Chapter 2
Response-Based Segmentation Using Finite Mixture Partial Least Squares
Theoretical Foundations and an Application to American Customer Satisfaction Index Data

Christian M. Ringle, Marko Sarstedt, and Erik A. Mooi

Abstract When applying multivariate analysis techniques in information systems and social science disciplines, such as management information systems (MIS) and marketing, the assumption that the empirical data originate from a single homogeneous population is often unrealistic. When applying a causal modeling approach, such as partial least squares (PLS) path modeling, segmentation is a key issue in coping with the problem of heterogeneity in estimated cause-and-effect relationships. This chapter presents a new PLS path modeling approach which classifies units on the basis of the heterogeneity of the estimates in the inner model. If unobserved heterogeneity significantly affects the estimated path model relationships on the aggregate data level, the methodology will allow homogenous groups of observations to be created that exhibit distinctive path model estimates. The approach will, thus, provide differentiated analytical outcomes that permit more precise interpretations of each segment formed. An application on a large data set in an example of the American customer satisfaction index (ACSI) substantiates the methodology's effectiveness in evaluating PLS path modeling results.

Christian M. Ringle
Institute for Industrial Management and Organizations, University of Hamburg, Von-Melle-Park 5, 20146 Hamburg, Germany, e-mail: cringle@econ.uni-hamburg.de, and Centre for Management and Organisation Studies (CMOS), University of Technology Sydney (UTS), 1-59 Quay Street, Haymarket, NSW 2001, Australia, e-mail: christian.ringle@uts.edu.au

Marko Sarstedt
Institute for Market-based Management, University of Munich, Kaulbachstr. 45, 80539 Munich, Germany, e-mail: sarstedt@bwl.lmu.de

Erik A. Mooi
Aston Business School, Aston University, Room NB233 Aston Triangle, Birmingham B47ET, UK, e-mail: e.a.mooi@aston.ac.uk

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2.1 Introduction

2.1.1 On the Use of PLS Path Modeling

Since the 1980s, applications of structural equation models (SEMs) and path modeling have increasingly found their way into academic journals and business practice. Currently, SEMs represent a quasi-standard in management research when it comes to analyzing the cause–effect relationships between latent variables. Covariance-based structural equation modeling [CBSEM; 38, 59] and partial least squares analysis [PLS; 43, 80] constitute the two matching statistical techniques for estimating causal models.

Whereas CBSEM has long been the predominant approach for estimating SEMs, PLS path modeling has recently gained increasing dissemination, especially in the field of consumer and service research. PLS path modeling has several advantages over CBSEM, for example, when sample sizes are small, the data are non-normally distributed, or non-convergent results are likely because complex models with many variables and parameters are estimated [e.g., 20, 4]. However, PLS path modeling should not simply be viewed as a less stringent alternative to CBSEM, but rather as a complementary modeling approach [43]. CBSEM, which was introduced as a confirmatory model, differs from PLS path modeling, which is prediction-oriented.

PLS path modeling is well established in the academic literature, which appreciates this methodology's advantages in specific research situations [20]. Important applications of PLS path modeling in the management sciences discipline are provided by [23, 24, 27, 76, 18]. The use of PLS path modeling can be predominantly found in the fields of marketing, strategic management, and management information systems (MIS). The employment of PLS path modeling in MIS draws mainly on Davis's [10] technology acceptance model [TAM; e.g., 1, 25, 36]. In marketing, the various customer satisfaction index models – such as the European customer satisfaction index [ECSI; e.g., 15, 30, 41] and Festge and Schwaiger's [18] driver analysis of customer satisfaction with industrial goods – represent key areas of PLS use. Moreover, in strategic management, Hulland [35] provides a review of PLS path modeling applications. More recent studies focus specifically on strategic success factor analyses [e.g., 62].

Figure 2.1 shows a typical path modeling application of the American customer satisfaction index model [ACSI; 21], which also serves as an example for our study. The squares in this figure illustrate the manifest variables (indicators) derived from a survey and represent customers' answers to questions while the circles illustrate latent, not directly observable, variables. The PLS path analysis predominantly focuses on estimating and analyzing the relationships between the latent variables in the inner model. However, latent variables are measured by means of a block of manifest variables, with each of these indicators associated with a particular latent variable. Two basic types of outer relationships are relevant to PLS path modeling: formative and reflective models [e.g., 29]. While a formative measurement model has cause–effect relationships between the manifest variables and the latent index (independent causes), a reflective measurement model involves paths from the latent construct to the manifest variables (dependent effects).

The selection of either the formative or the reflective outer mode with respect to the relationships between a latent variable and its block of manifest variables builds on theoretical assumptions [e.g., 44] and requires an evaluation by means of empirical data [e.g., 29]. The differences between formative and reflective measurement models and the choice of the correct approach have been intensively discussed in the literature [3, 7, 11, 12, 19, 33, 34, 68, 69]. An appropriate choice of measurement model is a fundamental issue if the negative effects of measurement model misspecification are to be avoided [44].

