Clusterwise pls-path modelling for customer loyalty analysis in heterogeneous markets: a case study on the customers of a superstore

CLUSTERWISE PLS-PATH MODELLING FOR CUSTOMER LOYALTY ANALYSIS IN HETEROGENEOUS MARKETS: A CASE STUDY ON THE CUSTOMERS OF A SUPERSTORE

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Abstract *Customer loyalty analysis aims at detecting suitable strategies to strengthen loyalty of customers. Like in customer satisfaction analysis, PLS-Path Modeling (PLS-PM) appears to be a suitable technique to attain this goal. Basic PLS-PM assumes homogeneity over population so, since customers have different loyalty behaviors, a PLS-path model should be applied to each homogeneous subgroup. Nevertheless, as this grouping is unknown before starting customer loyalty analysis, two ways are practicable:* (i) *to carry out* a-priori *marketing segmentation followed by local PLS-path models;* (ii) *to carry out both actions by model-based segmentation. This paper puts forward some considerations about these two different approaches.*

Keywords: *Customer loyalty, PLS-path modeling, REBUS.*

1. INTRODUCTION

Usually, capturing new customers is more onerous than keeping the existing ones and becomes even more difficult in the course of economic recession periods. Therefore, pleasing the customers adopting efficient loyalty politics becomes more important in time of crisis - as the current one - than in expansion phases.

Nevertheless, identifying proper Customer Loyalty (CL) strategies should take into account a right comprehension of psychological processes underlying customers' loyalty toward a brand or a provider. The relevant questions are: what does the customer take into account when he decides to purchase again a product or renew a service? What can induce him to choose a different brand or to switch the provider? CL models try to provide suitable answers to these questions (Jacoby and Chestnut, 1978; Rundle-Thiele, 2005). The parameters estimation of these models allows to evaluate how much these issues act on customers' loyalty and, consequently, suggests the most suitable policy of CL.

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Let us suppose, for example, that a CL model identifies the economic convenience of the offer (cheapness) as the most important factor affecting the customers' loyalty toward a given brand. Then, to keep the customers loyal toward the brand, the marketing director will have to get under control their perception of cheapness of the brand. But loyalty behaviors of the customers cannot be considered homogeneous. In fact, some customers could consider more important the cheapness while others could give more relevance to the perception of trust (quality and reliability) evoked by the brand. Moreover, some customers could have an innate predisposition to be loyal, so their behaviour does not depend on the brand, but on their own way of being. It is clear that these peculiarities do not emerge if a model is estimated on the overall clientele because the information extracted could be unhelpful to define appropriate policies of CL. Properly, the model should be estimated on each different segment (Montinaro and Sciascia, 2011). Nevertheless, two orders of reasons make not easy an *a priori* identification of such segments:

1. often the segments available to the market analyst are not suitable for the evaluation of loyalty;

2. the differences among segments should be related to different customers' behaviors toward the brand, but these differences can be underlined only after the estimation of a CL model.

1.1. MARKETING SEGMENTATION AND CUSTOMER LOYALTY

Typically, marketing segmentation should aim at defining clusters of customers satisfied by the same product. Among these, the company identifies the most interesting ones (targets) and offers them products or services developed to satisfy their specific requests. The variables used to this purpose are *the segmentation basis*, which may concern the benefits requested (*benefit segmentation*), psychological profile (*psychographic segmentation*) and demographic characteristics (*demographic segmentation*) (Wedel and Kamakura, 1998). Generally, such variables are observed by surveys carried out *ad hoc*.

Demographic segmentation is the easiest to carry out, but only in few cases people with the same demographic profile can be satisfied by the same product. So, it seems unsuitable to define successful strategies of loyalty.

Benefit segmentation is the most suitable kind of segmentation because is the most market oriented, but its implementation needs an a-priori clear idea about

Table 1: Segmentation efficacy for CL

Segmentation	efficacy
Demographic	low
Benefit	middle
Psychographic	high (in theory)

the possible benefits requested by the market. It is useful to define the product or service that should satisfy the customers (Haley, 1984). In some cases, individuals having the same requests (for example those who want a not expensive city-car) could have the same behaviour about loyalty (i.e. giving more importance to cheapness). As a result, such a segmentation could be suitable to identify different loyalty behaviors.

