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Abstract

Partial least squares-based path modeling with latent variables is a methodology that allows to estimate complex cause-effect relationships using empirical data. The assumption that the data is collected from a single homogeneous population is often unrealistic. Identification of different groups of consumers in connection with estimates in the inner path model constitutes a critical issue for applying the path modeling methodology to form effective marketing strategies. Sequential clustering strategies often fail to provide useful results for segment-specific partial least squares analyses. For that reason, the purpose of this paper is fourfold. First, it presents a finite mixture path modeling methodology for separating data based on the heterogeneity of estimates in the inner path model, as it is implemented in a software application for statistical computation. This new approach permits reliable identification of distinctive customer segments with their characteristic estimates for relationships of latent variables in the structural model. Second, it presents an application of the approach to two numerical examples, using experimental and empirical data, as a means of verifying the methodology's usefulness for multigroup path analyses in marketing research. Third, it analyses the advantages of finite mixture partial least squares to a sequential clustering strategy. Fourth, the initial application and critical review of the new segmentation technique for partial least squares path modeling allows us to unveil and discuss some of the technique's problematic aspects and to address significant areas of future research.

Key words: segmentation, latent variable models, mixture models measurement, customer satisfaction, brand preference

1. Introduction

Structural equation modeling (SEM) and path modeling with latent variables (LVP) are used to measure complex cause-effect relationships (Fornell/Larcker 1981; Chin 1998a; Steenkamp/ Baumgartner 2000). Such models are often applied in marketing to perform research on brand equity (Yoo et al. 2000), consumer behavior (Sargeant et al. 2006) or customer satisfaction (Anderson/Sullivan 1993; Chun/Davies 2006). Covariance-based structural equation modeling (CBSEM, Jöreskog 1978) and partial least squares analysis (PLS, Lohmöller 1989) constitute the two corresponding, yet distinctive (Schneeweiß 1991), statistical techniques for assessing cause-effect-relationship-models with latent variables. Compared to CBSEM, Wold's (1982) basic PLS design or basic method of soft modeling is rather a different than alternative methodology for estimating these models (Fornell/Bookstein 1982). Soft modeling refers to the ability of PLS to be more flexible in handling various modeling problems in situations where it is difficult or impossible to meet the hard assumptions of more traditional multivariate statistics. Within this context, "soft" is only attributed to distributional assumptions and not to the concepts, the models or the estimation techniques (Lohmöller 1989). However, CBSEM is customarily used in marketing to estimate relationships in cause-effect models via latent variables and empirical data. Apparently, there has been little concern about the frequent inability of marketing data to meet methodological requirements or about the common occurrence of improper solutions (Fornell/ Bookstein 1982; Baumgartner/Homburg 1996). Representing a well-substantiated alternative to CBSEM, PLS is relatively unknown and rarely used in marketing research, which fails to appreciate its importance for estimating LVP in a variety of contexts, ranging from theoretical and applied research in marketing, management and other social sciences disciplines. Recognizable PLS-based LVP analyses in business research are presented by, for example, Fornell et al. (1985); Fornell et al. (1990); Fornell et al. (1996); Gray/Meister (2004); Venkatesh/Agarwal (2006). Nevertheless, the statistical instruments needed to complement the PLS method for business research are not well developed.

This paper addresses a key extension of PLS for segmenting data on the heterogeneity in inner path model estimates. We focus on customer satisfaction to identify and treat heterogeneity among consumers by segmentation as a means of presenting the benefits of the method for PLS path modeling in marketing research. Customer satisfaction has become a fundamental and well documented construct in marketing that is critical to demand and to any business's success given its importance and established relation to customer retention and corporate profitability (Anderson et al. 1994; Mittal et al. 2005; Morgan et al. 2005). Although it is often acknowledged that truly homogeneous segments of consumers do not exist, recent studies report that unobserved customer heterogeneity does exists within a given product or service class (Wu/Desarbo 2005). This is critical for forming groups of consumers that are homogeneous in terms of the benefits they seek or their response to marketing programs (e.g. product offering, price discounts). Segmentation is therefore a key element for marketers in developing and improving their targeted marketing strategies.

Since its formal introduction in the 1950s, market segmentation remains one of the primary marketing ideas for product development, marketing strategy and understanding customers. However, the true distribution heterogeneity is never known a priori and, thus, there are cases where it is hard to find homogeneous customer segments. The development of analytic methods for segmenting markets has lagged behind their need in business applications (Cohen/Ramaswamy 1998). In SEM, for example, sequential clustering techniques, such as K-means or tree clustering, usually do not provide outcomes that further distinguish segment-specific estimates because they cannot account for heterogeneity of latent variables and their relationships within the structural model. We believe that latent segmentation models will assume an imperative role in enhancing CBSEM and PLS in the next wave of analytic procedures.

Latent class modeling (Kamakura/Russell 1989) is a useful classification tools for uncovering groups of persons with similar preferences and sensitivities. In CBSEM, Jedidi et al. (1997) pioneered this field of research and proposed the finite mixture SEM approach, i.e., a procedure that blends finite mixture models and the expectation-maximization (EM) algorithm (McLachlan/Basford 1988; Wedel/Kamakura 2000; McLachlan/Krishnan 2004). Although the original technique extends CBSEM, and is implemented in software packages for statistical computations, e.g. Mplus (Muthén/Muthén 1998), it is inappropriate for PLS because of dissimilar methodological assumptions (Fornell/Bookstein 1982). For this reason, Hahn et al. (2002) introduced the finite mixture partial least squares (FIMIX-PLS) method that combines a finite mixture procedure with an EM-algorithm specifically coping with the ordinary least squares (OLS)-based predictions of PLS.

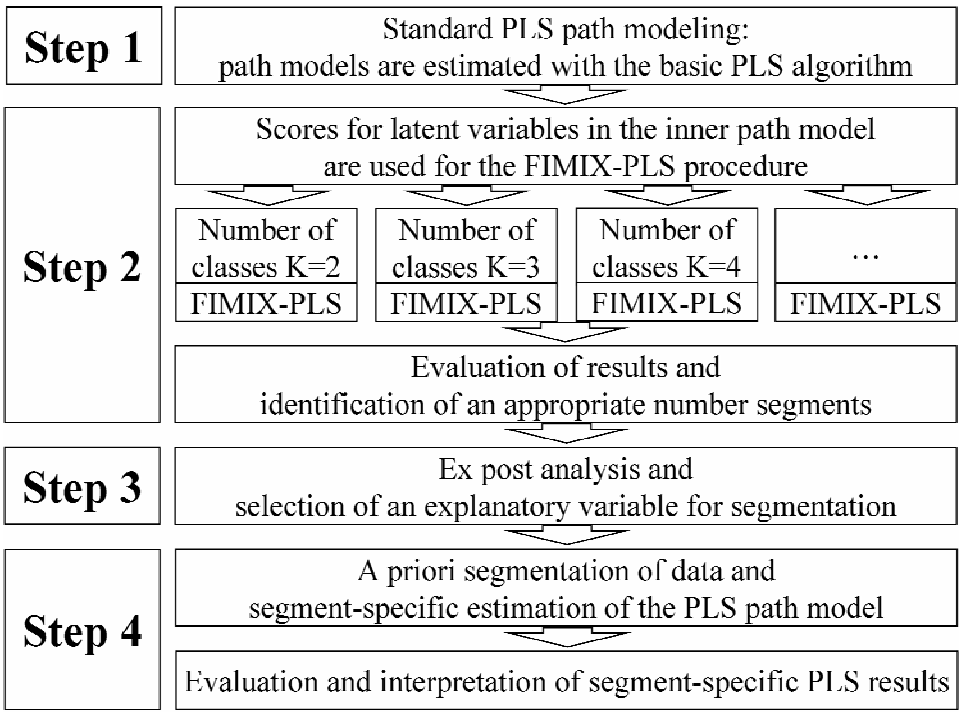

Figure 1: Analytical steps of FIMIX-PLS

Building on the guiding articles by Jedidi et al. (1997) and Hahn et al. (2002), this paper presents FIMIX-PLS as it is implemented for the first time in a statistical software application and, thereby, is made broadly applicable for research in social sciences as primary approach for segmenting data based on PLS path modeling results. This research is important to expand the methodological toolbox in PLS. We systematically apply FIMIX-PLS, as depicted in Figure 1, on the first numerical example presented in literature with experimental data and on the second application with empirical data. These kinds of segmentation results allow to further differentiate standard PLS path modeling estimates and, hence, to demonstrate the potentials of FIMIX-PLS for uncovering distinctive groups of customers for the relationships within the inner PLS path model. Furthermore, these analyses reveal important methodological implications that have not been addressed yet.

The following sections of this paper, which introduce the methodology, evaluate results and cover ex post analysis of FIMIX-PLS results, are dedicated to the different analytical steps presented in Figure 1. We particularly focus on step two to show that FIMIX-PLS accurately identifies a priori created segments for the simulated data presented in section 4. In section 5, we employ a marketing related LVP example and empirical data to apply all four steps of FIMIX-PLS for identifying a key customer segment for shaping targeted marketing strategies. Finally, we address the issue of whether the new segmentation technique is advantageous for PLS path modeling compared with a sequential data analysis strategy (section 6). Before drawing our conclusions (section 8), we distinguish, in section 7, sets of problems and discuss the need for future research that emerges from our numerical examples and initial review of the FIMIX-PLS methodology.