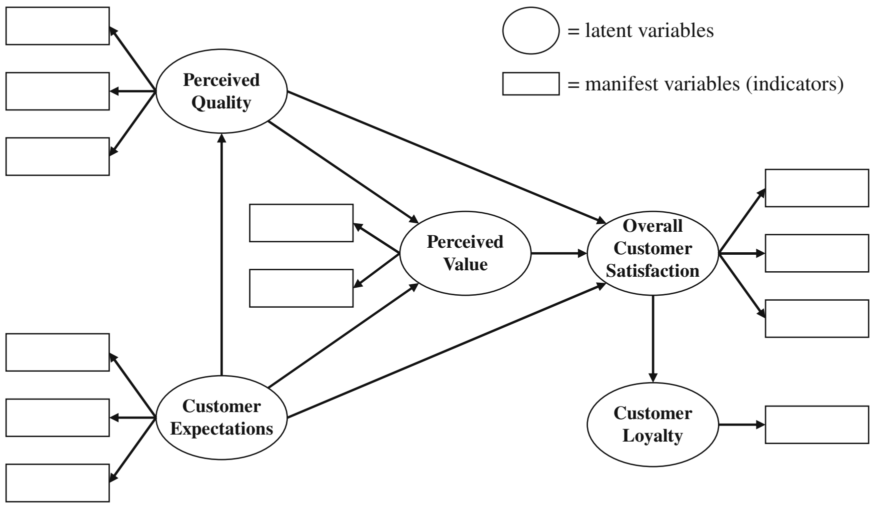

Fig. 2.1 Application of the ACSI model

While the outer model determines each latent variable, the inner path model involves the causal links between the latent variables, which are usually a hypothesized theoretical model. In Fig. 2.1, for example, the latent construct “Overall Customer Satisfaction” is hypothesized to explain the latent construct “Customer Loyalty.” The goal of prediction-oriented PLS path modeling method is to minimize the residual variance of the endogenous latent variables in the inner model and, thus, to maximize their R^2 values (i.e., for the key endogenous latent variables such as customer satisfaction and customer loyalty in an ACSI application). This goal underlines the prediction-oriented character of PLS path modeling.

2.1.2 Problem Statement

While the use of PLS path modeling is becoming more common in management disciplines such as MIS, marketing management, and strategic management, there are at least two critical issues that have received little attention in prior work. First, unobserved heterogeneity and measurement errors are endemic in social sciences. However, PLS path modeling applications are usually based on the assumption that the analyzed data originate from a single population. This assumption of homogeneity is often unrealistic, as individuals are likely to be heterogeneous in their perceptions and evaluations of latent constructs. For example, in customer satisfaction studies, users may form different segments, each with different drivers of satisfaction. This heterogeneity can affect both the measurement part (e.g., different latent variable means in each segment) and the structural part (e.g., different relationships between the latent variables in each segment) of a causal model [79]. In their customer satisfaction studies, Jedidi et al. [37] Hahn et al. [31] as well as Sarstedt, Ringle and Schwaiger [72] show that an aggregate analysis can be seriously misleading when there are significant differences between segment-specific parameter estimates. Muthén [54] too describes several examples, showing that if heterogeneity is not handled properly, SEM analysis can be seriously distorted. Further evidence of this can be found in [16, 66, 73]. Consequently, the identification of different groups of consumers in connection with estimates in the inner path model is a serious issue when applying the path modeling methodology to arrive at decisive interpretations [61]. Analyses in a path modeling framework usually do not address the problem of heterogeneity, and this failure may lead to inappropriate interpretations of PLS estimations and, therefore, to incomplete and ineffective conclusions that may need to be revised.

Second, there are no well-developed statistical instruments with which to extend and complement the PLS path modeling approach. Progress toward uncovering unobserved heterogeneity and analytical methods for clustering data have specifically lagged behind their need in PLS path modeling applications. Traditionally, heterogeneity in causal models is taken into account by assuming that observations can be assigned to segments a priori on the basis of, for example, geographic or demographic variables. In the case of a customer satisfaction analysis, this may be achieved by identifying high and low-income user segments and carrying out multigroup structural equation modeling. However, forming segments based on a priori information has serious limitations. In many instances there is no or only incomplete substantive theory regarding the variables that cause heterogeneity. Furthermore, observable characteristics such as gender, age, or usage frequency are often insufficient to capture heterogeneity adequately [77]. Sequential clustering procedures have been proposed as an alternative. A researcher can partition the sample into segments by applying a clustering algorithm, such as k-means or k-medoids, with respect to the indicator variables and then use multigroup structural equation modeling for each segment. However, this approach has conceptual shortcomings: “Whereas researchers typically develop specific hypotheses about the relationships between the variables of interest, which is mirrored in the structural equation model tested in the second step, traditional cluster analysis assumes independence among these variables" [79, p. 2]. Thus, classical segmentation strategies cannot account for heterogeneity in the relationships between latent variables and are often inappropriate for forming groups of data with distinctive inner model estimates [37, 61, 73, 71].