Psychographic segmentation is based on the idea that individuals showing similar behaviors require similar products (or services). The basis of this segmentation are behavioral variables related to consumption in general; usually this segmentation is performed on large population by specialized agencies of marketing consulting. This type of segmentation can be helpful to analyze CL if behavioral variables pertaining to Loyalty are included among the basis. Table 1 reports the efficacy of these kinds of segmentation for CL analysis.

2. PLS-PATH MODELING IN CUSTOMER LOYALTY ANALYSIS

The loyalty degree of a customer or a client toward a product or service is not a construct easy to be measured directly. Moreover, such latent construct is linked to other latent constructs like *Trust*, *Cheapness*, *Inertia*, etc.
For these reasons *Structural Equation Modeling* (SEM) (Bollen, 1989) is clearly suitable for CL analysis. Indeed, SEM includes a class of statistical methodologies meant to estimate a network of causal relationships, defined according to a theoretical model, that link two or more latent constructs (*Latent Variables*, LVs), each measured through a number of observable indicators (*Manifest Variables*, MVs) (Esposito Vinzi et al., 2010). In the field of SEM, two main approaches have become prominent:

- Covariance-based SEM "the hard modeling" (Jöreskog, 1973);

- Component-based SEM "the soft modeling", based on partial least square (PLS) method (Wold, 1985).

The first approach focuses on the estimation of the covariance matrix of the latent constructs and needs large samples (more than 100 subjects and preferably more than 200 subjects). Estimation methods used for covariance-based SEM, like Maximum Likelihood (ML) or Unweighted Least Squares (ULS), require restrictive assumptions. In this sense, the Covariance-based SEM is sometime called "hard modeling".

The second approach is a two-step method: *(i)* LV scores (component scores) are computed using the PLS algorithm; *(ii)* OLS regressions are carried out on the LV scores for estimating the structural equations (Tenenhaus, 2008). More specifically, such modeling consists of a main model (inner model) which relates the LVs (ξ_j) by linear regressions:

$$\xi_j = \sum_{j' \to j} \beta_{j'} \xi_{j'} + \zeta_j \tag{1}$$

where ζ_j is the regression error.
Each of these LVs is measured indirectly by a block of MVs ($x_{j,1}, x_{j,2}, \ldots$) according to a measurement model (outer model), that can be either reflective:

$$x_{j,k} = \alpha_{j,k} \xi_j + \varepsilon_{j,k} \tag{2}$$

or, in some cases, formative:

$$\xi_j = \sum_k \omega_{j,k} x_{j,k} + \varepsilon_j \tag{3}$$

The reflective measurement is clearly a factorial model and is efficient if the MVs are highly correlated (uni-dimensionality) and are a homogeneous system of measurement.
The component-based SEM can be considered as an extension of principal component analysis to path modeling, hence the name *PLS-Path Modeling* (PLS-PM). PLS-PM is mainly used for score computation and can be carried out on very small

samples, moreover it does not require distributional assumptions (soft modeling). For these features PLS-PM is usually preferred in the assessment of *customer satisfaction* and *customer loyalty*.
Nevertheless, while segmentation in covariance-based SEM is well-established (McLachlan and Peel, 2000), segmentation in PLS-PM is more recent. Among the methodologies recently developed, that we will call *clusterwise PLS-PM* in analogy with clusterwise regression (Späth, 1979), we will briefly review the following methods: *Finite mixture Partial Least Squares* (FIMIX-PLS), *Partial Least Squares Typological Path Modeling* (PLS-TPM) and *REsponse Based Units Segmentation* (REBUS-PLS).

