Original Article

Model-based *post hoc* segmentation (with REBUS-PLS) for capturing heterogeneous consumer behaviour

Received (in revised form): 25th October 2011

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ABSTRACT There is in the marketing literature a consensus that consumer behaviour varies across segments. Capturing this heterogeneity poses a considerable challenge for marketing scientists. Several researchers have consequently formulated *a priori* and *post hoc* techniques for detecting consumer heterogeneity. One such recent *post hoc* technique is model-based segmentation enabled by REBUS-PLS (response-based procedure for detecting unit segments in partial least squares), which has been developed within the framework of partial least squares approach to structural equation modelling. This article argues that model-based segmentation, as opposed to the alternative techniques, is a more objective and reliable approach for capturing heterogeneity in consumer behaviour. Moreover, this article illustrates how a model-based segmentation can be performed using REBUS-PLS through a set of consumer data, and explains conceptually the advantages of this statistical procedure. From a practical point of view, the article also proposes that model-based segmentation with REBUS-PLS or similar statistical procedures can contribute to the appeal of segmentation studies in the eyes of marketing managers.

Journal of Targeting, Measurement and Analysis for Marketing (2011) **19**, 165–172. doi:10.1057/jt.2011.17;

published online 21 November 2011

Keywords: PLS; SEM; segmentation; consumer behaviour; latent class; path modelling

INTRODUCTION

Since its formal introduction by Smith,¹ market segmentation as a strategic concept has become one of the corner stones of marketing,^{2–4} receiving accordingly ample attention from marketing scientists. This recognition has also contributed to the proliferation of various statistical techniques for segmentation purposes. Segmentation analysis has been performed with the employment of either *predictive* (for example,

discriminant analysis) or *descriptive* (for example, cluster analysis (CA)) techniques.⁵ One recent and more sophisticated *predictive* (that is, model-based) technique that holds considerable promise for market-segmentation studies is structural equation modelling (SEM).⁶

In particular, owing to the limitations associated both with *a priori* segmentation in general and *post hoc* segmentation using *descriptive* techniques, some researchers consider the SEM approach (that is, latent class detection method) to be invaluable for capturing consumer heterogeneity in a *post hoc* manner. There exist, however, two different SEM methods for such a

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purpose: the maximum-likelihood approach to structural equation modelling (ML-SEM) and the partial least squares approach to structural equation modelling (PLS-SEM).⁷ Whereas the model-based approach for detecting latent classes in ML-SEM has been in use since 1990s, the same approach in PLS-SEM has only recently received attention in marketing research literature.⁸

Consequently, over the past decade, several techniques in the PLS-SEM domain for model-based segmentation have arisen, one of which is the REBUS-PLS (response-based procedure for detecting unit segments in partial least squares) proposed by Esposito Vinzi *et al.*⁹ The purpose of this article is first to provide a rationale for the use of model-based segmentation, and then to exhibit how a *post hoc* model-based segmentation can be performed with the use of REBUS-PLS on a set of consumer-behaviour data.

CAPTURING HETEROGENEOUS CONSUMER BEHAVIOUR

Human beings, as a unique species, exhibit pronounced behavioural differences caused naturally by the interactions that take place between individual's environments and genetic compositions. These dissimilarities are often existent but not readily observable in social data, such as consumer-behaviour patterns. This is why Jedidi *et al.*¹⁰ consider this unobserved heterogeneity to be a paramount endemic problem that any researcher in the social sciences, including marketing, must face. To be able to overcome this challenge, marketing scientists have over the past decades developed different segmentation methods for capturing heterogeneous consumer behaviour. These methods can be explained along two dimensions: the approach to determining the number and type of segments (*a priori/post hoc*) and the nature of statistical procedures (*descriptive/predictive*) used (see Wedel and Kamakura, 1998⁵).

The first segmentation method adopts an *a priori* approach that makes use of *descriptive* statistical procedures (for example, cross-tabulations) in which the researcher in advance of the data analysis determines both the number (for example, two) and type (for example, buyers and

non-buyers) of the segments. The second method also adopts an *a priori* approach but instead uses *predictive* (that is, model-based) statistical procedures (for example, logistic regression analysis). The third segmentation method employs a *post hoc* approach that utilises *descriptive* statistical procedures (for example, CA) in which the number (for example, two) and type (price-sensitive and quality-orientated consumers) of the segments emerge as a result of the data analysis itself. The final segmentation method also employs a *post hoc* approach and makes use of *predictive* statistical procedures (for example, latent class detection).

