APPLICATION OF CLUSTER ANALYSIS TO IDENTIFICATION OF INNOVATION CATEGORIES OF SLOVAK SMALL AND MEDIUM ENTERPRISES

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Abstract

When studying key factors and barriers determining innovation activities of enterprises, we need to identify unique categories of enterprises which provides us with a good representation of innovation focused behavior of enterprises. Based on their innovation activities, enterprises are usually classified into two basic categories: innovative enterprises and non-innovative enterprises. Innovation activities of an enterprise could result in various types of innovations - product innovations, process innovations, organizational innovations and marketing innovations. These types of innovations could be combined for each enterprise in very different and unique way, which results in high variability of differences among enterprises. Consequently, standard classification into two groups seems to be unnecessary rough one. In our contribution, we aim to identify a more suitable set of innovation categories by applying various clustering methods to data of Slovak medium and small enterprises collected in the period November 2015–January 2016. Identified innovation categories will be examined more closely via descriptive statistics and exploratory graphical techniques.

Keywords: *small and medium enterprises, cluster analysis, innovations*

JEL Codes: *C38, O30*

1. Introduction

The current approach to innovations maintains that innovation is a key word for entrepreneurs, it emphasizes a global approach to innovations as a philosophy (way of managing enterprises) which influences all parts of transformation process in the enterprise (marketing, research and development, planning, manufacturing, managing, etc.) (Adair, 2009). The guidelines on measurement of innovation the OSLO Manual (OECD, 2005) define innovation as “the implementation of a new or significantly improved product (good or service) or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations”.

According to Bessant and Tidd (2011), for small and medium enterprises (SMEs), innovation can be a way to gain a competitive advantage. Cooke and Wills (1999) stress that innovations help reinforce the market position or gain a larger market share, increase the effectiveness of operations and improve the reputation. Thus, the ability to compete in innovations plays a very important role as a factor of competitiveness and strengthening innovation activities is one of the main tasks of all types of businesses.

In the last years the role of innovation on SMEs survival has received in theoretical and managerial literature a great deal of attention (Di Cintio ., 2017; Cheah *et al*., 2014; Lee *et al.*, 2017). Much of the research has expanded its scope and included different types of innovation in the research (Maletič *et al*., 2014). A wide range of new themes has appeared.

In majority of literature devoted to innovations in SMEs, only two categories of enterprises are usually used – innovation leaders and non-innovative enterprises (Hoffman *et al*., 1998; Keizer *et al.*, 2002; Radas and Božič, 2009; Szczepańska-Woszczyna, 2014). It is assumed implicitly that such a classification of enterprises represents adequately various types of innovative activities of the enterprises leading to product innovations, process innovations, organizational innovations and marketing innovations. On the other hand, various types of innovations could be combined for each enterprise in very different and unique way, which results in high differences among enterprises. Consequently, standard classification into two groups seems to be unnecessary rough one.

In (Lesáková *et al*., 2017), authors claimed that if we aim at identification of differences in key factors and barriers determining innovation activities, more detailed classification is needed, and they proposed, guided by the number of clusters identified using k-means method, the following three categories of Slovak SMEs – innovation leaders, innovation followers and non-innovative enterprises. Innovation leaders were defined enterprises with at least three product and process innovations and at least five organizational and marketing innovations in the period of six years. Non-innovative enterprises were those without product and process innovations in the observed period. Enterprises not belonging to either of these two groups were identified as innovation followers.

In our contribution, we apply a heuristic approach to the data used in (Lesáková *et al*., 2017). We identify an alternative set of innovation categories of Slovak enterprises by applying various clustering methods, namely partitioning around medoids and hierarchical clustering, and then characterize them via descriptive statistics and exploratory graphical techniques.

The remainder of the paper is structured as follows. In Section 2, we provide reader with some details regarding the clustering methods and data utilized in our analyses. Section 3 presents and discuss the obtained results. Finally, in Section 4, we give some conclusions and sketch possible paths for our further research.

2. Data and Methodology

In this section, we provide reader with description of the analyzed data set, some theoretical background regarding the utilized clustering methods and software solutions used to perform analyses.