FIMIX-PLS (Hann et al., 2002; McLachlan and Peel, 2000) is based on the assumption that, if separate classes exist among the units, the heterogeneity will be concentrated in the structural model, i.e. in the relationships among latent variables. The first step of FIMIX-PLS consists of estimating the path model through the PLS-PM algorithm. Then the estimated latent variable scores are used to detect the classes by an Expectation-Maximization procedure (McLachlan and Peel, 2000). Besides, since the number of groups is not known, the FIMIX-PLS is repeated for different numbers of groups. Consequently, different global measures of fit or entropy statistics, indicating the degree of separation in the estimated individual group probabilities, have to be used to choose the appropriate number of groups. However, several problems could arise in order to ensure model identification: a normality assumption is required at least for the endogenous latent variables; even if a strong robustness has been shown by FIMIX-PLS when data are non-normal, the technique captures heterogeneity only with respect to the structural model; the number of classes has to be known a priori; it can occur in local optima.

PLS-TPM (Esposito Vinzi et al., 2004; Squillacciotti, 2010), more coherently with PLS models, does not require any distributional assumption on latent or observed variables. It is an iterative method determining groups that modify themselves at each iteration, according to unit-model distances. Such unit-model distances are computed on the basis of the structural model and the measurement model of a target variable. PLS-TPM starts from the estimation of the global PLS path model, and then - after choosing the number of classes and assigning randomly each unit to a class - iteratively and until convergence, it estimates one local model for each class and re-assigns the units to the closest local model on the basis of unit-model distances. Nevertheless, a formal proof of convergence does not exist. It has been implemented only for models with reflective endogenous

Table 2: Features of clusterwise PLS-PM

Features	FIMIX	TPM	REBUS
distributional assumption	yes	no	no
different outer models	no	no	yes
formative measurement	yes	no	no
number of groups fixed a priori	yes	yes	no

blocks. Still, no indicator of group separation is available in PLS-TPM procedure, and a unique well-identified target endogenous variable is required.

REBUS-PLS (Esposito Vinzi et al., 2010, 2008) can be seen as a development of the PLS-TPM. It does not require distributional hypothesis neither on latent nor on observed variables and can be applied only to models involving reflective blocks. However, it captures heterogeneity taking into account both inner and outer model (it does not require the identification of a target variable). It starts estimating the overall model; through the analysis of residuals, it carries out a hierarchical cluster analysis of them defining the number of groups. Then it estimates the local models of each group and, according to a closeness measure (CM) of the units to the models - conceived following the GoF structure - assigns each unit to the closest local model. The iterations are stopped when the clusters do not change.
In Table 2 these methods are compared with reference to some features.

3. A CASE STUDY

In autumn of 2010 a sample of customers of a superstore in Turin was interviewed to analyze their loyalty to the superstore. According to previous analysis in the same field (Chirico and Lo Presti, 2011), the customer's willingness to continue to purchase in the superstore in the short period (namely *Behavioral Loyalty*, BL) was assumed depending on the following three constructs:

- **Trust**, that identifies the customers' opinion about the quality of goods and the purchasing service.
- **Cheapness**, that identifies the possibility of cheap shopping in the superstore.

Table 3: Manifest Variables

LVs	MVs/Statements
Trust	I believe the staff suggestions I believe in the high quality of goods
Cheapness	The good prices are generally low There are a lot of promotions
Inertia	I like to know where my favorite brands are I prefer a store which is easy to reach
Behavioral Loyalty	I will be shopping again here

Table 4: Bootstrap Validation of path-coefficients in the global model

path	Original	Mean.Boot	Std.Error	perc.05	perc.95
INER→CHEAP	-0.03	-0.03	0.09	-0.17	0.12
INER→TRUST	0.01	0.00	0.09	-0.14	0.15
INER→BL	0.20	0.20	0.05	0.11	0.30
CHEAP→TRUST	0.02	0.03	0.09	-0.10	0.17
CHEAP→BL	0.62	0.62	0.07	0.51	0.72
TRUST→BL	0.39	0.38	0.07	0.27	0.48

- **Inertia**, that concerns inertial factors (Blomer and Casper, 1995), (Oliver, 1999) like "the distance from other superstores" or "psychological aversion to switch" that can affect *Behavioral Loyalty*.

Such constructs and BL were indirectly measured, according to a reflective measurement, by blocks of MVs; each MV consisted in a statement, whose importance/truth was assessed by the surveyed customers using a ten-point scale (Table 3).