2. Methodology

SmartPLS 2.0 (Ringle et al. 2005) was the first statistical software application for (graphical) path modeling with latent variables employing both the basic PLS algorithm (Wold 1982, 1985; Lohmöller 1989) as well as FIMIX-PLS capabilities for the kind of segmentation proposed by Hahn et al. (2002). This section concisely presents the new approach for segmentation as it is implemented into the statistical software application. In the first step of FIMIX-PLS (Figure 1), a path model is estimated by using the PLS algorithm for LVP and (empirical) data for manifest variables in the outer measurement models. The resulting scores for latent variables in the inner path model are then employed to run the FIMIX-PLS algorithm in a second methodological step (Figure 1). The equation below expresses a modified presentation of the relationships (Table 11 in the appendix provides a description of all of the symbols used in the equations presented in this paper):

$$B\eta_i + \Gamma\xi_i = \zeta_i \tag{1}$$

Segment-specific heterogeneity of path models is concentrated in the estimated relationships between latent variables. FIMIX-PLS captures this heterogeneity and calculates the probability of each observation so that it fits into each of the predetermined K numbers of classes. The segment-specific distributional function is defined as follows, assuming that η_i is distributed as a finite mixture of conditional multivariate normal densities $f_{i|k}(\cdot)$:

$$\eta_i \sim \sum_{k=1}^{K} \rho_k f_{i|k}(\eta_i \mid \xi_i, B_k, \Gamma_k, \Psi_k) \tag{2}$$

Substituting $f_{i|k}(\eta_i \mid \xi_i, B_k, \Gamma_k, \Psi_k)$ results in the following equation:

$$\eta_i \sim \sum_{k=1}^{K} \rho_k \left[\frac{|B_k|}{\sqrt[M]{2\pi}\sqrt{|\Psi_k|}} e^{-\frac{1}{2}(B_k\eta_i + \Gamma_k\xi_i)'\Psi_k^{-1}(B_k\eta_i + \Gamma_k\xi_i))} \right] \tag{3}$$

Equation (4) represents an EM-formulation of the log-likelihood ($\ln L$) as the objective function for maximization:

$$\ln L = \sum_i \sum_k z_{ik} \ln(f(\eta_i \mid \xi_i, B_k, \Gamma_k, \Psi_k)) + \sum_i \sum_k z_{ik} \ln(\rho_k) \tag{4}$$

An EM-formulation of the FIMIX-PLS algorithm (figure Figure 2) is used for statistical computations to maximize the likelihood and to ensure convergence in this model. The expectation of Equation (4) is calculated in the E-step, where z_{ik} is 1 if subject i belongs to class k (or 0 otherwise). The segment size ρ_k, the parameters ξ_i, B_k, Γ_k and Ψ_k of the conditional probability function are stated (as results of the M-step), and provisional estimates (expected values), $E(z_{ik}) = P_{ik}$, for z_{ik} are computed according to Bayes' (1763/1958) theorem (E-step in Figure 2).

// initial E-step

set random starting values for P_{ik}; set $last_{lnL} = V$; set $0 < S < 1$

repeat do

begin

    // the M-step starts here

    $$\rho_k = \frac{\sum_{i=1}^{I} P_{ik}}{I} \quad \forall k$$

    determine B_k, Γ_k, Ψ_k, $\forall k$

    calculate $current_{lnL}$

    $\Delta = current_{lnL} - last_{lnL}$

    // the E-step starts here

    if $\Delta \geq S$ then

    begin

    $$P_{ik} = \frac{\rho_k f_{i|k}(\eta_i \mid \xi_i, B_k, \Gamma_k, \Psi_k)}{\sum_{k=1}^{K} \rho_k f_{i|k}(\eta_i \mid \xi_i, B_k, \Gamma_k, \Psi_k)} \quad \forall i, k$$

    $last_{lnL} = current_{lnL}$

    end

end

until $\Delta < S$

Figure 2: The FIMIX-PLS algorithm

Equation (4) is maximized in the M-step (Figure 2). This part of the FIMIX-PLS algorithm accounts for the most important changes to fit the finite mixture approach to PLS compared with the original finite mixture structural equation modeling technique (Jedidi et al. 1997). Initially, new mixing proportions ρ_k are calculated by the average of adjusted expected values P_{ik} that result from the previous E-step. Thereafter, optimal parameters for B_k, Γ_k and Ψ_k are determined by independent OLS regressions (one for each relationship between latent variables in the structural model). ML estimators of coefficients and variances are assumed to be identical to OLS predictions. The following equations are applied to obtain the regression parameters for latent endogenous variables:

$$Y_{mi} = \eta_{mi} \quad \text{and} \quad X_{mi} = (E_{mi}, N_{mi})' \tag{5}$$

$$E_{mi} = \begin{cases} \{\xi_1, \ldots, \xi_{A_m}\}, A_m \geq 1, a_m = 1, \ldots, A_m \wedge \xi_{a_m} \text{ is regressor of } m \\ \varnothing \text{ else} \end{cases} \tag{6}$$

$$N_{mi} = \begin{cases} \{\eta_1,\ldots,\eta_{B_m}\}, B_m \geq 1, b_m = 1,\ldots,B_m \wedge \eta_{b_m} \text{ is regressor of m} \\ \varnothing \text{ else} \end{cases} \tag{7}$$

The closed form OLS analytic formula for τ_{mk} and ω_{mk} is expressed as follows:

$$\tau_{mk} = \left((\gamma_{a_m}mk),(\beta_{b_m}mk)\right) = \left[\sum_i P_{ik}(X'_{mi}X_{mi})\right]^{-1}\left[\sum_i P_{ik}(X'_{mi}Y_{mi})\right] \tag{8}$$

$$\omega_{mk} = \text{cell}\,(m \times m) \text{ of } \Psi_k = \frac{\sum_i P_{ik}(Y_{mi} - X_{mi}\tau_{mk})(Y_{mi} - X_{mi}\tau_{mk})'}{I\rho_k} \tag{9}$$

As a result, the M-step determines new mixing proportions ρ_k, and the independent OLS regressions are used in the next E-step iteration to improve the outcomes for P_{ik}. The EM-algorithm stops whenever $\ln L$ hardly improves, and an a priori specified convergence criterion is reached. This and other problematical issues linked to FIMIX-PLS are pointed out in the following sections and summarized in section 7.

3. Identifying an appropriate number of segments and ex post analysis

The most important FIMIX-PLS computational results are the probability P_{ik}, the mixing proportions ρ_k, class-specific estimates B_k and Γ_k for the inner relationships of the path model and Ψ_k for the regression variances. In particular, with regard to the finite mixture's probabilities P_{ik} of observations to fit into the predetermined number classes, it must be decided if FIMIX-PLS allows to detect and treat heterogeneity among consumers in the inner PLS path model estimates by (unobservable) discrete moderating factors. This is explored in the next analytical step with analyses for different numbers of K classes (step 3 in Figure 1).

The number of segments is usually unknown and the process of identifying an appropriate number of classes is not clear-cut when applying FIMIX-PLS. A statistically satisfactory solution for this analytical procedure does not exist for several reasons (Wedel/Kamakura 2000). One reason is that the mixture models are not asymptotically distributed as chi-squares and disallow the likelihood ratio statistic. Consequently, the FIMIX-PLS procedure must be repeatedly performed with consecutive numbers of latent classes K (e.g. 2 to 10). Another reason is that the algorithm (Figure 2) converges for any given number of K classes. This means that statistically non-interpretable outcomes for the class-specific estimates B_k and Γ_k of the inner path model relationships and for Ψ_k of the regression variances for latent endogenous variables are computed when the number of classes is increased. Segment size is a useful indicator for stopping the analysis of additional numbers of latent classes for the sake of avoiding unreasonable FIMIX-PLS results is the segment size (section 5). At a certain point, an additional class has only a small segment size, which explains a marginal portion of heterogeneity in the overall set of data.

The emerging statistically comprehensible FIMIX-PLS estimates for different K numbers of classes are then compared for criteria such as the $\ln L_K$, the Akaike Information Criterion (AIC_K), the AIC Controlled ($AICC_K$) or the Bayesian Information Criterion (BIC_K). These heuristic measures permit an evaluation of FIMIX-PLS computations and the quality of their segmentation. The main goal of this analysis is to capture the heterogeneity of the inner PLS path model grouping data in accordance with the FIMIX-PLS results. Within this context, the normed entropy statistic (Ramaswamy et al. 1993) is a critical criterion for analyzing class specific FIMIX-PLS results. This criterion indicates the degree of separation for all observations and their estimated membership probabilities P_{ik} on a case-by-case basis, and it subsequently reveals the most appropriate number of latent classes for segmentation:

$$EN_K = 1 - \frac{\left[\sum_i \sum_k - P_{ik} \ln(P_{ik}) \right]}{I \ln(K)} \tag{10}$$

The EN is limited between 0 and 1, and the quality of separation of derived classes commensurate with the increase in EN_K. Application of FIMIX-PLS furnishes evidence that values of EN above 0.5 result in estimates for P_{ik} that permit unambiguous segmentation. The example with empirical data in section 5 demonstrates this kind of segmentation. In this case, most observations are associated with high probabilities of membership in a certain class. Hence, the entropy criterion is especially relevant for assessing whether a FIMIX-PLS solution is interpretable or not. The segments are fuzzy in situations where a certain number of classes is identified as most appropriate, based on the heuristic evaluation, but the EN_K is considerably below 0.5. This means that only parts of the subjects belong to a certain class. Fuzzy class memberships prevent meaningful a priori segmentation for specific PLS estimations, a comprehensible interpretation of results and sound establishment of managerial implications. Under such circumstances, and in cases where the differences between the evaluation criteria for FIMIX-PLS results of different numbers of classes only slightly differ, the highest probability per observation and its distribution regarding the entire set of data needs to be analyzed (section 5). The more that observations exhibit high membership probabilities, e.g. higher than 0.8, the better they uniquely belong to a specific class and can be well separated.