2.1.3 Objectives and Organization

A result of these limitations is that PLS path modeling requires complementary techniques for model-based segmentation, which allows treating heterogeneity in the inner path model relationships. Unlike basic clustering algorithms that identify clusters by optimizing a distance criterion between objects or pairs of objects, model-based clustering approaches in SEMs postulate a statistical model for the data. These are also often referred to as latent class segmentation approaches. Sarstedt [74] provides a taxonomy (Fig. 2.2) and a review of recent latent class segmentation approaches to PLS path modeling such as PATHMOX [70], FIMIX-PLS [31, 61, 64, 66], PLS genetic algorithm segmentation [63, 67], Fuzzy PLS Path Modeling [57], or REBUS-PLS [16, 17]. While most of these methodologies are in an early or experimental stage of development, Sarstedt [74] concludes that the finite mixture partial least squares approach (FIMIX-PLS) can currently be viewed as the most comprehensive and commonly used approach to capture heterogeneity in PLS path modeling. Hahn et al. [31] pioneered this approach in that they also transferred Jedidi et al.'s [37] finite mixture SEM methodology to the field of PLS path modeling. However, knowledge about the capabilities of FIMIX-PLS is limited.

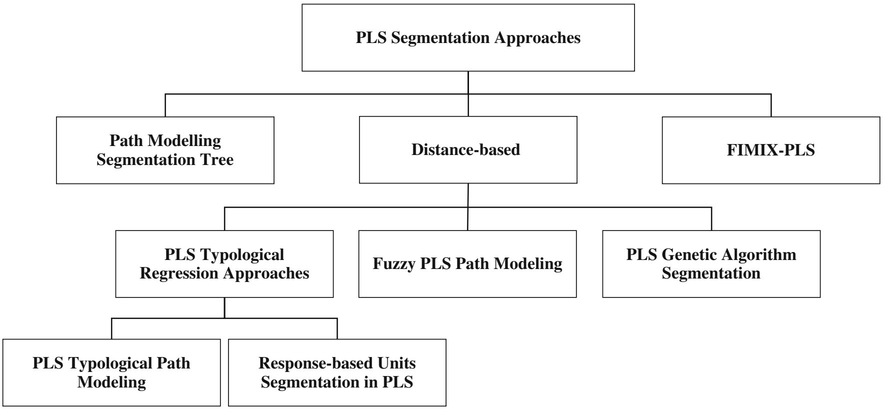

Fig. 2.2 Methodological taxonomy of latent class approaches to capture unobserved heterogeneity in PLS path models [74]

This chapter's main contribution to the body of knowledge on clustering data in PLS path modeling is twofold. First, we present FIMIX-PLS as recently implemented in the statistical software application SmartPLS [65] and, thereby, made broadly available for empirical research in the various social sciences disciplines. We thus present a systematic approach to applying FIMIX-PLS as an appropriate and necessary means to evaluate PLS path modeling results on an aggregate data level. PLS path modeling applications can exploit this approach to response-based market segmentation by identifying certain groups of customers in cases where unobserved moderating factors cause consumer heterogeneity within inner model relationships. Second, an application of the methodology to a well-established marketing example substantiates the requirement and applicability of FIMIX-PLS as an analytical extension of and standard test procedure for PLS path modeling.

This study is particularly important for researchers and practitioners who can exploit the capabilities of FIMIX-PLS to ensure that the results on the aggregate data level are not affected by unobserved heterogeneity in the inner path model estimates. Furthermore, FIMIX-PLS indicates that this problem can be handled by forming groups of data. A multigroup comparison [13, 32] of the resulting segments indicates whether segment-specific PLS path estimates are significantly different. This allows researchers to further differentiate their analysis results. The availability of FIMIX-PLS capabilities (i.e., in the software application SmartPLS) paves the way to a systematic analytical approach, which we present in this chapter as a standard procedure to evaluate PLS path modeling results.

We organize the remainder of this chapter as follows: First, we introduce the PLS algorithm – an important issue associated with its application. Next, we present a systematic application of the FIMIX-PLS methodology to uncover unobserved heterogeneity and form groups of data. Thereafter, this approach's application to a well-substantiated and broadly acknowledged path modeling application in marketing research illustrates its effectiveness and the need to use it in the evaluation process of PLS estimations. The final section concludes with implications for PLS path modeling and directions regarding future research.