2.1 Data

All analyses were performed on questionnaire data of 51 SMEs collected in the period November 2015–January 2016. The questionnaire was aimed at identification of key factors determining innovation activities and main innovation barriers. More detailed description of the data set we used for the presented analyses can be found in (Lesáková *et al*., 2017). One piece of information collected was the number of different types of innovation - product innovations, process innovations, organizational innovations and marketing innovations which occurred in an enterprise each year in the period 2010–2015. As we are not interested in individual paths of enterprises over time, these longitudinal data about innovation activities of SMEs were aggregated and four variables consisting of the total number of innovations of a particular kind in the period were added to data. Because of such a small number of variables, we do not apply any dimension reduction technique before application of the cluster analysis methods. We also use unscaled data as the variables have a coherent meaning and their corresponding descriptive statistics (means, standard deviations etc.) are very similar (see Table 1).

2.2 Methods

Our analysis is a two-stage process. In the first stage, we identify the appropriate number of clusters using a heuristic approach based on internal validation criteria, i.e., on various indices proposed in literature (Charrad *et al*., 2014). For each selected clustering method, we compute selected evaluable indices and the preferable number of clusters is then determined using a majority vote. Once the optimal number of clusters is determined, we apply partitioning around medoids to create the selected number of clusters without providing an initial set of medoids. Finally, the resulting clustering are explored via descriptive statistics.

Table 1: Descriptive statistics of analyzed data

Statistics	Variables			
	Number of product innovations	Number of process innovations	Number of organizational innovations	Number of marketing innovations
Mean (SD)	3.06 (1.94)	3.20 (1.85)	3.49 (1.96)	3.20 (2.10)
Min, Max	0, 5	0, 5	0, 5	0, 5
Q1, Q2, Q3	1, 4, 5	2, 4, 5	2.5, 4, 5	0, 4, 5

Notes: SD = Standard deviation, Q1 = First Quartile, Q2 = Median, Q3 = Third Quartile.
Source: The author's work.

Our analysis is based on the following strong assumptions:

- We assume that the number of cluster should not exceed *five* given the low number of variables we use for clustering and possible difficulties to interpret the resulting innovation categories of Slovak SMEs.
- Although our data are discrete, we apply standard methods and distances used in the case of continuous data, e.g. we use the Euclidean distance, Ward linkage etc.

We assume the following clustering methods for identification of the optimal clustering

- partitioning around medoids
- agglomerative hierarchical clustering (Hastie *et al*., 2009; James *et al*., 2013) using the Euclidean, Chebyshev and Manhattan distances, and the following linkages (Charrad *et al*., 2014)
    - Ward
    - single
    - complete
    - average
    - median.

The partitioning around medoids (PAM) algorithm was introduced by Kaufman and Rousseeuw (1987). Contrary to k-means, we create here clusters not around artificial centroids but around medoids which are always elements of the dataset. As in the case of k-means, we are minimizing distances of elements of clusters from medoids representing clusters. The number of clusters in the PAM algorithm is usually determined using the average silhouette width index proposed by Rousseeuw (1987). The average silhouette width of the k-th cluster is given as follows (Charrad *et al*., 2014)

$$s_k = \frac{\sum_{i=1}^{n_k} \frac{b(i)-a(i)}{\max(b(i),a(i))}}{n_k}, \tag{1}$$

where $a(i)$ denotes an average distance (dissimilarity) of the *i*-th object belonging to a cluster k to all other objects within the same cluster, $b(i)$ denotes the lowest average distance (dissimilarity) of the *i*-th object to other clusters. The average silhouette width (silhouette index) for the whole data is then defined as follows

$$\overline{s} = \frac{\sum_{k=1}^{K} s_k n_k}{\sum_{k=1}^{K} n_k}, \tag{2}$$

where K denotes the number of clusters. We choose the number of clusters maximizing the criterion (Kaufman and Rousseeuw, 1990).
An alternative is to use the Calinski-Harabasz criterion (Calinski and Harabasz, 1974) defined using the following equation (Charrad *et al.*, 2014)

$$CH(K) = \frac{\text{trace}(B_K)/(K-1)}{\text{trace}(W_K)/(n-K)}, \tag{3}$$

where K denotes the number of clusters, n is the number of objects, B_k represents the between-group dispersion matrix for data clustered into K clusters and W_k is the within-group dispersion matrix for data clustered into K clusters. We choose the number of clusters maximizing the criterion.