An explanatory variable must be uncovered in the ex post analysis (step 4 in Figure 1) in situations where FIMIX-PLS results indicate that heterogeneity in the overall set of data can be reduced by segmentation using the best fitting number of K classes. Correspondingly, data is segmented and used as new input for segment-specific LVP computations with PLS. This process produces differentiated PLS modeling results and facilitates multigroup PLS analyses (Chin/ Dibbern 2006). An explanatory variable must include both similar grouping of data, as indicated by the FIMIX-PLS results, and interpretability of the distinctive clusters. This kind of analysis is essential for exploiting FIMIX-PLS findings for PLS path modeling, and it is the most challenging analytical step to accomplish. For this reason, an ex post analysis of the estimated FIMIX-PLS probabilities of membership employs an approach proposed by Ramaswamy et al. (1993). While this systematical search uncovers explanatory variables that fit well with the FIMIX-PLS results in terms of data grouping, a logical search alternatively focuses for the most part on the interpretation of results. In this case, certain variables with high relevance for explaining the expected differences in segment-specific PLS path model computations are examined for their ability to form groups of observations that match FIMIX-PLS results. Both approaches may lead to different nonetheless reasonable results as demonstrated by a full FIMIX-PLS analysis in the example using empirical data (section 5).

4. Numerical example using experimental data

Suppose that a market researcher has formulated a LVP on theoretically well developed cause-effect relationships. The researcher suspects, however, that an unobserved moderating factor accounts for heterogeneity or that the data belongs to a finite number of segments. In this instance, the theoretical assumptions can be used to identify a priori moderating factors that account for consumer heterogeneity in PLS path models. But this strategy is not feasible in many marketing applications (Jedidi et al. 1997) and gives rise to analytical techniques like FIMIX-PLS. To demonstrate the potentials of FIMIX-PLS to detect and treat unobserved heterogeneity in the inner path model relationships, this methodology is applied on a numerical example using experimental data for the manifest indicator variables in the outer measurement model. Although the process of naming variables in this test set is not relevant, we use a marketing related example to demonstrate that FIMIX-PLS reliably identifies and separates distinctive groups of customers in the overall set of simulated data. In terms of heterogeneity in the structural model, it might be desirable to identify and describe price sensitive consumers (Kim et al. 1999) and consumers who have the strongest preference for another particular product attribute (Allenby et al. 1998), e.g. quality. Thus, the path model for our example with experimental data consists of one endogenous latent variable *Satisfaction*, two exogenous latent variables *Price* and *Quality* in the inner model (Dillon et al. 1997; Desarbo et al. 2001). The used experimental set of data consist of the following equally sized segments:

- Price-oriented customers (segment 1): This segment is characterized by a strong relationship between *Price* and *Satisfaction* and a weak relationship between *Quality* and *Satisfaction*.
- Quality-oriented customers (segment 2): This segment is characterized by a strong relationship between *Quality* and *Satisfaction* and a weak relationship between *Price* and *Satisfaction*.

Each latent exogenous variable (*Price* and *Quality*) is operationalized with seven reflective indicator variables. The latent endogenous variable (*Satisfaction*) is measured by two manifest variables in a reflective measurement model. According to format presented in Table 1, the underlying case values of the manifest variables are generated on a scale ranging from 1 to 7. For instance, the case values 1 to 20 of the manifest indicators *Price1* to *Price7*, *Satisfaction1* and *Satisfaction2* are normally distributed random numbers, with $\mu = 6$ and $\sigma = 0.1$. The case values 1 to 20 of the manifest indicators *Quality1* to *Quality7* are normally distributed random numbers, with $\mu = 4$ and $\sigma = 1$.

Case	Price	Quality	Satisfaction
$1-20$	$\mu = 6.0 / \sigma = 0.1$	$\mu = 4.0 / \sigma = 1.0$	$\mu = 6.0 / \sigma = 0.1$
$21-40$	$\mu = 4.0 / \sigma = 1.0$	$\mu = 6.0 / \sigma = 0.1$	$\mu = 6.0 / \sigma = 0.1$
$41-60$	$\mu = 2.0 / \sigma = 0.1$	$\mu = 4.0 / \sigma = 1.0$	$\mu = 2.0 / \sigma = 0.1$
$61-80$	$\mu = 4.0 / \sigma = 1.0$	$\mu = 2.0 / \sigma = 0.1$	$\mu = 2.0 / \sigma = 0.1$

Table 1: Data generation scheme

We use the SmartPLS 2.0 (Ringle et al. 2005) software application for the PLS path model estimation and the FIMIX-PLS analysis. The standard PLS procedure is executed with the overall set of simulated data for manifest variables as input to measure the LVP (step 1 in Figure 1). All estimates for path coefficients are at high levels. We follow the suggestion for a PLS model evaluation by Chin (1998b), and all minimum requirements for the outer and inner measurement model are met (Table 12, appendix). For example, the outer loadings are all above 0.7 while the inner model weights of *Price* and *Quality* on *Satisfaction* both have a value of 0.7 and therefore attain highly significant levels. This causes a substantial R^2 of 0.932 for the latent endogenous variable *Satisfaction*.

This kind of analysis determines the quality of PLS path model estimations by assessing outer and inner measurement models and, thus, partial model structures for certain non-parametric evaluation criteria that must satisfy minimum requirements (Wold 1980; Chin 1998b). Methodological implications of PLS path modeling (Wold 1982, 1985; Lohmöller 1989), especially its distribution-free character, do not permit the application of parametric global goodness of fit measures that are used for CBSEM (Jöreskog 1993). As a substitute, Tenenhaus et al. (2005) propose the geometric mean of the average communality (outer model) and the average R^2 (inner model) that is limited between values of 0 and 1 as overall goodness of fit (GoF) measure for PLS:

$$\mathrm{GoF} = \sqrt{\overline{\text{communality}} \cdot \overline{R^2}} = \sqrt{0.865 \cdot 0.932} = 0.898 \tag{11}$$

An interpretation of these PLS path modeling results - without testing for different segments in relation to heterogeneity in the estimates for the inner model - causes insufficient and misleading conclusions. In our example, *Satisfaction* could be comprehended as being explained by the *Price* and by the *Quality* construct for all customers, accompanied by recommendations that are adjusted accordingly for the marketing strategy (Dillon et al. 1997). By contrast, application of FIMIX-PLS uncovers heterogeneity and permits further differentiated conclusions. The consequences are demonstrated by applying FIMIX-PLS to $K = 2$ classes and the latent variable scores that emerge from the standard PLS procedure (step 2 in Figure 1). Since the customer segments for the underlying simulated data is known, testing different numbers of classes and comparing the results for FIMIX-PLS evaluation criteria is not required for this example. An analysis for an unknown number of K classes is presented in section 5.

The FIMIX-PLS results in Table 2 show that both groups of consumers in the experimental set of data are identified. Segment 1 has a strong effect of *Price* on *Satisfaction* and indicates a week relationship between *Quality* and *Satisfaction*. Segment 2 has a strong effect of *Quality* on *Satisfaction* and indicates a week relationship between *Price* and *Satisfaction*. Cases $1-20$ and cases $41-60$ are perfectly assigned to segment 1, and cases $21-40$ and cases $61-80$ are perfectly assigned to segment 2 (P_{ik} has either a value of 0 or 1 for the final segmentation). Consequently, EN has a value of 1.0 indicating perfect separation of the two groups of observations.

	$Price \rightarrow Satisfaction$	$Quality \rightarrow Satisfaction$
Standard PLS	0.7	0.7
FIMIX-PLS segment 1	0.7	0.0
FIMIX-PLS segment 2	0.0	0.7

Table 2: Inner model weights

In the above numerical example with simulated data, we do not perform step 3 of the full FIMIX-PLS analysis. Rather we test the FIMIX-PLS results for segment-specific PLS analyses according to step 4 in Figure 1. Therefore, the full set of experimental data is divided into two sets of data regarding the probability of membership P_{ik} of case i to class k. This data is separately used as input matrices for manifest variables to estimate the path model for each group of consumers with PLS. This final analytical step essentially achieves the FIMIX-PLS results for segment-specific relationships in the structural model. While the lower relationship in the inner path model for each group of price or quality oriented consumers remains at a value of 0.0, the stronger relationship rises above 0.7 causing excellent levels in the values for R^2 of *Satisfaction*. As illustrated by this numerical example with simulated data, FIMIX-PLS is capable to identify and treat heterogeneity of inner path model estimates by segmentation. Subsequent group-specific PLS analyses are important for further differentiated path model estimates for heterogeneous groups of consumers in the overall set of observations to guide additional interpretations and specific recommendations for the targeted use of the marketing-mix instruments.