Initially, a global PLS-path model, including both direct and indirect paths to BL, was estimated. The path coefficients and their bootstrap validation (100 resamples) are reported in Figure 1 and in Table 4; Table 5 and Table 6 report some quality indices about the outer model and the inner model. All the elaborations were performed using R package "plspm" (Sanchez and Trinchera, 2010).

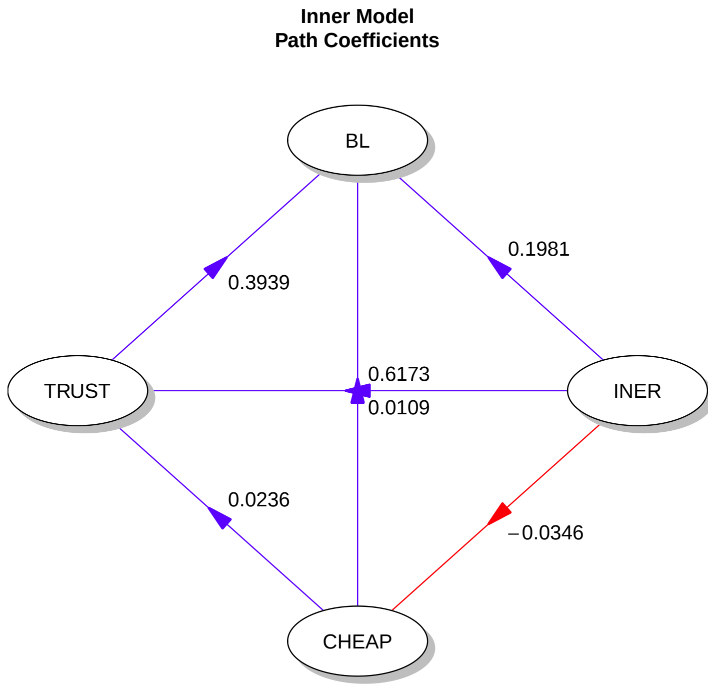

Figure 1: The global model

Table 5: Blocks unidimensionality

LVs	MVs	C.alpha	DG.rho	eig.1st	eig.2nd
INER	2	0.94	0.97	1.88	0.12
CHEAP	2	0.95	0.97	1.90	0.10
TRUST	2	0.90	0.95	1.82	0.18
BL	1	1.00	1.00	1.00	0.00

Table 6: Fit indices of the global model

index	value	index	value
R2.CHEAP	0.00	R2.BL	0.58
R2.TRUST	0.00	GoF	0.43

We can note that the indirect paths (INER$\rightarrow$CHEAP, INER$\rightarrow$TRUST, CHEAP $\rightarrow$ TRUST) are not significant: the confidence intervals of path coefficients include the zero and the corresponding R^2s are almost zero. On the other hand, the direct paths (INER$\rightarrow$BL, CHEAP$\rightarrow$BL, TRUST$\rightarrow$BL) are significant. The outer model works very well since each measurement block is uni-dimensional (see the eigenvalues in Table 5), but the inner model does not seem to be as good as the outer model: the R^2 of BL is not very high (0.58). Even if some authors consider this value to be quite good for a PLS-path model, we believe it is not so good and it could be a sign of heterogeneity in the data. Therefore, we carried out a model-based segmentation oriented to detect clusters characterized by different PLS-path models. To this end, we adopted the REBUS algorithm (subsection 3.1), because, in our opinion, it has the best features in clusterwise PLS-PM (Table 2). Then, its results (subsection 3.2) were compared with the results of local PLS-path models in segments detected by an *a-priori* hierarchical cluster analysis (subsection 3.3).