2.2 Partial Least Squares Path Modeling

The PLS path modeling approach is a general method for estimating causal relationships in path models that involve latent constructs which are indirectly measured by various indicators. Prior publications [80, 43, 8, 75, 32] provide the methodological foundations, techniques for evaluating the results [8, 32, 43, 75, 80], and some examples of this methodology. The estimation of a path model, such as the ACSI example in Fig. 2.1, builds on two sets of outer and inner model linear equations. The basic PLS algorithm, as proposed by Lohmöller [43], allows the linear relationships' parameters to be estimated and includes two stages, as presented in Table 2.1.

Table 2.1 The basic PLS algorithm [43]

Stage 1: Iterative estimation of latent variable scores

#1 Inner weights

$$v_{ji} = \begin{cases} \text{sign cov}(Y_j; Y_i) & \text{if } Y_j \text{ and } Y_i \text{ are adjacent} \\ 0 & \text{otherwise} \end{cases}$$

#2 Inside approximation

$$\tilde{Y}_j := \sum_i v_{ji} Y_i$$

#3 Outer weights; solve for

$$y_{kjn} = \tilde{w}_{k_j} \tilde{Y}_{jn} + e_{k_{jn}} \quad \text{Mode A}$$

$$\tilde{Y}_{jn} = \sum_{k_j} \tilde{w}_{k_j} y_{k_{jn}} + d_{jn} \quad \text{Mode B}$$

#4 Outside approximation

$$Y_{jn} := \sum_{k_j} \tilde{w}_{k_j} y_{k_j n}$$

Variables:
y = manifest variables (data)
Y = latent variables
d = validity residuals
e = outer residuals

Parameters:
v = inner weights
w = weight coefficients

Indices:
$i = 1, \ldots, I$ for blocks of manifest variables
$j = 1, \ldots, J$ for latent variables
$k_j = 1, \ldots, K$ for manifest variables counted within block j
$n = 1, \ldots, N$ for observational units (cases)

Stage 2: Estimation of outer weights, outer loadings, and inner path model coefficients

In the measurement model, manifest variables' data – on a metric or quasi-metric scale (e.g., a seven-point Likert scale) – are the input for the PLS algorithm that starts in step 4 and uses initial values for the weight coefficients (e.g., "+1" for all weight coefficients). Step 1 provides values for the inner relationships and Step 3 for the outer relationships, while Steps 2 and 4 compute standardized latent variable scores. Consequently, the basic PLS algorithm distinguishes between reflective (Mode A) and formative (Mode B) relationships in step 3, which affects the generation of the final latent variable scores. In step 3, the algorithm uses Mode A to obtain the outer weights of reflective measurement models (single regressions for the relationships between the latent variable and each of its indicators) and Mode B for formative measurement models (multiple regressions through which the latent variable is the dependent variable). In practical applications, the analysis of reflective measurement models focuses on the loading, whereas the weights are used to analyze formative relationships. Steps 1 to 4 in the first stage are repeated until convergence is obtained (e.g., the sum of changes of the outer weight coefficients in step 4 is below a threshold value of 0.001). The first stage provides estimates for the latent variable scores. The second stage uses these latent variable scores for ordinary least squares (OLS) regressions to generate the final (standardized) path coefficients for the relationships between the latent variables in the inner model as well as the final (standardized) outer weights and loadings for the relationships between a latent variable and its block of manifest variables [32].

A key issue in PLS path modeling is the evaluation of results. Since the PLS algorithm does not optimize any global scalar function, fit measures that are well known from CBSEM are not available for the nonparametric PLS path modeling approach. Chin [8] therefore presents a catalog of nonparametric criteria to separately assess the different model structures' results. A systematic application of these criteria is a two-step process [32]. The evaluation of PLS estimates begins with the measurement models and employs decisive criteria that are specifically associated with the formative outer mode (e.g., significance, multicollinearity) or reflective outer mode (e.g., indicator reliability, construct reliability, discriminant validity). Only if the latent variable scores show evidence of sufficient reliability and validity is it worth pursuing the evaluation of inner path model estimates (e.g., significance of path coefficients, effect sizes, R^2 values of latent endogenous variables). This assessment also includes an analysis of the PLS path model estimates regarding their capabilities to predict the observed data (i.e., the predictive relevance). The estimated values of the inner path coefficients allow the relative importance of each exogenous latent variable to be decided in order to explain an endogenous latent variable in the model (i.e., R^2 value). The higher the (standardized) path coefficients – for example, in the relationship between "Overall Customer Satisfaction" and "Customer Loyalty" in Fig. 2.1 – the higher the relevance of the latent predecessor variable in explaining the latent successor variable. The ACSI model assumes significant inner path model relationships between the key constructs "Overall Customer Satisfaction" and "Customer Loyalty" as well as substantial R^2 values for these latent variables.