Besides the two criteria mentioned above, in the case of agglomerative hierarchical clustering, we use also the following indices (Charrad *et al*., 2014):

Duda index, Pseudot2 index, C-Index, Beale index, CCC index, Ptbiserial index, DB index, Frey index, Hartigan index, Ratkowsky index, Scott index, Marriot index, Ball index, Trcovw index, Tracew index, McClain index, Rubin index, KL index, D-index, Dunn index, Hubert statistic, SD index, SD bw index. We do not present here the corresponding formulas for these indices due to limited length of our contribution and because we are using hierarchical clustering merely as a supportive analysis for the determination of the number of clusters.

As the presented linkages and distances are standard, we again do not list their formulas in the paper. Readers can find the corresponding formulas in (Hastie *et al*., 2009; James *et al*., 2013; Charrad *et al*., 2014).

2.3 Software

We use statistical system R 3.4.1 (R Core Team, 2017) and R packages `cluster` (Maechler *et al*., 2015), `fpc` (Hennig, 2015), `Nbclust` (Charrad *et al*., 2014), `psych` (Revelle, 2017) as our analytical toolbox.

3. Results

Assuming that the number of cluster should not be exceeding five, the PAM algorithm identified four clusters using both average silhouette width and the Calinski-Harabasz criterion for the Euclidean distance and three clusters using both average silhouette width and the Calinski-Harabasz criterion for the Manhattan distance. In both cases, the same medoids were selected regardless the criterion. For the Chebyshev distance, five clusters were selected using the average silhouette width criterion and two clusters were selected using the Calinski-Harabasz criterion.

The number of clusters identified by the PAM algorithm was also verified using hierarchical clustering with various evaluating coefficients and different definitions of distances and linkages applied. In most of the cases, three clusters were identified as the optimal number of clusters in our data.

Based on results of the first step of our analysis, we decided to create clustering using the PAM algorithm assuming both three clusters (as identified using the Manhattan distance) and four clusters (as identified using the Euclidean distance) assuming both the Euclidean and Manhattan distances. Some parameters of the resulting clusterings are listed in Tables 2–7.

Table 2: Clusters identified by the PAM algorithm

Number of clusters	Distance	ID of medoids	Number of objects in clusters
3	Euclidean	6, 35, 9	23, 17, 11
3	Manhattan	10, 8, 32	29, 11, 11
4	Euclidean	6, 35, 9, 32	15, 17, 11, 11
4	Manhattan	15, 35, 8, 32	13, 16, 1, 6

Source: The author's work.

Table 3: Medoids identified by the PAM algorithm

ID of medoid	Variables			
	Number of product innovations	Number of process innovations	Number of organizational innovations	Number of marketing innovations
6	3	3	3	3
8	0	0	0	4
9	0	0	2	2
10	4	4	5	5
15	3	3	4	4
32	4	4	5	0
35	5	5	5	5

Source: The author's work.

Based on medoids identified in Table 3, descriptive statistics (min, max, quantiles) of clusters presented in Tables 4–7, we can interpret cluster 2 as the one consisting of the most innovation focused enterprises and cluster 3 as the one consisting of non-innovative enterprises. Cluster 1 represents innovation followers. In the case of four clusters, both cluster 1 and cluster 4 represent innovation followers, where cluster 4 consists of those enterprises with stronger focus on organizational innovations but neglecting marketing innovations.