5. Marketing example using empirical data

When researchers work with empirical data and do not have a priori segmentation assumptions to capture unobserved heterogeneity in the inner PLS path model relationships, FIMIX-PLS is often not as clear-cut as demonstrated in the foregoing example that is based on simulated data. Until now, research efforts to apply FIMIX-PLS and to assess its usefulness for expanding the methodological toolbox in marketing was restricted by the unavailability of a statistical software application for this kind of analysis. Since such functionalities are provided as presented in section 2, extensive use of FIMIX-PLS with empirical data in future research ought to furnish additional findings about the methodology and its applicability. For this reason, we make use of that technique for a marketing related path model and empirical data from Gruner+Jahr's 'Brigitte Communication Analysis 2002'.

Gruner+Jahr is one of the leading publishers of printed magazines in Germany. They have been conducting their Communication Analysis Survey every other year since 1984. In the survey, over 5,000 women answer numerous questions on brands in different product categories and questions regarding their personality. The women represent a cross section of the German female population. We choose answers to questions on the Benetton fashion brand name (on a four-point scale from 'low' to 'high') in order to use the survey as a marketing-related example of FIMIX-PLS-based customer segmentation. We assume that Benetton's aggressive and provocative advertising in the 1990s resulted in a lingering customer heterogeneity that is more distinctive and easier to identify compared with other fashion brands in the Communication Analysis Survey (e.g. Esprit or S.Oliver).

The scope of this paper does not include a presentation of a theoretically hypothesized LVP in the field of marketing and its PLS-based estimation by empirical means (Bagozzi 1994). Consequently, we do not provide an extensive presentation of the survey data or a discussion if one ought use CBSEM or PLS to estimate model parameters (Bagozzi/Yi 1994) or if the measurement models of the latent variables should be operationalized as formative or reflective (Diamantopoulos/Winklhofer 2001; Rossiter 2002; Jarvis et al. 2003; MacKenzie et al. 2005). Our goal is to demonstrate the applicability of FIMIX-PLS to empirical data and to illustrate a reduced cause-effect-relationship-model on branding (Yoo et al. 2000) that principally guides all kinds of marketing-based LVP analyses that employ the new segmentation technique. The PLS path model for Benetton's brand preference consists of one latent endogenous *Brand Preference* variable, and two latent exogenous variables, i.e., *Image* and *Person*, in the inner model. All latent variables are operationalized via a reflective measurement model and the manifest variables from Gruner+Jahr's 'Brigitte Communication Analysis 2002'. Figure 3 illustrates the path model that employs the latent and the particular manifest variables. The basic PLS algorithm Loh89 is applied to estimate LVP using the SmartPLS 2.0 software application (step 1 in Figure 1).

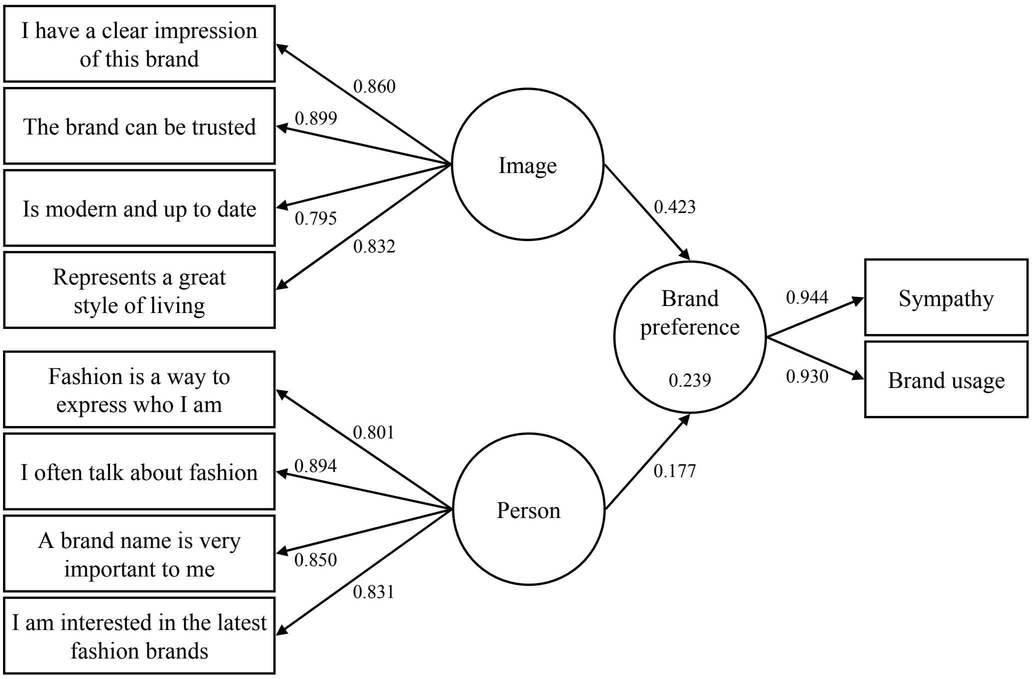

Figure 3: The brand preference model

As in section 4, we follow the suggestions of Chin (1998b) for evaluating PLS estimates. An overview of the evaluation criteria for the results of PLS path modeling is provided in table Table 13 in the appendix. All relationships in the reflective measurement models have factor loadings at sufficiently high levels (the smallest loading has a value of 0.795). Moreover, the average variance extracted (AVE) and ρ_c exhibit satisfactory results. Both relationships in the inner path model are at statistically significant levels for explaining the latent endogenous variable (Table 13 in the appendix provides results of the bootstrapping procedure). The latent exogenous *Image* variable (weight of 0.423) exhibits a strong relationship to the latent endogenous *Brand Preference* variable while the influence of the latent exogenous *Person* variable is considerably weaker (weight of 0.174). Thus, the R^2 of *Brand Preference* has a value of 0.239, which is a moderate level for PLS path models. The average communality of the three reflective measurement models is relatively high, so that R^2 of the latent endogenous *Brand Preference* variable mainly causes a GoF outcome that only is at a moderate level:

$$\text{GoF} = \sqrt{\overline{\text{communality}} \cdot \overline{R^2}} = \sqrt{0.748 \cdot 0.239} = 0.423 \tag{12}$$

In the next analytical step, the FIMIX-PLS module of SmartPLS 2.0 is applied to customer segmentation based on the estimated scores for latent variables (step 2 in Figure 1). In this example, FIMIX-PLS results are computed for two classes. Thereafter, the number of K classes is successively increased. A comparison of the class-specific FIMIX-PLS computations for heuristic evaluation criteria (section 3), as presented in Table 3, reveals that the choice of two groups is appropriate for customer segmentation purposes. All relevant evaluation criteria considerably decrease in the ensuing numbers of classes.

Number of segments	lnL	AIC	BIC	AICC	EN
$K = 2$	-713.233	1448.466	1493.520	1493.545	0.501
$K = 3$	-942.215	1954.431	2097.784	2097.863	0.216
$K = 4$	-1053.389	2192.793	2450.830	2450.972	0.230
$K = 5$	-1117.976	2441.388	2846.874	2847.097	0.214
$K = 6$	-1140.018	2326.037	2420.241	2420.293	0.270

Table 3: Model selection

The choice of two groups for a priori segmentation of the data is primarily supported by the EN of 0.501 for $K = 2$ classes. It is at a relatively high level compared to the EN of 0.43 arrived at in the only other proficient FIMIX-PLS segmentation presented thus far in literature by Hahn et al. (2002). As illustrated in Table 4, two thirds of all our observations are well assigned to one of the two classes with a probability P_{ik} of more than 0.7. These probabilities considerably decline for higher numbers of K classes, which indicates an increased fuzziness of segmentation that is also depicted by the lower EN. Consequently, a result of EN of 0.5 or higher for a certain number of FIMIX-PLS classes permits unambiguous segmentation of data.

P_{ik}	$K = 2$	$K = 3$	$K = 4$	$K = 5$	$K = 6$
0.900 – 1.000	0.491				
0.800 – 0.900	0.063			0.002	
0.700 – 0.800	0.083			0.011	
0.600 – 0.700	0.128	0.250	0.002	0.306	
0.500 – 0.600	0.234	0.320	0.011	0.221	0.339
0.400 – 0.500		0.387	0.761	0.227	0.232
0.300 – 0.400		0.043	0.225	0.232	0.369
0.200 – 0.300					
0.100 – 0.200					
0.000 – 0.100					
Sum	1.000	1.000	1.000	1.000	1.000

Table 4: Overview of observations' highest probability of assignment to a certain class

Table 5 indicates additional kinds of assumptions regarding the number of classes and the kind of data heterogeneity in the inner PLS path model. (a) As the number of classes increases, the large sized class is mainly reduced to create additional segments, while the size of the smaller class remains relatively stable (about 0.19 for $K = 2$ to $K = 4$ classes and about 0.145 for $K = 5$ and $K = 6$ classes). (b) Considering the decline of the outcomes for additional numbers of classes based on the EN criterion, it can be concluded that the overall set of observations for this particular analysis of the Benetton brand preference consists of a large, fuzzy group of female consumers and a small homogeneous group of female consumers. (c) The fuzziness of the larger segment cannot be further reduced by FIMIX-PLS. In the process of selecting additional classes, FIMIX-

PLS can still identify the smaller group of consumers with comparable probabilities of membership, but is somehow ambivalent when processing the large group with heterogeneous observations. The additional classes are mainly created by splitting the larger segment. As a consequence the probability of membership P_{ik} declines resulting in the drop of EN. This indicates methodological complexity in the process of assigning the observations in this set of data to additional classes. FIMIX-PLS computation forces observations to fit into a given number of K classes. As a result, FIMIX-PLS generates outcomes that are statistically problematical for the segment-specific estimates B_k and for Γ_k, i.e., for the inner relationships of the path model, and for Ψ_k, i.e., for the regression variances of latent endogenous variables. In this example, such results exhibiting inner path model relationships and/or regression variances above one are obtained for $K = 7$ classes. Consequently, the analysis of additional numbers of classes can stop at this juncture in accordance with development of segment sizes in Table 5.

