

	Fractional Programming	Linear Programming	Dual Programming (Envelopment form)
CCR-I (CRS)	$\frac{\mathbf{u}\cdot\mathbf{y}_1}{\mathbf{v}\cdot\mathbf{x}_1} \to \max$ s.t. $\frac{\mathbf{u}\cdot\mathbf{y}_j}{\mathbf{v}\cdot\mathbf{x}_j} \leq 1;$ $j = 1, 2, ..., p.$ $\mathbf{u} \geq \varepsilon \cdot \mathbf{1},\ \mathbf{v} \geq \varepsilon \cdot \mathbf{1}$	$\mathbf{u}\cdot\mathbf{y}_1 \to \max$ s.t. $\mathbf{v}\cdot\mathbf{x}_1 = 1,$ $\mathbf{u}\cdot\mathbf{y}_j - \mathbf{v}\cdot\mathbf{x}_j \leq 0;$ $j = 1, 2, ..., p.$ $u \geq \varepsilon \cdot \mathbf{1},\ v \geq \varepsilon \cdot \mathbf{1}.$	$\theta - \varepsilon\cdot\mathbf{1}\cdot\mathbf{s}^- - \varepsilon\cdot\mathbf{1}\cdot\mathbf{s}^+ \to \min$ s.t. $\theta\cdot\mathbf{x}_1 - \mathbf{X}'\cdot\boldsymbol{\lambda} - \mathbf{s}^- = 0$ $\mathbf{Y}'\cdot\boldsymbol{\lambda} - \mathbf{s}^+ = \mathbf{y}_1$ $\boldsymbol{\lambda} \geq \mathbf{0},\ \mathbf{s}^- \geq \mathbf{0},\ \mathbf{s}^+ \geq \mathbf{0},$ $\theta \in \mathbb{R}.$
BCC-I (VRS)	$\frac{\mathbf{u}\cdot\mathbf{y}_1 - u_0}{\mathbf{v}\cdot\mathbf{x}_1} \to \max$ s.t. $\frac{\mathbf{u}\cdot\mathbf{y}_j - u_0}{\mathbf{v}\cdot\mathbf{x}_j} \leq 1;$ $j = 1, 2, ..., p.$ $\mathbf{u} \geq \varepsilon \cdot \mathbf{1},\ \mathbf{v} \geq \varepsilon \cdot \mathbf{1},$ $u_0 \in \mathbb{R}.$	$\mathbf{u}\cdot\mathbf{y}_1 - \mathbf{v}\cdot\mathbf{x}_1 - u_0 \to \max$ s.t. $\mathbf{v}\cdot\mathbf{x}_1 = 1,$ $\mathbf{u}\cdot\mathbf{y}_j - \mathbf{v}\cdot\mathbf{x}_j - u_0 \leq 0;$ $j = 1, 2, ..., p.$ $\mathbf{u} \geq \varepsilon \cdot \mathbf{1},\ \mathbf{v} \geq \varepsilon \cdot \mathbf{1},$ $u_0 \in \mathbb{R}.$	$\theta - \varepsilon\cdot\mathbf{1}\cdot\mathbf{s}^- - \varepsilon\cdot\mathbf{1}\cdot\mathbf{s}^+ \to \min$ s.t. $\theta\cdot\mathbf{x}_1 - \mathbf{X}'\cdot\boldsymbol{\lambda} - \mathbf{s}^- = 0$ $\mathbf{Y}'\cdot\boldsymbol{\lambda} - \mathbf{s}^+ = \mathbf{y}_1$ $\mathbf{1}\cdot\boldsymbol{\lambda} = 1$ $\boldsymbol{\lambda} \geq \mathbf{0},\ \mathbf{s}^- \geq \mathbf{0},\ \mathbf{s}^+ \geq \mathbf{0},$ $\theta \in \mathbb{R}.$
ADD	$\mathbf{u}\cdot\mathbf{y}_1 - \mathbf{v}\cdot\mathbf{x}_1 - u_0 \to \max$ s.t. $\frac{\mathbf{u}\cdot\mathbf{y}_j - u_0}{\mathbf{v}\cdot\mathbf{x}_j} \leq 1;$ $j = 1, 2, ..., p.$ $\mathbf{u} \geq \varepsilon \cdot \mathbf{1},\ \mathbf{v} \geq \varepsilon \cdot \mathbf{1},$ $u_0 \in \mathbb{R}.$	$\mathbf{u}\cdot\mathbf{y}_1 - \mathbf{v}\cdot\mathbf{x}_1 - u_0 \to \max$ s.t. $\mathbf{u}\cdot\mathbf{y}_j - \mathbf{v}\cdot\mathbf{x}_j - u_0 \leq 0;$ $j = 1, 2, ..., p.$ $\mathbf{u} \geq \varepsilon \cdot \mathbf{1},\ \mathbf{v} \geq \varepsilon \cdot \mathbf{1},$ $u_0 \in \mathbb{R}.$	$-\varepsilon\cdot\mathbf{1}\cdot\mathbf{s}^- - \varepsilon\cdot\mathbf{1}\cdot\mathbf{s}^+ \to \min$ s.t. $-\mathbf{X}'\cdot\boldsymbol{\lambda} - \mathbf{s}^- = 0$ $\mathbf{Y}'\cdot\boldsymbol{\lambda} - \mathbf{s}^+ = \mathbf{y}_1$ $\mathbf{1}\cdot\boldsymbol{\lambda} = 1$ $\boldsymbol{\lambda} \geq \mathbf{0},\ \mathbf{s}^- \geq \mathbf{0},\ \mathbf{s}^+ \geq \mathbf{0}.$