Certain marketing scientists have, however, rightly criticised the *a priori* approach on the grounds that *a priori* information (that is, theory) regarding the number or type of segments is not always available and that well-known observable segmentation variables (for example, buyers and non-buyers) rarely capture heterogeneity.¹¹ Also, because the *post hoc* approach with *descriptive* analysis is not model-based, some scholars have expressed concern about its highly subjective nature,¹² and the possibility of overlooking information on heterogeneity, which models would have accounted for.¹³ A rather specific and relatively typical case of *descriptive post hoc* approach to segmentation is the sequential use of principal component analysis (PCA) and CA. The use of the sequential approach becomes even more problematic because PCA assumes homogeneity (that is, one population) and CA asserts heterogeneity (that is, multiple segments or populations).¹⁰ Furthermore, composite scores (that is, indexes) computed on the basis of PCA results assume τ equivalence, which may not always be the case in reality, and this is a condition that further jeopardises the credibility of the cluster solution.

To be able to overcome the drawbacks associated with the aforementioned three segmentation methods, the use of *post hoc* approach with a model-based (that is, *predictive*) statistical procedure is highly recommended for capturing consumer heterogeneity. These types of segmentation methods are usually summarised under the term 'latent class-detection'

approach in the domain of SEM.⁸ The latent class-detection approach was first introduced to marketing scientists through the ML-SEM-based finite-mixture model,¹⁰ whereby segmentation is performed by taking into account the defined model and the implied relationships among variables.⁷ However, owing to the high dependency of ML-SEM (latent class approach) on multivariate normality and large sample sizes, several scholars prefer the PLS-SEM (latent class approach) because it is often better adapted to empirical data.^{9,11,14}

Over the last decade, several latent class approaches have been developed in the domain of PLS-SEM in order to deal with unobserved heterogeneity (see Sarstedt, 2008⁸). The three most commonly used approaches are the finite mixture PLS (FIMIX-PLS), PLS typological path-modelling (PLS-TPM) and response-based procedure for detecting unit segments in partial least squares (REBUS-PLS).¹⁴ Although both FIMIX-PLS and PLS-TPM may prove to be successful in detecting heterogeneity in some cases, as opposed to REBUS-PLS, they suffer from a major common limitation in that they both require *a priori* known number of classes or segments, which is rarely the case in an exploratory research.¹³ Furthermore, in contrast to FIMIX-PLS and PLS-TPM, REBUS-PLS involves a new 'distance' measure that takes into account all of the endogenous variables and the measurement models of all blocks, thus obviating the requirement of a well-identified target endogenous variable.¹⁴ As REBUS-PLS is the most recently developed PLS-SEM latent detection approach and overcomes the drawbacks of its counterparts,⁹ this current study has chosen REBUS-PLS as the statistical procedure to perform a *post hoc* model-based segmentation.

REBUS-PLS

REBUS-PLS is an iterative algorithm that allows for the simultaneous estimation of both the unit (for example, person) membership to latent classes (that is, segment) and the class-specific parameters (that is, loadings and path coefficients) of the local models (that is, models for segments).¹⁴ The core of the algorithm is referred to as the

closeness measure (CM) between units and models based on residuals related to the structural and measurement models for all available variables,⁹ and it detects latent classes (if any exist) containing units sharing similar models.¹⁵ This ultimately suggests that if a unit is assigned to the correct latent class, then its performance in the local model computed for that specific class will be better than the performance of the same unit that is considered supplementary in the other local models.¹⁵ In order to obtain local models with a better fit than that of the global model (that is, whole sample), the CM is decided according to the structure of Goodness-of-Fit (GoF) index, which is the geometric mean of the average communality and the average R^2 values.¹⁴ Hence, a model with a high GoF value exhibits an overall better performance on both the structural and the measurement models.¹⁴ Incidentally, the bounds of the GoF index are between 0 and 1, and one can consider those models exhibiting *relative GoF* values equal to or higher than 0.90 to be good.¹⁵

APPLICATION TO CONSUMER BEHAVIOUR DATA

The article will illustrate model-based *post hoc* segmentation (with REBUS-PLS) by using a set of data collected in a cruise-experience setting in 2010. The sample contains 408 respondents who completed a questionnaire that included questions mainly about activities participated in on the cruise, the importance of motives for spending money on a cruise, the consideration of several cruise-experience attributes, as well as socio-demographic features.