Number of K classes	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Sum
2	0.809	0.191					1.000
3	0.525	0.288	0.188				1.000
4	0.390	0.191	0.222	0.197			1.000
5	0.487	0.256	0.149	0.092	0.017		1.000
6	0.441	0.233	0.143	0.115	0.038	0.031	1.000

Table 5: Segment sizes for different numbers of classes

Table 6 presents the FIMIX-PLS results for two latent classes. In a large segment (size of 0.809), the explained variance of the latent endogenous *Brand Preference* variable is at a relatively weak level for PLS path models ($R^2 = 0.108$). The variance is explained by the latent exogenous *Image* variable, with its weight of 0.343, and the latent exogenous *Person* variable, with its weight of 0.177. A smaller segment (size of 0.191) has a relatively high R^2 for *Brand Preference* (value of 0.930). The influence of the *Person* variable does not change much for this segment. However, the weight of the *Image* variable is more than twice as high and has a value of 0.759. This result reveals that the preference for Benetton is explained to a high degree whenever the image of this brand is far more important than the individuals' personality.

	$K = 1$	$K = 2$
Segment size	0.809	0.191
R^2 (of *Brand Preference*)	0.108	0.930
Image $\rightarrow$ *Brand Preference*	0.343	0.759
Person $\rightarrow$ *Brand Preference*	0.177	0.170

Table 6: Disaggregate results (solution for two latent classes)

The next step of FIMIX-PLS involves identification of a certain variable to characterize the two uncovered customer segments. For this reason, we conducted an ex post analysis for finite mixture models according to the approach proposed by Ramaswamy et al. (1993). We reviewed several potential explanatory variables. Our review analysis identifies: *I am very interested in the latest fashion trends*, *I get information about current fashion from magazines for women Brand names are very important for sports wear* and *I like to buy fashion designers' perfumes* as significant descriptors for segmentation (t-statistics ranging from 1.462 to 2.177). These variables may be appropriate for Benetton's brand preference PLS path model as a means of explaining the separation of female consumers in the underlying survey into two groups to account for heterogeneity in the inner model relationships. Table 7 shows PLS results using the *I like to buy fashion designers' perfumes* variable for an a priori customer segmentation into two classes. Both outcomes for segment-specific LVP estimations (Table 13 in the appendix) satisfy the relevant criteria for model evaluation (Chin 1998b). Segment 1 represents customers that are not interested in fashion designers' perfumes (size of 0.223). By contrast, segment 2 (size of 0.777) is characterized by female consumers that are attracted to Benetton and who would enjoy using Benetton products in other product categories, such as perfumes. From a marketing viewpoint, these customers are very important to fashion designers who want to plan brand extensions.

	Segment 1	Segment 2
GoF	0.387	0.470
R^2 (of *Brand Preference*)	0.204	0.323
Image $\rightarrow$ *Brand Preference*	0.394	0.562
Person $\rightarrow$ *Brand Preference*	0.164	0.104

Table 7: A priori segmentation based on "I like to buy fashion designers' perfumes"

Besides their applicability to explaining the FIMIX-PLS segmentation for the structural model, the variables identified in the ex post analysis do not offer much potential for meaningful a priori segmentation, except for the *I like to buy fashion designers' perfumes* variable. The other three variables with high t-statistics do not result in different measurements for segment-specific path models when segmented a priori into two classes. We therefore consider reasonable alternatives and test the *Customers' age* variable for an a priori segmentation of Benetton's brand preference LVP. The ex post analysis of FIMIX-PLS results using the method of Ramaswamy et al. (1993) fails to furnish evidence for the relevance of this variable (t-statistic = 0.690). This fact reveals potential problems of this technique for PLS path modeling. Yet, when creating a customer segment for females over age 28 years (segment 1; segment size: 0.793) and for younger women (segment 2; segment size: 0.207), we do achieve a result (Table 8) that is nearly identical to the a priori segmentation using *I like to buy fashion designers' perfumes*. Evaluation of the PLS path modeling estimates (Chin 1998b) for these two a priori segmented sets of data related to *Customers' age* confirms satisfactory results (Table 13 in the appendix). In this case, another important marketing result is achieved by separating out Benetton's target segment of customers.

	Segment 1	Segment 2
GoF	0.355	0.521
R^2 (for *Brand Preference*)	0.172	0.356
Image $\rightarrow$ *Brand Preference*	0.364	0.559
Person $\rightarrow$ *Brand Preference*	0.158	0.110

Table 8: A priori segmentation based on "Customers' age"

Overall PLS path model estimates must provide satisfactory results Jedidi et al. (1997) whenever FIMIX-PLS is applied for additional analytic purposes. This rule applies to our numerical example with empirical data. FIMIX-PLS can be employed for guiding essential differentiations of overall PLS path model estimations by detecting and treating unobserved heterogeneity in the inner path model. According to the results of analyzing $K = 2$ classes, a smaller and a larger group of distinctive female consumers is identified for Benetton's brand preference. Two kinds of analytical results can be obtained from this FIMIX-PLS analysis:

- Identification of two homogeneous segments that both have improved results compared to the overall PLS path model estimates. This is the more common kind of result that one would expect from the example with simulated data in section 4. Distinction of one segment with improved results and another segment with estimates at comparable levels in terms of overall PLS model estimates. This is the more unusual kind of outcome that fits the example with empirical data presented in this section.
- The larger segment tends to have a lower R^2 for the latent endogenous variable *Brand Preference* compared to overall model estimates. Most important, the larger segment is fuzzy and cannot be segmented into further numbers of classes. This group of customers is not the subject of supplementary findings. Thus, this group of customers is not the subject of supplementary findings and the analysis must focus on the smaller segment. According to the small changes of its segment size when additional numbers of K classes are analyzed as well as the results for EN, R^2 and probabilities P_{ik}, this group of consumers is relative homogeneous and well separable.

The small segment exhibits a substantial relationship between *Image* and *Brand Preference*, and it is highly relevant from a marketing perspective. Regarding this group of female consumers, *Brand Preference* of Benetton is primarily explained by aspects that marketing activities can potentially control to create a specific *Image*. Characteristics of the individual *Person* that are more difficult to influence are not an issue for Benetton's brand preference in this segment of costumers. Furthermore, two kinds of explanatory variables are uncovered. The smaller group of consumers is accordingly characterized by females who would also like to buy Benetton's perfume or by younger female consumers. The process of forming these segments a priori and subsequently performing a specific PLS path analysis on them produces further differentiated results. In the example of Benetton's brand preference model, the PLS outcomes for the smaller group of customers are particularly significant for originating marketing strategies in terms of potential brand extensions or this brand's target group of customers.

6. Comparison of FIMIX-PLS to sequential data analysis

The subject arises, when applying FIMIX-PLS, of whether similar results could be achieved with traditional clustering methods for manifest variable scores. K-means Wedel/Kamakura (2000) is one of the best clustering techniques for market segmentation. Parallel to reviewing analyses by Jedidi et al. (1997) or Hofstede et al. (1999), we compare the effectiveness of FIMIX-PLS to a sequential data analysis strategy by performing a K-means cluster analysis of the observed variables followed by multigroup PLS path modeling. We ensure comparability with prior FIMIX-PLS findings by using K-means to split both manifest experimental data and empirical data into two clusters. We likewise cluster the latent variables scores of both previous LVP examples into two segments with K-means since FIMIX-PLS uses inner path model estimates. The clustering results are then used for an a priori segmentation of data and for computing their specific PLS path model (Table 9 and Table 10).

	PLS path model estimations for segment 1	PLS path model estimations for segment 2
A priori K-means segmentation (for two classes) manifest variables	Segment size: 0.5 R^2: 0.931 GoF: 0.860 $Price \to Satisfaction$: 0.522 $Quality \to Satisfaction$: 0.474	Segment size: 0.5 R^2: 0.933 GoF: 0.861 $Price \to Satisfaction$: 0.468 $Quality \to Satisfaction$: 0.529
A priori K-means segmentation (for two classes) latent variables	Segment size: 0.5 R^2: 0.151 GoF: 0.320 $Price \to Satisfaction$: 0.447 $Quality \to Satisfaction$: 0.464	Segment size: 0.5 R^2: 0.158 GoF: 0.323 $Price \to Satisfaction$: 0.439 $Quality \to Satisfaction$: 0.413

Table 9: K-means segmentation of experimental data

The above analysis of manifest variables for the example with experimental and empirical data produces estimated weights in the structural model where one relationship is higher than the other. Values for R^2 and GoF remain at levels comparable to PLS results for the full set of data. In contrast, K-means clustering of latent variable scores and segment-specific LVP computation with PLS provides very similar estimates for the two relationships in the inner path model. Although these weights only slightly differ for segment one and two of the experimental set of data, they are considerably lower for segment two compared to segment one in the example with empirical data. Employing K-means clustering results of latent variable scores might cause segment-specific inner path model weights at considerable levels. Nevertheless, R^2 and GoF are extremely low in the examples. These PLS estimates are subsequently not useful for additional segment-specific LVP interpretations and conclusions.