Using the obtained results, we can operationalize definitions of categories of Slovak SMEs characterizing intensity of their innovation activities as follows:

- Innovation leaders based on min and max values – enterprises that introduced at least three product innovations, at least four process innovations, at least four organizational and at least four marketing innovations in the period 2010–2015.
- Non-innovators based on min and max values – enterprises that have at most two product innovations and at most two process innovations in the period.
- Innovation followers based on min and max values – enterprises that are neither innovation leaders based on min and max nor non-innovators based in min and max. From the category of innovation followers based on min and max, we can further distinguish those enterprises without any marketing innovations.
- Innovation leaders based on quantiles – enterprises that introduced at least four product innovations, at least four process innovations, at least five organizational and at least five marketing innovations in the period.
- Non-innovators based on quantiles – enterprises that has at most one product innovation and at most one process innovation.
- Innovation followers based on quantiles – enterprises that are neither innovation leaders based on quantiles nor non-innovators based on quantiles. From the category of innovation followers, we can again separate enterprises without any marketing innovations.
- Innovation leaders based on medoids – enterprises that introduced at least five product innovations, at least five process innovations, at least five organizational and at least five marketing innovations in the period.
- Non-innovators based on medoids – enterprises that introduced no product innovations, no process innovations and no organizational innovations in the period.
- Innovation followers based on medoids – enterprises that are neither innovation leaders based on medoids nor non-innovators based on medoids. We can once again separate enterprises without any marketing innovations.

Table 4: Descriptive statistics of clusters (4 clusters, the Euclidean distance)

	Number of product innovations			
Statistics	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Mean (SD)	3.13 (1.55)	4.47 (0.62)	0.45 (0.69)	3.5(2.2)
Min, Max	0, 5	3, 5	0, 2	0, 5
Q1, Q2, Q3	3, 3, 4	4, 5, 5	0, 0, 1	3, 4.5, 5
	Number of process innovations			
Statistics	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Mean (SD)	3.33 (1.23)	4.65 (0.49)	0.55 (0.82)	3.5 (1.93)
Min, Max	0, 5	4, 5	0, 2	0, 5
Q1, Q2, Q3	3, 3, 4	4, 5, 5	0, 0, 1	3.25, 4, 5
	Number of organizational innovations			
Statistics	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Mean (SD)	2.27 (1.98)	4.94 (0.24)	2.09 (2.07)	4.62 (0.74)
Min, Max	0, 5	4, 5	0, 5	3, 5
Q1, Q2, Q3	0, 3, 4	5, 5, 5	0, 2, 4	4.75, 5, 5
	Number of marketing innovations			
Statistics	Cluster 1	Cluster 2	Cluster 3	Cluster 4

Mean (SD)	3.93 (1.33)	4.76 (0.44)	2.09 (2.17)	0 (0)
Min, Max	0, 5	4, 5	0, 5	0, 0
Q1, Q2, Q3	3.5, 4, 5	5, 5, 5	0, 2, 4	0, 0, 0

Notes: SD = Standard deviation, Q1 = First Quartile, Q2 = Median, Q3 = Third Quartile.
Source: The author's work.

Table 5: Descriptive statistics of clusters (4 clusters, the Manhattan distance)

	Number of product innovations			
Statistics	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Mean (SD)	3.38 (1.33)	4.56 (0.63)	0.55(0.93)	3 (2.14)
Min, Max	0, 5	3, 5	0, 3	0, 5
Q1, Q2, Q3	3, 4, 4	4, 5, 5	0, 0, 1	0, 4, 5
	Number of process innovations			
Statistics	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Mean (SD)	3.38 (0.65)	4.75 (0.45)	0.82 (1.54)	3.09 (1.97)
Min, Max	2, 4	4, 5	0, 5	0, 5
Q1, Q2, Q3	3, 3, 4	4.75, 5, 5	0, 0, 1	0, 4, 4
	Number of organizational innovations			
Statistics	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Mean (SD)	3.38 (1.66)	4.62 (1.26)	1.27 (1.79)	4.18 (1.54)
Min, Max	0, 5	0, 5	0, 5	0, 5
Q1, Q2, Q3	3, 4, 4	5, 5, 5	0, 0, 2	0, 5, 5
	Number of marketing innovations			
Statistics	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Mean (SD)	4.08(0.76)	4.81(0.4)	3 (2.14)	0 (0)
Min, Max	3, 5	4, 5	0, 5	0, 0
Q1, Q2, Q3	4, 4, 5	5, 5, 5	1, 4, 5	0, 0, 0

Notes: SD = Standard deviation, Q1 = First Quartile, Q2 = Median, Q3 = Third Quartile.
Source: The author's work.