2.3 Finite Mixture Partial Least Squares Segmentation

2.3.1 Foundations

Since its formal introduction in the 1950s, market segmentation has been one of the primary marketing concepts for product development, marketing strategy, and understanding customers. To segment data in a SEM context, researches frequently use sequential procedures in which homogenous subgroups are formed by means of a priori information to explain heterogeneity, or they revert to the application of cluster analysis techniques, followed by multigroup structural equation modeling. However, none of these approaches is considered satisfactory, as observable characteristics often gloss over the true sources of heterogeneity [77]. Conversely, the application of traditional cluster analysis techniques suffers from conceptual shortcomings and cannot account for heterogeneity in the relationships between latent variables. This weakness is broadly recognized in the literature and, consequently, there has been a call for model-based clustering methods.

In data mining, model-based clustering algorithms have recently gained increasing attention, mainly because they allow researchers to identify clusters based on their shape and structure rather than on proximity between data points [50]. Several approaches, which form a statistical model based on large data sets, have been proposed. For example, Wehrens et al. [78] propose methods that use one or several samples of data to construct a statistical model which serves as a basis for a subsequent application on the entire data set. Other authors [e.g., 45] developed procedures to identify a set of data points which can be reasonably classified into clusters and iterate the procedure on the remainder. Different procedures do not derive a statistical model from a sample but apply strategies to scale down massive data sets [14] or use reweighted data to fit a new cluster to the mixture model [49]. Whereas these approaches to model-based clustering have been developed within a data mining context and are thus exploratory in nature, SEMs rely on a confirmatory concept as researchers need to specify a hypothesized path model in the first step of the analysis. This path model serves as the basis for subsequent cluster analyses but is supposed to remain constant across all segments.

In CBSEM, Jedidi et al. [37] 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 [46, 47, 77]. Although the original technique extends CBSEM and is implemented in software packages for statistical computations [e.g., Mplus; 55], the method is inappropriate for PLS path modeling due to unlike methodological assumptions. Consequently, Hahn et al. [31] introduced the finite FIMIX-PLS method that combines the strengths of the PLS path modeling method with the maximum likelihood estimation's advantages when deriving market segments with the help of finite mixture models. A finite mixture approach to model-based clustering assumes that the data originate from several subpopulations or segments [48]. Each segment is modeled separately and the overall population is a mixture of segment-specific density functions. Consequently, homogeneity is no longer defined in terms of a set of common scores, but at a distributional level. Thus, finite mixture modeling enables marketers to cope with heterogeneity in data by clustering observations and estimating parameters simultaneously, thus avoiding well-known biases that occur when models are estimated separately [37]. Moreover, there are many versatile or parsimonious models, as well as clustering algorithms available that can be customized with respect to a wide range of substantial problems [48].

Based on this concept, the FIMIX-PLS approach simultaneously estimates the model parameters and ascertains the heterogeneity of the data structure within a PLS path modeling framework. FIMIX-PLS is based on the assumption that heterogeneity is concentrated in the inner model relationships. The approach captures this heterogeneity by assuming that each endogenous latent variable η_i is distributed as a finite mixture of conditional multivariate normal densities. According to Hahn et al. [31, p. 249], since "the endogenous variables of the inner model are a function of the exogenous variables, the assumption of the conditional multivariate normal distribution of the η_i is sufficient." From a strictly theoretical viewpoint, the imposition of a distributional assumption on the endogenous latent variable may prove to be problematic. This criticism gains force when one considers that PLS path modeling is generally preferred to covariance structure analysis in circumstances where assumptions of multivariate normality cannot be made [4, 20]. However, recent simulation evidence shows the algorithm to be robust, even in the face of distributional misspecification [18]. By differentiating between dependent (i.e., endogenous latent) and explanatory (i.e., exogenous latent) variables in the inner model, the approach follows a mixture regression concept [77] that allows the estimation of separate linear regression functions and the corresponding object memberships of several segments.

2.3.2 Methodology

Drawing on a modified presentation of the relationships in the inner model (Table 2.2 provides a description of all the symbols used in the equations presented in this chapter.),

$$\mathrm{B}\eta_i + \Gamma\xi_i = \zeta_i, \tag{2.1}$$

it is assumed that η_i is distributed as a finite mixture of densities $f_{i|k}(\cdot)$ with K ($K < \infty$) segments

$$\eta_i \sim \sum_{k=1}^{K} \rho_k f_{i|k}(\eta_i|\xi_i, B_k, \Gamma_k, \Psi_k), \tag{2.2}$$

whereby $\rho_k > 0\ \forall k$, $\sum_{k=1}^{K} \rho_k = 1$ and ξ_i, B_k, Γ_k, Ψ_k depict the segment-specific vector of unknown parameters for each segment k. The set of mixing proportions ρ determines the relative mixing of the K segments in the mixture. Substituting $f_{i|k}(\eta_i|\xi_i, B_k, \Gamma_k, \Psi_k)$ results in the following equation:[1]

$$\eta_i \sim \sum_{k=1}^{K} \rho_k \left[\frac{1}{(2\pi)^{M/2}\sqrt{|\Psi_k|}}\right] e^{-\frac{1}{2}\left((\tilde{I}-B_k)\eta_i+(-\Gamma_k)\xi_i\right)'\Psi_k^{-1}\left((\tilde{I}-B_k)\eta_i+(-\Gamma_k)\xi_i\right)}. \tag{2.3}$$