Table 1: *The Programming models of the three basic DEA models.*

Models of Table 1. be solved for each DMU (in our case, for all suppliers) to determine the respective efficiencies. Commercial software can be used to solve this problem. For our analysis, Microsoft Excel Solver was applied. Onion peeling, or tiered DEA (TDEA), is a recognised method for revealing which DMUs are at which efficiency level [25]. The peeling technique is a sequential method, as shown in the enumeration list below [4].

1) Initialise: t $\leftarrow$ 1, $D^{[1]} \leftarrow D$
2) While $D^{[t]} \neq \emptyset$ do:
   a) Apply a DEA model to the DMUs in set $D^{[t]}$ to identify $E_{[t]}$.
   b) $I^*_{[t]} = D^{[t]} - E^*_{[t]}$.
   c) t $\leftarrow$ t + 1.
   d) $D^{[t]} = I^*_{[t]}$.

where t is a tier index and $E^*_{[t]}$ and $I^*_{[t]}$ are the sets of efficient and inefficient DMUs on tier t, respectively, relative to set $D^{[t]}$.

The peeling technique is a sequential method, as shown in the enumeration list above. We first examine each supplier and see which of them are effective – that is, which have the same Data Envelopment Analysis (DEA) efficiency. We then take these suppliers out and run another efficiency analysis on the remaining suppliers. The analysis is reiterated in as many steps as possible.

4. Numerical Examples

In this section, we use a previously published numerical example [32] to demonstrate how the two methods work. First Tiered Data Envelopment Analysis (TDEA) method, then Cluster Analysis (CA) will be applied to the same dataset. The dataset used can be found as Table 2.

Supplier	Input criteria			Output criteria	
	Lead time (day)	CO_2 emission (g/t)	Price ($)	Reusability (%)	Quality (%)
1	-2	-30	-2	70	80
2	-1	-10	-3	50	70
3	-3	-15	-5	60	90
4	-2	-20	-1	40	85
5	-2.5	-35	-2.5	65	75
6	-2	-25	-4	90	95
7	-3	-15	-1.5	75	80
8	-1.5	-20	-3.5	85	85
9	-1	-10	-3.5	55	70
10	-2.5	-10	-4	45	75
11	-3.5	-25	-2.5	80	90
12	-2	-20	-1.5	50	65
13	-3	-15	-3	75	85
14	-1.5	-20	-4.5	85	70
15	-1	-15	-2	75	65

Table 2: *Data for numerical example.*

4.1. Results of TDEA algorithm

Three onion peels were formed by the peeling technique. The steps of the calculation and results are presented in Table 3, with the DEA efficiencies in steps.