	PLS path model estimations for segment 1	PLS path model estimations for segment 2
A priori K-means segmentation (for two classes) manifest variables	Segment size: 0.476 R^2: 0.241 GoF: 0.407 $Price \to Satisfaction$: 0.480 $Quality \to Satisfaction$: 0.131	Segment size: 0.523 R^2: 0.172 GoF: 0.385 $Price \to Satisfaction$: 0.371 $Quality \to Satisfaction$: 0.195
A priori K-means segmentation (for two classes) latent variables	Segment size: 0.329 R^2: 0.005 GoF: 0.165 $Price \to Satisfaction$: 0.193 $Quality \to Satisfaction$: 0.156	Segment size: 0.671 R^2: 0.016 GoF: 0.102 $Price \to Satisfaction$: 0.090 $Quality \to Satisfaction$: 0.078

Table 10: K-means segmentation of empirical data

Using traditional segmentation techniques such as K-means should be based on data for manifest variables. This will provide two equally sized groups for the empirical example, with each group having similar relationships in the inner path model compared to the original LVP estimation (section 5). In this instance, the weight is slightly higher for one path and somewhat lower for the other path in the structural model of segment one, while the opposite finding hold for segment two. This process will identify a group of customers with higher differences (segment one) and a group with lower (segment two) differences between the two weights in the structural model. However, these groups of customers are not as distinctive as they are in FIMIX-PLS segmentation. It is also important to note, regarding the numerical example with experimental data (section 4), that K-means clustering does not identify the two groups of price- and quality-oriented customers and their distinctive segment-specific path coefficients within the structural model.

The results of these kinds of comparisons show that FIMIX-PLS supplements traditional segmentation techniques as a useful methodology for further differentiating PLS-based LVP. Both techniques have much in common, i.e., the extraction of several homogeneous groups for achieving a more diverse and heterogeneous data set (Cohen/Ramaswamy 1998). FIMIX-PLS nevertheless consistently outperforms the sequential data analysis strategy (Jedidi et al. 1997) for two main reasons:

- In contrast to deterministic classification with K-means, FIMIX-PLS uses a probabilistic classification method that accounts for different segment sizes (Hofstede et al. 1999).
- FIMIX-PLS differs from the data-driven traditional approach in terms of its simultaneous model-based segmentation and prediction. One regression equation for each segment captures the predictor-outcome relationship at the same time that the uncovered segments are captured, and this process accounts for heterogeneity in the inner path model. Cluster analysis, by contrast, is a descriptive methodology with no independent-dependent, predictor-outcome relationship (Cohen/Ramaswamy 1998).

K-means performs well in classifying observations but is poor in parameter recovery if data is separated well into a finite number of classes. K-Means performs poor in both classification and parameter recovery, if data is not well separated. In contrast, finite mixture performs well in all cases and provides useful diagnostic information (Jedidi et al. 1997). Distinctive groups of observations in the overall set of data cause heterogeneity in the estimates for the structural model. FIMIX-PLS, in comparison, provides superior results compared to sequential data analysis techniques whenever the researcher is interested in improved inner path model estimates for more homogeneous groups of observations.

7. Methodological problems and fields of future research

The FIMIX-PLS approach is theoretically linked to finite mixture models. It shares methodological implications and problems. Incorporating this approach into statistical software and applying it, also reveals new problems that were not addressed prior to its initial introduction to social science research. Most important problems and fields of future research are connected to local optimum solutions, inappropriate FIMIX-PLS estimates and the identification of an explanatory variable in the ex post analysis.

Finite mixture models are subject to local optimum problems (Jedidi et al. 1997). The EM-algorithm always converges and monotonically increases $\ln L$ towards an optimum. The stop is more a measure of lack of progress than a measure of convergence, and there is evidence that the algorithm is often stopped too early (Wedel/Kamakura 2000). Experience shows that FIMIX-PLS frequently stops in local optimum solutions. This is caused by multimodality of the likelihood causing the algorithm's sensitivity to starting values. Moreover, the problem of convergence in local optima seems to increase in relevance whenever component densities are not well separated, the number of parameters estimated is large and the information embedded in each observation is limited. This results in relatively weak updates of membership probabilities in the E-step. Some examples of simple strategies for escaping local optima include beginning the EM-algorithm from a wide range of (random) starting values or using clustering procedures, such as K-means, to obtain an initial partition of data (Wedel/Kamakura 2000). If alternative initializations (starting values) of the algorithm result in different local optima, then the solution with the maximum value of likelihood is recommended as the best solution. Concerns still remain whether this kind of unsystematically selected solution reaches the global optimum. Future research is required to determine appropriate strategies for identifying convergence towards local optimum FIMIX-PLS solutions.

Another implication addresses the FIMIX-PLS segment-specific estimates for relationships in the structural model and the R^2 of latent endogenous variables. FIMIX-PLS is successively run with increasing numbers of classes to determine an appropriate number of segments. Ideally, the evaluation criteria should improve and then worsen while successively running the FIMIX-PLS procedure with increased numbers of classes. The outcome for the evaluation criteria indicates if an appropriate number of segments is identified. However, running this procedure often produces segment-specific FIMIX-PLS results that are improper for reasonable analyses. In most cases, the standardized weights in the structural model report values that are higher than one and/or the residual variance of latent endogenous variables exceeds the value of one (or becomes negative). Such outcomes might indicate that the heterogeneity in the structural model cannot be segmented by FIMIX-PLS for the chosen number of classes. These findings indicate the need for further improvement of this methodology. Hahn et al. (2002) suggest to limit segment-specific FIMIX-PLS estimates between reasonable bounds. Future research will need to determine if any such bounds for FIMIX-PLS computation impart useful methodological improvements in terms of identifying an appropriate number of segments.

The ex post analysis is essential for this kind of methodology. It confronts the researcher with the task that is most difficult to accomplish. This task involves identifying of an explanatory variable that permits a priori grouping of data for segment-specific PLS path modeling, which fits the FIMIX-PLS results and that also offers a characteristic interpretation of the formed groups. A technique for uncovering such variables proposed by Ramaswamy et al. (1993) does not imply coherent results for PLS path modeling, as demonstrated in the example with empirical data (section 5). Consequently, significant FIMIX-PLS analysis must be conducted, by means of complicated trial and error testing routines, until future research presents reliable procedures for identifying appropriate explanatory variables.

8. Summary and Conclusion

Unobserved heterogeneity and measurement errors are epidemic problems in social sciences. Jedidi et al. (1997) have addressed these problems for SEM. Hahn et al. (2002) have further developed their finite-mixture SEM methodology for PLS path modeling, which represents an important alternative to CBSEM for researchers and practitioners. This paper introduces the FIMIX-PLS approach implemented for the first time into a statistical software application. We show that FIMIX-PLS is applicable for LVP with PLS in marketing, management and other social science fields. For example, marketing-related PLS path modeling can exploit this approach for response-based market segmentation by identifying certain groups of customers provided that unobserved moderating factors account for consumer heterogeneity within inner path model relationships. We demonstrate the potentials of FIMIX-PLS by presenting the first published numerical example ever that uses experimental data and the second published numerical example ever that uses empirical data. Our pioneering work in this field also involves comparing the results from our applications with a sequential data analysis strategy.

Our fist example application, which uses experimental data, shows how FIMIX-PLS identifies and separates two a priori created segments of price- and quality-oriented customers and our second example application, which is based on empirical data, involves a marketing-related path model for Benetton's brand preference. It also demonstrates that FIMIX-PLS reliably identifies an appropriate number of customer segments provided that distinctive groups of customers exist that result in heterogeneity within the inner model. In this case, FIMIX-PLS enables us to identify: (1) a large segment of female consumers that shows similar results when compared to the original model estimation and (2) a smaller segment of female customers that reveals a strong relationship between *Image* and *Brand Preference*. Furthermore, two kinds of explanatory variables for a priori segmentation are uncovered. The smaller group of consumers is characterized by females who would also like to buy Benetton's perfume or by younger female consumers. We accordingly conclude that FIMIX-PLS reliably identifies distinctive customer segments, if heterogeneity exists within the structural model. These kinds of findings result in segment-specific LVP estimations and provide a platform for arriving at further conclusions for differentiated, segment-specific PLS path modeling. The additional analytic potentials are particularly relevant for LVP-based customer segmentation and multigroup path analyses in terms of forming effective marketing strategies.