Equation 2.4 represents an EM formulation of the complete log-likelihood (lnL_c) as the objective function for maximization:

$$\mathrm{Ln}L_C = \sum_{i=1}^{I}\sum_{k=1}^{K} z_{ik} \ln(f(\eta_i|\xi_i, B_k, \Gamma_k, \Psi_k)) + \sum_{i=1}^{I}\sum_{k=1}^{K} z_{ik} \ln(\rho_k) \tag{2.4}$$

An EM formulation of the FIMIX-PLS algorithm (Table 2.3) is used for statistical computations to maximize the likelihood and to ensure convergence in this model. The expectation of Equation 2.4 is calculated in the E-step, where z_{ik} is 1

[1] Note that the following presentations slightly differ from Hahn et al.'s [31] original paper.

Table 2.2 Explanation of symbols

A_m	Number of exogenous variables as regressors in regression m
a_m	exogenous variable a_m with $a_m = 1,\ldots,A_m$
B_m	number of endogenous variables as regressors in regression m
b_m	endogenous variable b_m with $b_m = 1,\ldots,B_m$
$\gamma_{a_m mk}$	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) of Ψ_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 $i = 1,\ldots,I$
J	number of exogenous variables
j	exogenous variable j with $j = 1,\ldots,J$
K	number of classes
k	class or segment k with $k = 1,\ldots,K$
M	number of endogenous variables
m	endogenous variable m with $m = 1,\ldots,M$
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 for the relationships between endogenous latent variables
Γ	$M \times J$ path coefficient matrix of the inner model for the relationships between exogenous and endogenous latent variables
$\tilde{I}$	$M \times M$ identity matrix
Δ	difference of $current_{lnL_c}$ and $last_{lnL_c}$
B_k	$M \times M$ path coefficient matrix of the inner model for latent class k for the relationships between endogenous latent variables
Γ_k	$M \times J$ path coefficient matrix of the inner model for latent class k for the relationships between exogenous and endogenous latent variables
Ψ_k	$M \times M$ matrix for latent class k containing the regression variances
ρ	$(\rho_1,\ldots,\rho_K)$, vector of the K mixing proportions of the finite mixture
ρ_k	mixing proportion of latent class k

iff subject i belongs to class k (or 0 otherwise). The mixing proportion ρ_k (i.e., the relative segment size) and the parameters ξ_i, B_k, Γ_k, and Ψ_k of the conditional probability function are given (as results of the M-step), and provisional estimates (expected values) $E(z_{ik}) = P_{ik}$, for z_{ik} are computed according to Bayes's [5] theorem (Table 2.3).

Table 2.3 The FIMIX-PLS algorithm

set random starting values for P_{ik} ; set $last_{lnL_C} = V$; set $0 < S < 1$
// run initial M-step
// run EM-algorithm until convergence
repeat do
// the E-step starts here
if $\Delta \geq S$ then
$P_{ik} = \frac{\rho_k f_{i\|k}(\eta_i\|\xi_i, B_k, \Gamma_k, \Psi_k)}{\sum_{k=1}^{K} \rho_k f_{i\|k}(\eta_i\|\xi_i, B_k, \Gamma_k, \Psi_k)} \forall i, k$
$last_{lnL_C} = current_{lnL_C}$
// the M-step starts here
$\rho_k = \frac{\sum_{i=1}^{I} P_{ik}}{I} \forall k$
determine B_k, Γ_k, Ψ_k, $\forall k$
calculate $current_{lnL_C}$
$\Delta = current_{lnL_C} - last_{lnL_C}$
until $\Delta < S$

Equation 2.4 is maximized in the M-step (Table 2.3). This part of the FIMIX-PLS algorithm accounts for the most important changes in order to fit the finite mixture approach to PLS path modeling, compared to the original finite mixture structural equation modeling technique [37]. Initially, we calculate new mixing proportions ρ_k through the average of the adjusted expected values P_{ik} that result from the previous E-step. Thereafter, optimal parameters are determined for B_k, Γ_k, and Ψ_k through independent OLS regressions (one for each relationship between the latent variables in the inner model). The ML estimators of coefficients and variances are assumed to be identical to OLS predictions. We subsequently apply the following equations to obtain the regression parameters for endogenous latent variables:

$$Y_{mi} = \eta_{mi} \quad and \quad X_{mi} = (E_{mi}, N_{mi})' \tag{2.5}$$

$$E_{mi} = \begin{cases} \{\xi_1, ..., \xi_{A_m}\}, A_m \geq 1, a_m = 1, ..., A_m \wedge \xi_{a_m} \text{is regressor of } m \\ \emptyset \text{ else} \end{cases} \tag{2.6}$$

$$N_{mi} = \begin{cases} \{\eta_1, ..., \eta_{B_m}\} B_m \geq 1, b_m = 1, ..., B_m \wedge \eta_{b_m} \text{is regressor of } m \\ \emptyset \text{ else} \end{cases} \tag{2.7}$$