Supplier	CCR-I	BCC-I	ADD	CCR-I	BCC-I	ADD	CCR-I	BCC-I	ADD
	DEA Efficiencies			DEA Efficiencies			DEA Efficiencies		
2	1.000	1.000	1.000						
4	1.000	1.000	1.000						
7	1.000	1.000	1.000						
9	1.000	1.000	1.000						
10	1.000	1.000	1.000						
15	1.000	1.000	1.000						
1	0.862	0.862	0.759	1.000	1.000	1.000			
3	0.837	0.837	0.803	1.000	1.000	1.000			
8	0.641	0.641	0.573	1.000	1.000	1.000			
11	0.768	0.768	0.751	1.000	1.000	1.000			
12	0.850	0.850	0.850	1.000	1.000	1.000			
13	0.736	0.736	0.731	1.000	1.000	1.000			
14	0.780	0.736	0.752	1.000	1.000	0.906			1.000
5	0.962	0.780	0.949	0.767	0.767	0.767	1.000	1.000	1.000
6	0.829	0.962	0.763	0.924	0.924	0.913	1.000	1.000	1.000

Table 3: *Results of peeling algorithm with DEA efficiencies for DEA models.*

An overview of onion peels is presented in Table 3. This suggests that the suppliers on the first onion peel or layer are both dominant and DEA efficient (Table 4).

Peel 1 (6 suppliers)	2, 4, 7, 9, 10, 15
Peel 2 (7 suppliers)	1, 3, 8, 11, 12, 13, 14
Peel 3 (2 suppliers)	5, 6, (14)

Table 4: *Onion peels of the suppliers.*

Table 3 and Table 4 show that the three methods in this example show almost identical results. The only difference is that in the additive DEA model, the 14th supplier is moved from the second to the third layer. This also indicates that one of the three DEA methods is sufficient in this case.

4.2. Segmentation of Suppliers with Cluster Analysis

Cluster analysis is a multivariate method that allows to group DMUs. In this case, the performance of 15 suppliers was analysed. The cluster analysis can be considered objective as suppliers could be divided into clusters based on similar characteristics. Three clusters were formed. The results of the cluster analysis are summarised in Figure 1, which also reveals how each group was formed. Since the scales of the variables are large, in the cluster analysis the data of the variables were transformed into data with 0 expected values and 1 standard deviation. The Euclidean distance function was applied to the distance between the data of the suppliers. For the distance between clusters, we applied the between-groups linkage in hierarchical clustering [28].