FIMIX-PLS performs well in both numerical examples and provides useful diagnostic information. By contrast, a sequential data analysis technique does not offer results that are exploitable for segment-specific analyses. K-means clustering will classify observations whenever data is heterogeneous and belongs to well separated numbers of finite groups. However, recovery of distinctive estimates for inner path model relationships is not satisfactory (example using experimental data). In situations when heterogeneity is caused by groups that are not well separated groups, K-means performs poorly both in classification and segment-specific PLS path model estimation (example using empirical data). Given that researchers cannot determine segments a priori and are primarily interested in accurately identifying different segments regarding the model structure, the prudent strategy is therefore to use the finite mixture approach. However, this methodology does not identify outliers (Jedidi et al. 1997). Researchers can exploit the potentials of FIMIX-PLS when theory essentially supports the LVP and data is heterogeneous and belongs to a finite number of groups. We expect that these conditions will hold true in many marketing related PLS path modeling applications. For this reason, we presume reasonable segmentation and multigroup analyses (e.g. regarding different groups of customers) based on the FIMIX-PLS results.

Future research will require extensive use of FIMIX-PLS on marketing examples, with typically heterogeneous data, to illustrate the applicability and the problematic aspects of FIMIX-PLS from a practical point of view. Researchers will also need to test FIMIX-PLS methodology based on simulated data, with a wide range of statistic distributions and a large variety of LVP, to gain additional implications. Finally, theoretical research should provide satisfactory improvements for problematic areas such as convergence to logical optimum solutions, computation of improper segment-specific FIMIX-PLS results and identification of suitable explanatory variables for a priori segmentation.

Appendix

A_m	number of exogenous variables as regressors in regression m
a_m	exogenous variable a_m with $a_m = 1,...,A_m$
B_m	number of endogenous variables as regressors in regression m
b_m	endogenous variable b_m with $b_m = 1,...,B_m$
$\gamma_{a_m mk}$	regression coefficient of a_m in regression m for class k
$\beta_{b_m mk}$	regression coefficient of b_m in regression m for class k
τ_{mk}	$((\gamma_{a_m mk}),(\beta_{b_m mk}))'$ vector of the regression coefficients
ω_{mk}	cell$(m \times m)$ofΨ_k
c	constant factor
$f_{i\|k}(\cdot)$	probability for case i given a class k and parameters $(\cdot)$
I	number of cases or observations
i	case or observation i with $i = 1,...,I$
J	number of exogenous variables
j	exogenous variable j with $j = 1,...,J$
K	number of classes
k	class or segment k with $k = 1,...,K$
M	number of endogenous variables
m	endogenous variable m with $m = 1,...,M$
N_k	number of free parameters defined as $(K-1)+KR+KM$
P_{ik}	probability of membership of case i to class k
R	number of predictor variables of all regressions in the inner model
S	stop or convergence criterion
V	large negative number
X_{mi}	case values of the regressors for regression m of individual i
Y_{mi}	case values of the regressant for regression m of individual i
z_{ik}	$z_{ik} = 1$, if the case i belongs to class k; $z_{ik} = 0$ otherwise
ζ_i	random vector of residuals in the inner model for case i
η_i	vector of endogenous variables in the inner model for case i
ξ_i	vector of exogenous variables in the inner model for case i
B $M \times M$	path coefficient matrix of the inner model
Γ $M \times J$	path coefficient matrix of the inner model
Δ	difference of $current_{lnL}$ and $last_{lnL}$
B_k $M \times M$	path coefficient matrix of the inner model for latent class k
Γ_k $M \times J$	path coefficient matrix of the inner model for latent class k
Ψ_k $M \times M$	matrix for latent class k containing the regression variances
ρ	$(\rho_1,...,\rho_K)$, vector of the K mixing proportions of the finite mixture
ρ_k	mixing proportion of latent class k

Table 11: Explanation of symbols

	PLS results for the full set of experimental data			Group 1: PLS results for a priori segmented experimental data			Group 2: PLS results for a priori segmented set of data		
	Price	*Quality*	*Satisfaction*	*Price*	*Quality*	*Satisfaction*	*Price*	*Quality*	*Satisfaction*
Price 1	0.951			0.998			-0.440		
Price 2	0.884			0.997			0.308		
Price 3	0.872			0.998			0.221		
Price 4	0.906			0.995			-0.835		
Price 5	0.898			1.000			-0.815		
Price 6	0.920			1.000			0.398		
Price 7	0.927			1.000			-0.176		
Quality 1		0.951			-0.440			0.998	
Quality 2		0.884			0.308			0.998	
Quality 3		0.875			0.221			1.000	
Quality 4		0.912			-0.835			1.000	
Quality 5		0.898			-0.815			1.000	
Quality 6		0.920			0.398			1.000	
Quality 7		0.927			-0.176			1.000	
Satisfaction 1			0.970			0.964			0.964
Satisfaction 2			0.971			0.976			0.976
AVE	0.825	0.828	0.941	0.996	0.270	0.941	0.270	0.999	0.941
ρc	0.971	0.971	0.970	0.999	0.260	0.969	0.260	1.000	0.969
R^2			0.932			0.999			0.999
GoF		0.898			0.857			0.856	
Segment size		(1.000)			0.500			0.500	

	Bootstrapping results for the full set of experimental data (500 subsamples; construct level change)		Group 1: Bootstrapping results for a priori segmented experimental data (500 subsamples; construct level change)		Group 2: Bootstrapping results for a priori segmented experimental data (500 subsamples; construct level change)	
	Price -> Satisfaction	*Quality -> Satisfaction*	*Price -> Satisfaction*	*Quality -> Satisfaction*	*Price -> Satisfaction*	*Quality -> Satisfaction*
Original estimation	0.682	0.682	0.999	-0.007	-0.008	1.000
Mean of all bootstrapping samples	0.677	0.679	0.999	-0.004	0.001	1.000
Standard error	0.049	0.049	0.001	0.005	0.003	0.001
T-value	13.827	13.829	675.397	1.537	2.510	1220.213

Table 12: PLS path modeling results for the example with experimental data

PLS results	Full set of empirical data: *Image*	*Person*	*B.P.*
I have a clear impression of this brand	0.860		
This brand can be trusted	0.899		
Is modern and up to date	0.795		
Represents a great style of living	0.832		
Fashion is a way to express who I am		0.801	
I often talk about fashion		0.894	
A brand name is very important to me		0.850	
I am interested in the latest trends		0.831	
Sympathy			0.944
Brand usage			0.930
AVE	0.710	0.725	0.881
ρc	0.910	0.922	0.937
R^2			0.239
GoF		0.423	
Segment size		(1.000)	

Bootstrapping results (500 subsamples; individual sign change)	Full set of empirical data: *Image -> B.P.*	*Person -> B.P.*
Original estimation	0.432	0.174
Mean of all bootstrapping samples	0.428	0.174
Standard error	0.041	0.036
T-value	10.361	4.875

PLS results	Group 1: a priori segmented data for explanatory variable "I like to buy fashion designers' perfumes" *Image*	*Person*	*B.P.*	Group 2: a priori segmented data for explanatory variable "I like to buy fashion designers' perfumes" *Image*	*Person*	*B.P.*
I have a clear impression of this brand	0.851			0.873		
This brand can be trusted	0.894			0.906		
Is modern and up to date	0.783			0.832		
Represents a great style of living	0.821			0.870		
Fashion is a way to express who I am		0.761			0.788	
I often talk about fashion		0.878			0.645	
A brand name is very important to me		0.851			0.747	
I am interested in the latest trends		0.823			0.718	
Sympathy			0.949			0.906
Brand usage			0.930			0.934
AVE	0.703	0.687	0.882	0.758	0.528	0.847
ρc	0.904	0.898	0.938	0.926	0.816	0.917
R^2			0.204			0.323
GoF		0.387			0.470	
Segment size		0.223			0.777	

Bootstrapping results (500 subsamples; individual sign change)	Group 1: a priori segmented data for explanatory variable "I like to buy fashion designers' perfumes" *Image -> B.P.*	*Person -> B.P.*	Group 2: a priori segmented data for explanatory variable "I like to buy fashion designers' perfumes" *Image -> B.P.*	*Person -> B.P.*
Original estimation	0.394	0.164	0.562	0.104
Mean of all bootstrapping samples	0.394	0.173	0.564	0.106
Standard error	0.041	0.037	0.034	0.063
T-value	9.562	4.492	15.020	1.662

PLS results	Group 1: a priori segmented data for explanatory variable "Age" *Image*	*Person*	*Brand Preference*	Group 2: a priori segmented data for explanatory variable "Age" *Image*	*Person*	*Brand Preference*
I have a clear impression of this brand	0.860			0.850		
This brand can be trusted	0.879			0.928		
Is modern and up to date	0.777			0.888		
Represents a great style of living	0.807			0.897		
Fashion is a way to express who I am		0.769			0.849	
I often talk about fashion		0.894			0.834	
A brand name is very important to me		0.867			0.752	
I am interested in the latest trends		0.831			0.818	
Sympathy			0.936			0.958
Brand usage			0.925			0.940
AVE	0.692	0.708	0.866	0.794	0.663	0.900
ρc	0.900	0.906	0.928	0.939	0.887	0.948
R^2			0.172			0.356
GoF		0.355			0.521	
Segment size		0.793			0.207	

Bootstrapping results (500 subsamples; individual sign change)	Group 1: a priori segmented data for explanatory variable "Age" *Image -> B.P.*	*Person -> B.P.*	Group 2: a priori segmented data for explanatory variable "Age" *Image -> B.P.*	*Person -> B.P.*
Original estimation	0.364	0.158	0.559	0.110
Mean of all bootstrapping samples	0.368	0.164	0.558	0.116
Standard error	0.041	0.034	0.031	0.034
T-value	8.796	4.639	17.931	3.218

Table 13: PLS path modeling results for the example with empirical data

Literature

Allenby, G.M./Arora, N./Ginter, J.L. (1998): On the heterogeneity of demand, in: Journal of Marketing Research, Vol. 35, No. 3, pp. 384-389.