3.1. THE REBUS ALGORITHM

According to Esposito Vinzi et al. (2008), the application of REBUS to the sample of superstore customers consisted in the following ten steps:

1. estimation of the global PLS-path model ($\widehat{\xi}_j, \widehat{\alpha}_{j,k}, \widehat{\beta}_j$);

2. computation of the measurement residuals ($e_{i,j,k}$) and the structural residuals (z_i) of each unit (i) from the global model:

$$e_{i,j,k} = x_{i,j,k} - \widehat{\alpha}_{j,k}\widehat{\xi}_{i,j} \tag{4}$$

$$z_i = \widehat{\xi}_i - \sum_j \widehat{\beta}_j \widehat{\xi}_{i,j} \tag{5}$$

3. hierarchical classification of the residuals computed at step 2;

4. choice of the number (S) of segments according to the dendrogram obtained at step 3;

5. assignment of the units to each segment according to the cluster analysis results;

6. estimation of S local PLS-path models, one for each segment;

7. computation of the *closeness measure* ($CM_{i,s}$) for each unit (i) with respect to each local model (s):

$$CM_{i,s} = \sqrt{\frac{\sum_j \sum_k \left[\frac{e^2_{i,j,k,s}}{communality(x_{j,k})}\right]}{\frac{\sum_i \sum_j \sum_k \left[\frac{e^2_{i,j,k,s}}{communality(x_{j,k})}\right]}{N_s-2}} \cdot \frac{\frac{z^2_{i,s}}{R^2(\xi)}}{\frac{\sum_i \left[\frac{z^2_{i,s}}{R^2(\xi)}\right]}{N_s-2}}} \qquad (6)$$

8. assignment of each unit to the closest local model;

9. assessment of the new partition: if the partition has changed (or has changed more than a significant proportion, go to step 6, else go to the final step;

10. description of the obtained classes according to differences among the local models.

3.2. THE MODEL-BASED SEGMENTATION

A new PLS-path model, including only direct paths to BL, was estimated and a hierarchical cluster analysis on the residuals was performed (steps 1-3 of REBUS). The relating dendrogram suggested a segmentation in two or three or, at most, four clusters (Figure 2); such segmentations are compared in Tables 7 and 8.

Table 7 reports the *Group Quality index*, GQI, for those segmentations. The index can be viewed as the equivalent of the GoF in clusterwise PLS-PM (Trinchera, 2011) and indicates the quality of the clusterwise PLS-path model. Obviously, the GQI increases with the number of clusters, and Trinchera (2011) advises to take into consideration a partition only if its GQI has increased at least by 25% respect to the global model (no partition). According to Trinchera (2011), the partition in two clusters should not be considered. Such conclusion is confirmed by the assessment of the path coefficients in the local inner models (Table 8): in the case of