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

$$\tau_{mk} = \left[X_m' P_k X_m)\right]^{-1} \left[X_m' P_k Y_m)\right] \tag{2.8}$$

$$\omega_{mk} = \left[(Y_m - X_m \tau_{mk})' \left((Y_m - X_m \tau_{mk}) P_k\right)\right] / \widetilde{I} \rho_k \tag{2.9}$$

As a result, the M-step determines the new mixing proportions ρ_k, and the independent OLS regressions are used in the next E-step iteration to improve the outcomes of P_{ik}. The EM algorithm stops whenever lnL_C no longer improves noticeably, and an a priori-specified convergence criterion is reached.

2.3.3 Systematic Application of FIMIX-PLS

To fully exploit the capabilities of the approach, we propose the systematic approach to FIMIX-PLS clustering as depicted in Fig. 2.3. In FIMIX-PLS step 1, the basic PLS algorithm provides path modeling results, using the aggregate set of data. Step 2 uses the resulting latent variable scores in the inner path model to run the FIMIX-PLS algorithm as described above. The most important computational results of this step are the probabilities 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 (unexplained) regression variances.

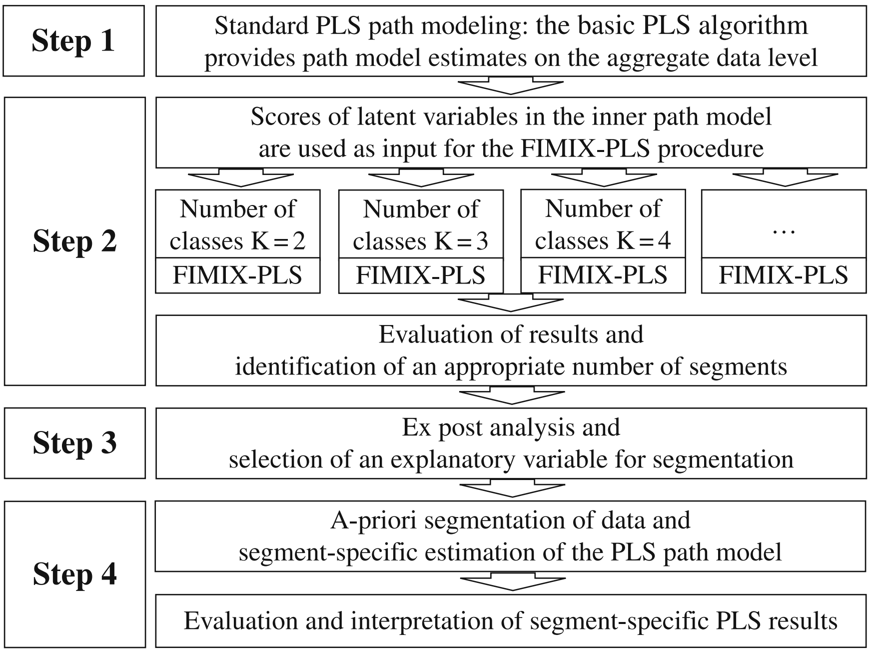

Fig. 2.3 Analytical steps of FIMIX-PLS

The methodology fits each observation with the finite mixture's probabilities P_{ik} into each of the predetermined number of classes. However, on the basis of the FIMIX-PLS results, it must be specifically decided whether the approach detects and treats heterogeneity in the inner PLS path model estimates by (unobservable) discrete moderating factors. This objective is explored in step 2 by analyzing the results of different numbers of K classes (approaches to guide this decision are presented in the next section).

When applying FIMIX-PLS, the number of segments is usually unknown. The process of identifying an appropriate number of classes is not straightforward. For various reasons, there is no statistically satisfactory solution for this analytical procedure [77]. One such reason is that the mixture models are not asymptotically chi-square distributed and do not allow the calculation of the likelihood ratio statistic with respect to obtaining a clear-cut decision criterion. Another reason is that the EM algorithm converges for any given number of K classes. One never knows if FIMIX-PLS stops at a local optimum solution. The algorithm should be started several times (e.g., 10 times) for each number of segments for different starting partitions [47]. Thereafter, the analysis should draw on the maximum log-likelihood outcome of each alternative number of classes. Moreover, the FIMIX-PLS model may result in the computation of non-interpretable segments for endogenous latent variables with respect to the class-specific estimates B_k and Γ_k of the inner path model relationships and with respect to the regression variances Ψ_k when the number of segments is increased. Consequently, segment size is a useful indicator to stop the analysis of additional numbers of latent classes to avoid incomprehensible FIMIX-PLS results. At a certain point, an additional segment is just very small, which explains the marginal heterogeneity in the overall data set.