Anderson, E.W./Fornell, C./Lehmann, D.R. (1994): Customer satisfaction, market share, and profitability: findings from Sweden, in: Journal of Marketing, Vol. 58, No. 3, pp. 53-66.

Anderson, E.W./Sullivan, M.W. (1993): The antecedents and consequences of customer satisfaction for firms, in: Marketing Science, Vol. 12, No. 2, pp. 125-143.

Bagozzi, R.P. (1994): Structural equation models in marketing research: basic principles, Blackwell, Oxford.

Bagozzi, R.P./Yi, Y. (1994): Advanced topics in structural equation models, Blackwell, Oxford.

Baumgartner, H./Homburg, C. (1996): Applications of structural equation modeling in marketing and consumer research: a review, in: Journal of Marketing Research, Vol. 13, No. 2, pp. 139-161.

Bayes, T. (1763/1958): Studies in the history of probability and statistics : IX. Thomas Bayes's essay towards solving a problem in the doctrine of chances ; Bayes's essay in modernized notation, in: Biometrika, Vol. 45, No., pp. 296-315.

Chin, W.W. (1998a): Issues and opinion on structural equation modeling, in: MIS Quarterly, Vol. 22, No. 1, pp. VII-XVI.

Chin, W.W. (1998b): The partial least squares approach to structural equation modeling, Lawrence Erlbaum Associates, Mahwah.

Chin, W.W./Dibbern, J. (2006): A permutation based procedure for multi-group PLS analysis: results of tests of differences on simulated data, Springer, Berlin et al.

Chun, R./Davies, G. (2006): The influence of corporate character on customers and employees: exploring similarities and differences, in: Academy of Marketing Science Journal, Vol. 34, No. 2, pp. 138-146.

Cohen, S.H./Ramaswamy, V. (1998): Latent segmentation models: new tools assist researchers in market segmentation, in: Marketing Research, Vol. 10, No. 2, pp. 14-21.

Desarbo, W.S./Jedidi, K./Sinha, I. (2001): Customer value analysis in a heterogeneous market, in: Strategic Management Journal, Vol. 22, No. 9, pp. 845-857.

Diamantopoulos, A./Winklhofer, H. (2001): Index construction with formative indicators: an alternative to scale development, in: Journal of Marketing Research, Vol. 38, No. 2, pp. 269-277.

Dillon, W.R./White, J.B./Rao, V.R./Filak, D. (1997): Good science: use structural equation models to decipher complex customer relationships, in: Marketing Research, Vol. 9, No. 4, pp. 22-31.

Fornell, C./Bookstein, F.L. (1982): Two structural equation models: LISREL and PLS applied to consumer exit-voice theory, in: Journal of Marketing Research, Vol. 19, No. 4, pp. 440-452.

Fornell, C./Johnson, M.D./Anderson, E.W./Jaesung, C./Bryant, B.E. (1996): The American Customer Satisfaction Index: nature, purpose, and findings, in: Journal of Marketing, Vol. 60, No. 4, pp. 7-18.

Fornell, C./Larcker, D.F. (1981): Structural equation models with unobservable variables and measurement error: algebra and statistics, in: Journal of Marketing Research, Vol. 18, No. 3, pp. 328-388.

Fornell, C./Lorange, P./Roos, J. (1990): The cooperative venture formation process: A latent variable structural modeling approach, in: Management Science, Vol. 36, No. 10, pp. 1246-1255.

Fornell, C./Robinson, W.T./Wernerfelt, B. (1985): Consumption experience and sales promotion expenditure, in: Management Science, Vol. 31, No. 9, pp. 1084-1105.

Gray, P.H./Meister, D.B. (2004): Knowledge sourcing effectiveness, in: Management Science, Vol. 50, No. 6, pp. 821-834.

Hahn, C./Johnson, M.D./Herrmann, A./Huber, F. (2002): Capturing customer heterogeneity using a finite mixture PLS approach, in: Schmalenbach Business Review, Vol. 54, No. 3, pp. 243-269.

Hofstede, F.t./Steenkamp, J.-B.E.M./Wedel, M. (1999): International market segmentation based on consumer-product relations, in: Journal of Marketing Research, Vol. 36, No. 1, pp. 1-17.

Jarvis, C.B./MacKenzie, S.B./Podsakoff, P.M. (2003): A critical review of construct indicators and measurement model misspecification in marketing and consumer research, in: Journal of Consumer Research, Vol. 30, No. 2, pp. 199-218.

Jedidi, K./Jagpal, H.S./DeSarbo, W.S. (1997): Finite-fixture structural equation models for response-based segmentation and unobserved heterogeneity, in: Marketing Science, Vol. 16, No. 1, pp. 39-59.

Jöreskog, K.G. (1978): Structural analysis of covariance and correlation matrices, in: Psychometrika, Vol. 43, No. 4, pp. 443-477.

Jöreskog, K.G. (1993): Testing Structural Equation Models, Sage, Newbury Park.

Kamakura, W.A./Russell, G.J. (1989): A probabilistic choice model for market segmentation and elasticity structure, in: Journal of Marketing Research, Vol. 26, No. 4, pp. 379-390.

Kim, B.-D./Srinivasan, K./Wilcox, R.T. (1999): Identifying price sensitve consumers: the relative merits of domogrphic vs. purchase pattern information, in: Journal of Retailing, Vol. 75, No. 2, pp. 173-193.

Lohmöller, J.-B. (1989): Latent variable path modeling with partial least squares, Physica-Verlag, Heidelberg.

MacKenzie, S.B./Podsakoff, P.M./Jarvis, C.B. (2005): The problem of measurement model misspecification in behavioral and organizational research and some recommended solutions, in: Journal of Applied Psychology, Vol. 90, No. 4, pp. 710-730.

McLachlan, G.J./Basford, K.E. (1988): Mixture models: inference and applications to clustering, Marcel Dekker, New York.

McLachlan, G.J./Krishnan, T. (2004): The EM algorithm and extensions, John Wiley & Sons, Chichester.

Mittal, V./Anderson, E.W./Sayrak, A./Tadikamalla, P. (2005): Dual emphasis and the long-term financial impact of customer satisfaction, in: Marketing Science, Vol. 24, No. 4, pp. 531-543.

Morgan, N./Anderson, E.W./Mittal, V. (2005): Understanding firms' customer satisfaction information usage, in: Journal of Marketing, Vol. 69, No. 3, pp. 121-135.

Muthén, L.K./Muthén, B.O. (1998): Mplus user's guide, 4th ed., Muthén & Muthén, Los Angeles.

Ramaswamy, V./DeSarbo, W.S./Reibstein, D.J./Robinson, W.T. (1993): An empirical pooling approach for estimating marketing mix elasticities with PIMS data, in: Marketing Science, Vol. 12, No. 1, pp. 103-124.

Ringle, C.M./Wende, S./Will, A. (2005): SmartPLS 2.0 (beta), www.smartpls.de, Hamburg..

Rossiter, J.R. (2002): The C-OAR-SE procedure for scale development in marketing, in: International Journal of Research in Marketing, Vol. 19, No. 4, pp. 305-335.

Sargeant, A./Ford, J.B./West, D.C. (2006): Perceptual determinants of nonprofit giving behavior, in: Journal of Business Research, Vol. 59, No. 2, pp. 155-165.

Schneeweiß, H. (1991): Models with latent variables: LISREL versus PLS, in: Statistica Neerlandica, Vol. 45, No. 2, pp. 145-157.

Steenkamp, J.-B./Baumgartner, H. (2000): On the use of structural equation models for marketing modeling, in: International Journal of Research in Marketing, Vol. 17, No. 2/3, pp. 195-202.

Tenenhaus, M./Vinzi, V.E./Chatelin, Y.-M./Lauro, C. (2005): PLS path modeling, in: Computational Statistics & Data Analysis, Vol. 48, No. 1, pp. 159-205.

Venkatesh, V./Agarwal, R. (2006): Turning visitors into customers: a usability-centric perspective on purchase behavior in electronic channels, in: Management Science, Vol. 52, No. 3, pp. 367-382.

Wedel, M./Kamakura, W. (2000): Market segmentation: conceptual and methodological foundations, 2nd ed., Kluwer Academic Publishers.

Wold, H. (1980): Model construction and evaluation when theoretical knowledge is scarce: theory and application of PLS, Academic Press, New York.

Wold, H. (1982): Soft modeling: the basic design and some extensions, North-Holland, Amsterdam.

Wold, H. (1985): Partial least squares, Wiley, New York.

Wu, J./Desarbo, W.S. (2005): Market segmentation for customer satisfaction studies via a new latent structure multidimensional scaling model, in: Applied Stochastic Models in Business and Industry, Vol. 21, No. 4/5, pp. 303-309.

Yoo, B./Donthu, N./Lee, S. (2000): An examination of selected marketing mix elements and brand equity, in: Academy of Marketing Science Journal, Vol. 28, No. 2, pp. 195-211.

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