Figure 1 depicts the model that lays the basis for segmenting the study's sample. Assuming that loyalty is a key variable in the context of a cruise experience, the model links both the tangible and atmospheric attributes (exogenous latent variables) to loyalty (endogenous latent variable). Incidentally, the reason why these two predictors are not modelled as being correlated with each other in Figure 1 is that the nature of the current investigation is exploratory, in that we do not have any specific hypothesis about the relationship between the two predictors. This is

also the reason for the use of PLS-SEM instead of its confirmatory counterpart ML-SEM.

A knowledge of different segments (if any exist) based on the drivers of loyalty will certainly help the cruise businesses to improve their marketing policies. As shown in Figure 1, all of the manifest variables (indicators) are reflective, just as REBUS-PLS requires.⁹

The questionnaire measured tangible attribute, atmospheric attribute and loyalty with an ordinal scale (1 = completely disagree; 7 = completely agree) by asking the respondents to indicate to what degree they agreed with the statements listed in Table 1.

First of all, one begins by running the model with XLSTAT-PLSPM software¹⁶ on the whole sample (that is, global model). Since the measurement model contains only reflective manifest variables, one should assess the measurement model on the basis of composite reliabilities, average variances extracted (AVE), item loadings' size and discriminant validity (see Liang, Saraf, Hu, and Xue, 2007¹⁷). Incidentally, as far as composite reliability is concerned, Chin¹⁸ suggests that Dillon-Goldstein's ρ (D.G. ρ) is a better measurement of reliability because the

D.G. ρ , in contrast to Cronbach's α , does not assume τ equivalence.

As shown in Table 2, all of the standardised loadings in the global model are clearly above the suggested threshold of 0.7, each of the individual communalities and AVE values also exceeds the recommended level of 0.5, and finally, all the three D.G. ρ values are above the suggested figure of 0.7 as well. These findings are indicative of convergent validity and reliability. Further, all of the average variance extracted values are larger than the squared correlations among the latent variables in global model, and thus demonstrates discriminant validity.

Table 3 shows the results from the structural part of the global model. Here, one readily observes that the tangible and atmospheric attributes have nearly equal (positive and statistically significant) effects on loyalty. Further, the GoF value is clearly above the suggested minimum level of 0.9, indicating that the model is a good one. Finally, the model explains about 50 per cent of the variation in the endogenous variable. Although the R^2 value can be considered relatively high here, there is still about 50 per cent unexplained variation,

Figure 1: The segmentation model.

Table 1: Content of the latent variables (LV) and manifest variables (MV)

LV	MV	Content
Tangible	Service	The staff are capable of helping me with any questions that I have
	Food	The quality of the food is good
	Hygiene	The cleaning of the cabins is satisfactory
Atmospheric	Lively	The ship has an atmosphere full of warmth
	Lighting	The lighting contributes to the warm atmosphere
Loyalty	Positive talk	I shall talk positively about this cruise ship
	Recommend	I shall recommend my friends to travel with this cruise ship

Table 2: Measurement model

Measures Sample LV	Loadings			Communality			D.G. ρ		
	Global	Class1	Class2	Global	Class1	Class2	Global	Class1	Class2
<i>Tangible</i>	—	—	—	0.656 ^a	0.595 ^a	0.712 ^a	0.851	0.851	0.880
Service	0.740	0.777	0.725	0.547	0.603	0.525	—	—	—
Food	0.855	0.760	0.904	0.730	0.578	0.816	—	—	—
Hygiene	0.831	0.777	0.891	0.690	0.603	0.793	—	—	—
<i>Atmospheric</i>	—	—	—	0.788 ^a	0.806 ^a	0.742 ^a	0.881	0.893	0.852
Lively	0.903	0.890	0.886	0.816	0.792	0.785	—	—	—
Lighting	0.872	0.906	0.836	0.760	0.821	0.699	—	—	—
<i>Loyalty</i>	—	—	—	0.898 ^a	0.848 ^a	0.783 ^a	0.946	0.918	0.878
Positive talk	0.954	0.923	0.915	0.910	0.852	0.837	—	—	—
Recommend	0.941	0.918	0.854	0.886	0.843	0.729	—	—	—

^aaverage variance explained.