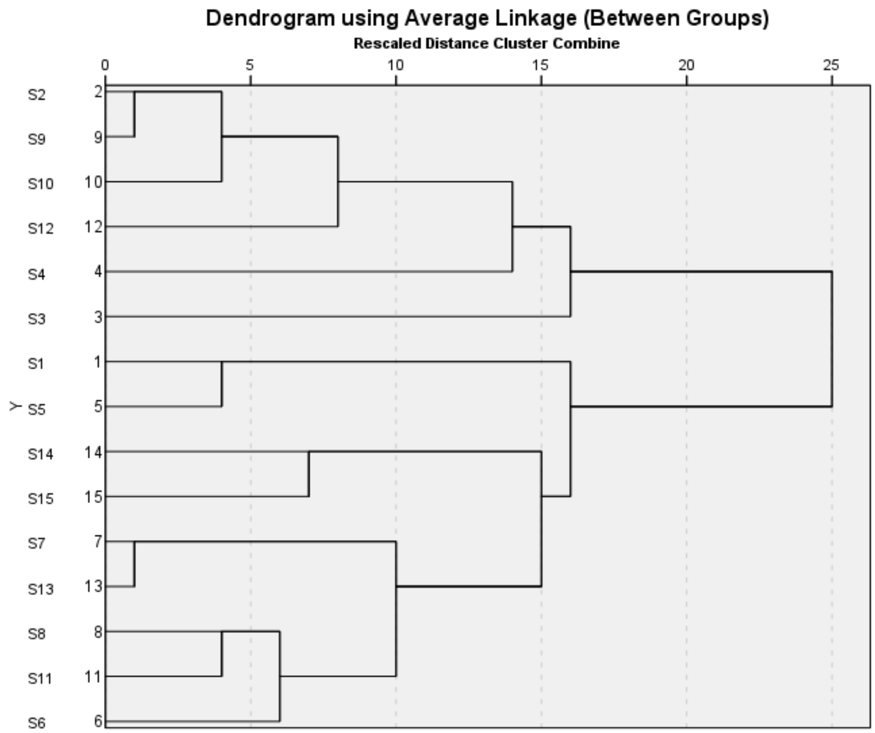

Figure 1: *Dendrogram of cluster analysis.*

Clusters	Suppliers
1 (5 suppliers)	2, 4, 9, 10, 12
2 (9 suppliers)	1, 5, 6, 7, 8, 11, 13, 14, 15
3 (1 suppliers)	3

Table 5: *Analysing the suppliers with cluster analysis.*

Table 5 presents the result of the cluster analysis.

We tried more clustering methods, where we changed the linkage between supplier sets while keeping the Euclidean distance. All seven SPSS linkage methods produced almost identical results, so the clustering presented can be considered satisfactory.

4.3. Matching of Tiered DEA Layers and Clusters

Table 6 summarises the results of the analysis of our data using the two methods.

Suppliers	TDEA Layers	CA Clusters
2	1	1
4	1	1
9	1	1
10	1	1
7	1	2
15	1	2
12	2	1
1	2	2
8	2	2
11	2	2
13	2	2
14	2	2
5	3	2
6	3	2
3	2	3
Number of groups	3	3

Table 6: *Comparison of the results of two methods.*

The results are similar, but the underlying logic of the methods is different, leading to obvious differences in the classification. If we compare the coloured groups, we can see that there are two groups (four suppliers each) into which both methods grouped the same suppliers. In our example, this was the case with the best suppliers. The assessment of the performance of outlier suppliers would depend on detailed knowledge of the circumstances of the rogue situation. Now let us compare the two classification methods. The TDEA procedure measures suppliers on an ordinal scale, because we always take the efficient suppliers from the set of suppliers. On the other hand, the solutions obtained with cluster analysis are more likely to give us groups interpreted on a nominal scale, since we can only determine which groups the suppliers belong to. The cross-tabulation of the two variables is shown in Table 7.

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="3">Layer</td><td rowspan="2">Total</td></tr>
<tr><td>1</td><td>2</td><td>3</td></tr>
<tr><td rowspan="3">Cluster</td><td>1</td><td>4</td><td>1</td><td>0</td><td>5</td></tr>
<tr><td>2</td><td>2</td><td>5</td><td>2</td><td>9</td></tr>
<tr><td>3</td><td>0</td><td>1</td><td>0</td><td>1</td></tr>
<tr><td colspan="2">Total</td><td>6</td><td>7</td><td>2</td><td>15</td></tr>
</table>

Table 7: *Comparison of layers and cluster.*

The two lists raise the question of whether the results of the two clustering procedures are independent and, if not, what linear relationship they have with each other. The question of independence can be tested using the Khi-square method, while the strength of the relationship can be tested using Cramér's V association measure. The results show that the Khi-square was 0.202, indicating that there is a dependence between the two groupings, i.e. the two groupings yield similar groups. Cramér's V value was 0.631, indicating a significant strong association relationship. This also indicates that we are free to choose between the two methods, but the disadvantage of cluster analysis is that we cannot establish an ordinal relationship between the groups. Tiered DEA is more suitable for this purpose.