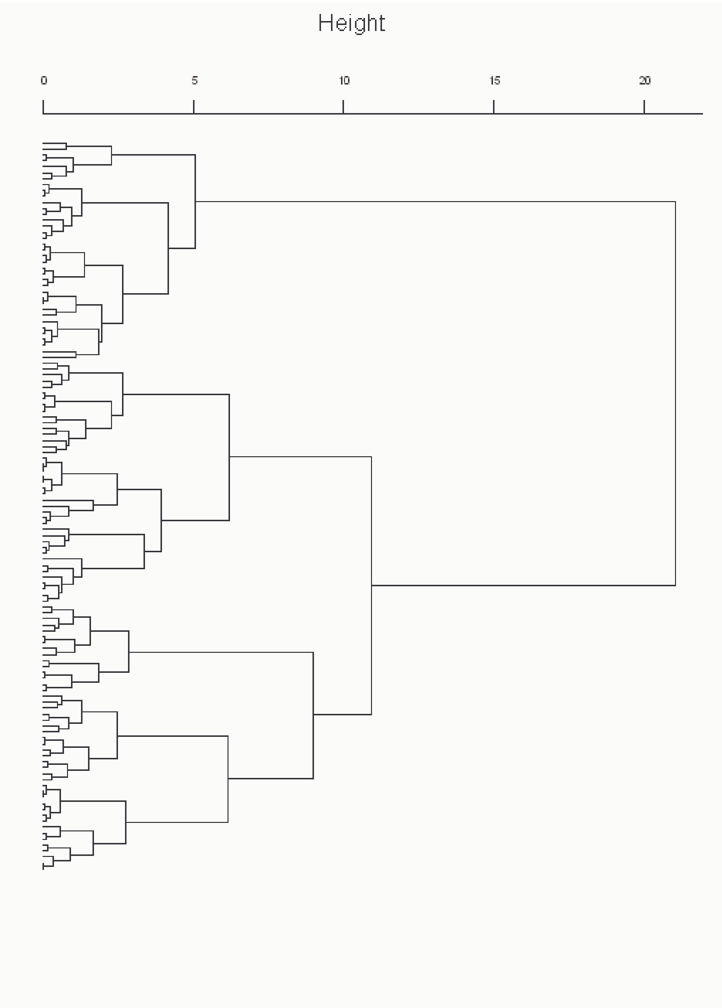

Figure 2: Dendrogram in REBUS approach

Table 7: Group Quality Indices

Partition	GQI	$\Delta(k,1)$	$\Delta(k,k-1)$
1 cluster	0.74		
2 clusters	0.89	20.9%	20.9%
3 clusters	0.94	28.4%	6.2%
4 clusters	0.96	30.6%	1.7%

Table 8: Local inner models

Partition	Clus.	%	TRUST	CHEAP	INER	R^2	*GoF*
2 clusters	1/2	53	0.56	0.71	0.34	0.85	0.89
	2/2	47	0.49	0.65	0.29	0.83	0.89
3 clusters	1/2	47	0.04	0.99	0.07	0.97	0.95
	2/2	20	0.82	0.58	0.51	0.96	0.95
	3/2	33	0.89	0.10	0.28	0.94	0.95
4 clusters	1/4	28	0.19	0.91	0.06	0.99	0.95
	2/4	18	0.74	0.37	0.43	0.98	0.95
	3/4	28	0.93	0.00	0.29	0.96	0.96
	4/4	25	0.15	1.04	0.19	0.99	0.97

two clusters, the path coefficients do not pick out two different behaviors. On the other hand, partitions in three and four clusters present an improvement of GQI greater than 25% (but the improvement in the GQI from three to four clusters is less than 2%). Multigroup Analysis on these partitions (100 permutations), especially on path coefficients (Table 9), points out that the clusters of three-partition are quite different, while the clusters of four-partition are not. Indeed, the path coefficients in the first and the fourth cluster of such partition are quite similar. Therefore, the partition in three clusters was preferred.

Considering the path coefficients in such segmentation and other variables of the survey (gender and age class), three different behaviors were detected:

- **The cheapness lovers** The customers of this segment (cluster 1; 47%) are oriented to Cheapness and their loyalty to the superstore only depends on the opportunity of cheap shopping and not on Trust or Inertia. They always

Table 9: Multigroup analysis

Partition	contrast	coefficient	first cluster	second cluster	diff.abs	p.value
two clusters	1-2	TRUST	0.56	0.49	0.07	0.60
		CHEAP	0.71	0.65	0.06	0.52
		INER	0.34	0.29	0.05	0.69
three clusters	1-2	TRUST	0.04	0.82	0.78	0.01
		CHEAP	0.99	0.58	0.41	0.01
		INER	0.07	0.51	0.44	0.01
	1-3	TRUST	0.04	0.89	0.85	0.01
		CHEAP	0.99	0.10	0.89	0.01
		INER	0.07	0.28	0.21	0.12
	2-3	TRUST	0.82	0.89	0.07	0.57
		CHEAP	0.58	0.10	0.48	0.01
		INER	0.51	0.28	0.23	0.14
four clusters	1-4	TRUST	0.19	0.15	0.03	0.63
		CHEAP	0.91	1.04	0.13	0.21
		INER	0.06	0.19	0.13	0.23

look for the best promotion and have no problems in changing the stores. The youngest age class (*the juniors*) is half of the segment.

- **Trust comes first** For these customers (cluster 3; 33%) Trust is the most important factor. As their loyalty does not depend so much on Inertia, they can choose another store if anything happens to affect their Trust. They are mainly middle aged women (41%).