Table 3: Structural model

Measure Sample Exogenous→Endogenous	Path coefficients		
	Global (N=408)	Class 1 (N=249)	Class 2 (N=159)
Tangible→Loyalty	0.426***	0.550***	0.322***
Atmospheric→Loyalty	0.389***	0.363***	0.547***
R^2	0.512	0.618	0.610
GoF	0.975	0.994	0.982

*** $P < 0.001$.

some of which may still be attributable to possible heterogeneity existent in the data. One can also theoretically justify this assumption because of the reasonable expectation that respondents in such a setting are more interested in the experiential (for example, atmospheric) aspect of the cruise.

As a result of these considerations, this study searched for probable latent homogeneous segments on the basis of the proposed model in Figure 1. The CA on the residuals from the global model pointed to a search for two or four clusters (see Figure 2). An examination of these two solutions revealed the two-class partition to be preferable because it can be supported theoretically, and that two of the classes obtained from the three-class partition are quite similar with respect to the magnitude of path coefficients. Incidentally, REBUS-PLS can generate local models that are different with respect to both measurement and structural models,⁹ it appears in our case that it clearly led to differing structural models (see Tables 2 and 3).

Figure 2: Dendrogram based on automatic partition.

The first class (segment) consists of 249 units making up 61 per cent of the entire sample. For this class, in contrast to the atmospheric attribute, the tangible attribute has a stronger effect on loyalty. Further, this effect is clearly larger for this class than it is for both the second class and the

Figure 3: Segments obtained based on models.

entire sample. Hence, the individuals in this class are called FUNCTIONALISTS (see Figure 3). Moreover, R^2 value and GoF value for this local model are both larger than those of the global model, which is a prerequisite for a class to be considered satisfactory⁷ or actionable (see Table 3).

The second class is composed of 159 units that correspond to 39 per cent of the whole sample. Here, unlike the tangible attribute, the atmospheric attribute has a stronger effect on loyalty. Moreover, this effect is evidently larger for this class than it is for the first class and the whole sample. Accordingly, the individuals in this class are named EXPERIENTIALISTS (see Figure 3). Finally, as seen in Table 3, R^2 value and GoF value for this local model are both larger than those of the global model, which counts as evidence of a satisfactory model.

A multi-group analysis based on permutation tests lend support to the two-class partition as it shows that the magnitude effects of the two predictors (that is, tangible and atmospheric) on loyalty statistically differ in the two local models ($\beta_{\text{DIFF}} = 0.228$, $P = 0.012$ for tangible and $\beta_{\text{DIFF}} = 0.184$, $P = 0.025$ for atmospheric). Although three of the standardized factor loadings statistically differ between the two models, as the measurement parts of both models exhibit superb construct validity (see Table 2) the multi-group analysis is deemed appropriate.

We can see that REBUS-PLS has been able to detect and identify two actionable classes (segments) with differing models. However, this knowledge of these two segments with different preferences should be supplemented with their profiles in relation to the socio-demographic data.⁹ As this option is not yet embedded in

Figure 4: The results of the CHAID analysis.

REBUS-PLS, we have chosen to run a chi-squared automatic interaction detector (CHAID) analysis in which the resulting two classes from the REBUS-PLS are used as a dichotomous dependent variable and a set of socio-demographic (gender, age, educational level and income level) are used as independent variables. The results of the CHAID analysis in Figure 4 show that there is a higher percentage of EXPERIENTIALISTS among people with a higher income and a larger share of FUNCTIONALISTS among those with a lower income.