	Group 1		Group 2		Group 3		Total
	L1	C1	L2	C2	L3	C3	
Suppliers (piece)	**6**	**5**	**7**	**9**	**2**	**1**	**15**
Lead Time	-1.667	-1.600	-2.357	-2.222	-2.250	-3.000	-2.067
CO2	-13.333	-14.000	-20.714	-22.222	-30.000	-15.000	-19.000
Price	-2.500	-2.600	-3.143	-2.833	-3.250	-5.000	-2.900
Reusability	56.667	48.000	72.143	77.778	77.500	60.000	66.667
Quality	74.167	73.000	80.714	80.556	85.000	90.000	78.667
Correlation	0.997		0.999		0.978		

Table 8: *Comparison of group means (in the headlines: L=Layer, C=Cluster).*

Table 8 illustrates the group means of the groups given by the two clustering procedures. The correlation between groups is shown in the last row. This indicates that the group means are closely related. When evaluating the analyses, it is worth noting that the first two of the two methods determine the supplier groups according to their own mathematical logic, whereas in the case of cluster analysis the analyst influences the result by specifying the optimal number of clusters.

5. Comparison of the Two Clustering Methods

Among the two grouping procedures, cluster analysis does not use a better or worse distinction between elements during group formation, but only differentiates groups, without any evaluation. Tiered DEA, on the other hand, selects the groups sequentially. The selection is based on DEA efficiency, that is, in each step, it divides the remaining elements into two sets, that is, efficient and inefficient. It therefore divides the sets into layers of sequentially decreasing efficiency. However, in this case, those elements that are Pareto efficient are grouped together. As in the case of tiered DEA, here too we form two sets in each step: the efficient and the inefficient. The set of Pareto efficient elements is separated from the others and the algorithm is continued on the remaining set. A comparison of the two clustering techniques is provided in Table 9. We will show below, since in cluster analysis we only define the distance between two elements, but we cannot determine which element is better than another. Among the two methods, since in cluster analysis we only define the distance between two elements, but we cannot determine which element is better than another. This we will show below.

Evaluation	Tiered DEA	Cluster Analysis
Difference between elements	Yes	None
Basis of Clustering	DEA Efficiency	Distance functions
Level of Grouping	Layers	Clusters
Available Softwares	DEAOS, PyDEA, MS Excel Solver etc.	SPSS, STAT/SAS etc.

Table 9: *Comparison of the two approaches.*

Paper [18] examined the relationship between DEA and Pareto efficient decision-making units. The set of Pareto efficient points was shown to be larger than that of DEA efficient points. This means that some of the Pareto efficient DMUs lie on the DEA production frontier, while others do not. Our numerical example also showed that the number of Pareto efficient suppliers was 13, and only 5 of them were also DEA efficient. Interestingly, there were Pareto efficient suppliers even on the third DEA layer, which suggests that the Tiered DEA method provides a more sophisticated classification of suppliers. At the same time, the numerical example shows that Tiered DEA proves to be a better method than cluster analysis, because as long as cluster analysis maps groups only on a nominal scale, Tiered DEA projects DMUs on an ordinal scale due to the introduction of DEA efficiency, in our case, the suppliers. Thus, in this case, the TDEA method proves to be more useful than the cluster analysis.

6. Conclusion

In this article, we have examined two segmentation methods. All of them are recognised, but they have not yet been compared in the literature on supplier segmentation. As managers are focusing nowadays rather on supply base management than on individual supplier selection decisions, it is important to identify what potential methods are available, and to develop an understanding of how to interpret the results. The presented examples and results show that the methods investigated do not provide a clear-cut solution, and more than one method may need to be applied. This paper reveals that the two methods lead to similar but not identical results. This suggests that further investigation of the DMUs in the analysis is necessary. The numerical example also highlights that the Tiered DEA method is the more sophisticated of the two methods, because it narrows the set of efficient points better. At the same time, the disadvantage of the cluster analysis method is that it is not possible to determine which of the DMUs is preferable. However, cluster analysis has the capacity more finely to divide suppliers into groups. If we could come up with a recommendation, we would first choose TDEA, then cluster analysis. The results of our study also show that the methods are suitable for supporting the classification of suppliers. A further research question that now arises concerns how variability in supplier performance may be reclassified. Answering this question is likely to require a sensitivity analysis.

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