- **Not only Trust** The loyalty of these customers (cluster 2; 20%) depends not only on Trust, but also on Cheapness and Inertia. They are the most inertial among the superstore customers. They change the store only if most of their Trust is affected. This class is mainly represented by *the seniors* (42%).

3.3. THE A-PRIORI SEGMENTATION

In order to better assess the results shown in section 3.2, we performed a hierarchical clustering on the MVs which led to the dendrogram in Figure 3. The customers of the superstore were accordingly segmented into three clusters, and a local model applied to each of them.

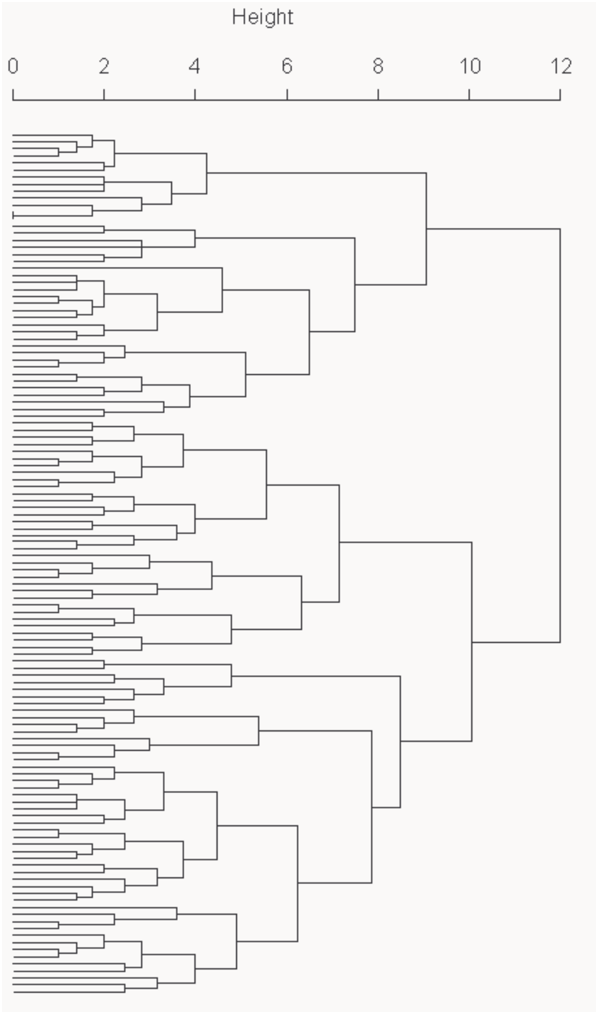

Figure 3: Dendrogram in *a priori* segmentation

As expected, the local models fit the data clearly worse than in REBUS (Table 10). Moreover, the behaviors about loyalty in the clusters are less well defined (see the path coefficients in Table 11).

Table 10: Quality Indexes in *a priori* segmentation

Index	Class.1	Class.2	Class.3
R2.BL	0.720	0.367	0.277
GoF	0.799	0.577	0.499
num.	41 (33.3%)	48 (39.0%)	34 (27.6%)

Table 11: Local Path Coefficients in *a priori* segmentation

LVs	Class.1	Class.2	Class.3
TRUST	0.244	0.364	0.346
CHEAP	0.839	0.408	0.166
INER	0.192	0.110	0.364

4. FINAL CONSIDERATIONS

The results of the case study show that the models performed by REBUS approach fit the data better than the models performed after *a-priori* segmentation. This is not surprising since this is the purpose of the model-based segmentation. However, it must be noted that by means of the variables involved in cluster analysis we are not able to obtain clusters referred to different behaviors. Certainly, the model based approach is preferable if the questionnaire does not include items that allow to perform a cluster analysis oriented to loyalty (for example: "indicate the most important factor acting on your loyalty").
Regarding the features of a suitable model-based method, it should allow:

- not to set a priori any number of segments (as in REBUS);
- to evaluate the best partition (as in FIMIX and REBUS);
- to obtain different outer models in different segments (as in REBUS);

- to manage both reflective and formative measurement models (as in FIMIX).

However, the segmentation in PLS-PM framework is constantly under study, and we trust in an improvement of these methods.

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