DISCUSSION AND CONCLUSION

Although in the current application the initial global model represents a good one with a relatively high R^2 value (0.50), REBUS-PLS still generates two distinctive local models, and each has a 20 per cent improved predictive power (> 0.60), which can be considered substantial, according to Chin's guidelines.¹⁸ Relatedly, the relative GoF values of both local models are

better than that of the global model, a fact suggesting a successful application of REBUS. Accordingly, this outcome makes REBUS-PLS a promising statistical procedure for detecting heterogeneity in consumer studies, which often rely on models with much lower predictive capability. Relatedly, it is to this author's surprise that many consumer studies have traditionally not interpreted weak predictive power as a consequence of possible heterogeneity in the data. They have instead settled for models (with path coefficients) that only reflect the average consumer. Searching for and capturing this heterogeneity through a model-based segmentation approach would most certainly contribute to the production not only of more nuanced statistical results, but also of more relevant information to marketing managers. Marketing scientists could then overcome what Dolnicar and Lazarevski¹⁹ refer to as *mechanical flaws*, a reason for the occurrence of theory/practice divide in the area of market segmentation. In other words, only methodologically sound segmentation solutions can help bridge this gap between theory and practice because they lay the basis for effective marketing strategies, which then may lead to substantial competitive advantage.²⁰

Model-based segmentation within the framework of REBUS-PLS may contribute further to increasing the quality of segmentation studies in consumer research, which indeed contains a considerable share of works dependent on the use of multi-dimensional constructs (for example, satisfaction, quality, image and so on). This potential lies in the ability of this approach to estimate more accurately and to take into account simultaneously both the relationships between indicators and their underlying components or factors and the associations among these components or factors when deriving latent classes in the data. This is generally not a feasible procedure with the conventional approaches to segmentation. Unlike the traditional approaches, a further possibility that REBUS-PLS framework offers is that a segmentation model with higher-order constructs (see for instance Wetzels, Odekerken-Schröder, and van Oppen,

2009²¹) can also easily be run. In addition, although REBUS-PLS is a latent-variable modelling procedure, it still can be used to construct and run models containing only single measures as long as these have a reflective character. Furthermore, one can also include observed or latent categorical variables in a segmentation model run within the framework of REBUS-PLS.

Harvesting the benefits provided by model-based segmentation with REBUS-PLS will, as expected, be dependent on not just the statistical merits, but also on the practical relevance of the model chosen for the segmentation. As Green²² also suggests, segmentation models work best when they are related to marketing-strategy considerations (for example, diversification). This requires, however, that the marketing scientist selects the most relevant key variables (both exogenous and endogenous) in the construction of a satisfactory model. Theoretical and contextual knowledge should in tandem be utilised for this challenging task. This basic principle in fact applies also to the issue of determining the number of latent segments to be searched for. As REBUS-PLS automatically generates a number of local models (that is, latent segments), it is suggested that the analyst examines all of the recommended partitions before finalising the optimal number of segments.

Because there is overwhelming evidence suggesting that consumer behaviour varies across segments and because many small- and medium-sized businesses do not possess enough resources to develop a marketing policy for every single segment, the need to identify correctly the most promising segment becomes even more imperative. Detecting and choosing attractive segments involve also a process of desegmenting other less appealing consumer segments. These crucial strategic decisions require, however, that model-based segmentation studies are conducted on the basis of strictly representative samples. Only in such studies can emerging local models (segments) with substantially high predictive power (that is, $R^2 > 0.60$) be considered credible and relevant for managerial purposes. This manner of carrying out segmentation also

confirms Hansen's (1972, cited in Dibb and Simkin, 1993²³) assumption that thinking in terms of segmentation contributes not only to adequately designing product offerings, but also to effectively allocating resources in a business.

Obtaining optimal segmentation models by itself is not sufficient for gearing marketing-mix activities towards a specific segment. One should thus supplement these segmentation models with a follow-up procedure that profiles individuals belonging to different models in relation to other relevant external variables, such socio-demographic data. Only then can model-based segmentation results be useful for marketing managers.¹¹ However, at the moment, such a follow-up procedure is not incorporated in the REBUS-PLS procedure. In the current work, we have chosen to make use of a data-mining technique (that is, CHAID analysis), which should be compatible with PLS-SEM because they both handle non-normally distributed data well. However, one should consider this two-stage approach merely to be *ad hoc*, and thus remains the need to develop suitable follow-up techniques within the framework of REBUS-PLS, as well as within the remaining PLS-based procedures for capturing consumer heterogeneity.

ACKNOWLEDGEMENTS

The author would like to thank the Norwegian Research Council for funding the research project *Innovation in the Tourism Industry* (no. 194527/V10) that this paper is a part of.

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