Table 6: Descriptive statistics of clusters (3 clusters, the Euclidean distance)

	Number of product innovations		
Statistics	Cluster 1	Cluster 2	Cluster 3
Mean (SD)	3.26 (1.76)	4.47 (0.62)	0.45 (0.69)
Min, Max	0, 5	3, 5	0, 2
Q1, Q2, Q3	3, 4, 5	4, 5, 5	0, 0, 1
	Number of process innovations		
Statistics	Cluster 1	Cluster 2	Cluster 3
Mean (SD)	3.39 (1.47)	4.65 (0.49)	0.55 (0.82)
Min, Max	0, 5	4, 5	0, 2
Q1, Q2, Q3	3, 4, 4	4, 5, 5	0, 0, 1
	Number of organizational innovations		
Statistics	Cluster 1	Cluster 2	Cluster 3
Mean (SD)	3.09 (2)	4.94 (0.24)	2.09 (2.07)
Min, Max	0, 5	4, 5	0, 5
Q1, Q2, Q3	1.5, 4, 5	5, 5, 5	0, 2, 4

Statistics	Number of marketing innovations		
	Cluster 1	Cluster 2	Cluster 3
Mean (SD)	2.57(2.19)	4.76 (0.44)	2.09 (2.17)
Min, Max	0, 5	4, 5	0, 5
Q1, Q2, Q3	0, 3, 4.5	5, 5, 5	0, 2, 4

Notes: SD = Standard deviation, Q1 = First Quartile, Q2 = Median, Q3 = Third Quartile.
Source: The author's work.

Table 7: Descriptive statistics of clusters (3 clusters, the Manhattan distance)

	Number of product innovations		
Statistics	Cluster 1	Cluster 2	Cluster 3
Mean (SD)	4.03 (1.15)	0.55 (0.93)	3(2.14)
Min, Max	0, 5	0, 3	0, 5
Q1, Q2, Q3	4, 4, 5	0, 0, 1	1, 4, 5
	Number of process innovations		
Statistics	Cluster 1	Cluster 2	Cluster 3
Mean (SD)	4.14 (0.88)	0.82 (1.54)	3.09 (1.97)
Min, Max	2, 5	0, 5	0, 5
Q1, Q2, Q3	4, 4, 5	0, 0, 1	1, 4, 4.5
	Number of organizational innovations		
Statistics	Cluster 1	Cluster 2	Cluster 3
Mean (SD)	4.07 (1.56)	1.27 (1.79)	4.18 (1.54)
Min, Max	0, 5	0, 5	0, 5
Q1, Q2, Q2	4, 5, 5	0, 0, 2	4, 5, 5
	Number of marketing innovations		
Statistics	Cluster 1	Cluster 2	Cluster 3
Mean (SD)	4.48(0.69)	3(2.14)	0 (0)
Min, Max	3, 5	0, 5	0, 0
Q1, Q2, Q3	4, 5, 5	1, 4, 5	0, 0, 0

Notes: SD = Standard deviation, Q1 = First Quartile, Q2 = Median, Q3 = Third Quartile.
Source: The author's work.

4. Conclusion

By analyzing data about Slovak SMEs from the period 2010–2015 using hierarchical clustering and partitioning around medoids, with the maximal number of clusters restricted to five, we have identified three and four different classes of enterprises with respect to their innovation activities. We used the identified clusters to operationalize the definitions of enterprises with the highest focus on innovations, non-innovative enterprises and innovation followers. In the paper we present three alternatives of such definitions which are based on minimal and maximal values and quantiles of clustering variables corresponding to identified clusters, and medoids of those clusters, respectively. In the case of four clusters, we identified also an additional subgroup among innovation followers.

The presented classes of Slovak SMEs with respect their innovation activities were derived using an aggregate data about the total number of innovation of given types in the selected time period (2010–2015), i.e. we were not interested in paths leading to the presented innovation profiles. In our future research, we will identify innovation categories of Slovak SMEs based on longitudinal data about their innovation activities.

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