In practical applications, researchers can compare estimates of different segment solutions by means of heuristic measures such as Akaike's information criterion (AIC), consistent AIC (CAIC), or Bayesian information criterion (BIC). These information criteria are based on a penalized form of the likelihood, as they simultaneously take a model's goodness-of-fit (likelihood) and the number of parameters used to achieve that fit into account. Information criteria generally favor models with a large log-likelihood and few parameters and are scaled so that a lower value represents a better fit. Operationally, researchers examine several competing models with varying numbers of segments and pick the model which minimizes the value of the information criterion. Researchers usually use a combination of criteria and simultaneously revert to logical considerations to guide the decision.

Although the preceding heuristics explain over-parameterization through the integration of a penalty term, they do not ensure that the segments are sufficiently separated in the selected solution. As the targeting of markets requires segments to be differentiable, i.e., the segments are conceptually distinguishable and respond differently to certain marketing mix elements and programs [40], this point is of great practical interest. Classification criteria that are based on an entropy statistic, which indicates the degree of separation between segments, can help to assess whether the analysis produces well-separated clusters [77]. Within this context, the normed entropy statistic [EN; 58] is a critical criterion for analyzing segment-specific FIMIX-PLS results. This criterion indicates the degree of all observations' classification and their estimated segment membership probabilities P_{ik} on a case-by-case basis and subsequently reveals the most appropriate number of latent segments for a clear-cut segmentation:

$$\mathrm{EN}_K = 1 - \frac{[\sum_i \sum_k -P_{ik} ln(P_{ik})]}{I ln(K)} \tag{2.10}$$

The EN ranges between 0 and 1 and the quality of the classification commensurates with the increase in EN_K. The more the observations exhibit high membership probabilities (e.g., higher than 0.7), the better they uniquely belong to a specific class and can thus be properly classified in accordance with high EN values. Hence, the entropy criterion is especially relevant for assessing whether a FIMIX-PLS solution is interpretable or not. Applications of FIMIX-PLS provide evidence that EN values above 0.5 result in estimates of P_{ik} that permit unambiguous segmentation [66, 71, 72].

An explanatory variable must be uncovered in the ex post analysis (step 3) in situations where FIMIX-PLS results indicate that heterogeneity in the overall data set can be reduced through segmentation by using the best fitting number of K classes. In this step, data are classified by means of an explanatory variable, which serves as input for segment-specific computations with PLS path modeling. An explanatory variable must include both the similar grouping of data, as indicated by the FIMIX-PLS results, and the interpretability of the distinctive clusters. However, the ex post analysis is a very challenging FIMIX-PLS analytical step. Ramaswamy et al. [58] propose a statistical procedure to conduct an ex post analysis of the estimated FIMIX-PLS probabilities. Logistic regressions, or in the case of large data sets, CHAID analyses, and classification and regression trees [9] may likewise be applied to identify variables that can be used to classify additional observations in one of the designed segments. While these systematic searches uncover explanatory variables that fit the FIMIX-PLS results well in terms of data structure, a logical search, in contrast, mostly focuses on the interpretation of results. In this case, certain variables with high relevance with respect to explaining the expected differences in segment-specific PLS path model computations are examined regarding their ability to form groups of observations that match FIMIX-PLS results.

The process of identifying an explanatory variable is essential for exploiting FIMIX-PLS results. The findings are also valuable to researchers to confirm that unobserved heterogeneity in the path model estimates is not an issue, or they allow this problem to be dealt with by means of segmentation and, thereby, facilitate multigroup PLS path modeling analyses [13, 32] in step 4. Significantly different group-specific path model estimations impart further differentiated interpretations of PLS modeling results and may foster the origination of more effective strategies.

2.4 Application of FIMIX-PLS

2.4.1 On Measuring Customer Satisfaction

When researchers work with empirical data and do not have a priori segmentation assumptions to capture heterogeneity in the inner PLS path model relationships, FIMIX-PLS is often not as clear-cut as in the simulation studies presented by Ringle [61] as well as Esposito Vinzi et al. [16]. To date, research efforts to apply FIMIX-PLS and assess its usefulness with respect to expanding the methodological toolbox were restricted by the lack of statistical software programs for this kind of analysis. Since such functionalities have recently been provided as a module in the SmartPLS software, FIMIX-PLS can be applied more easily to empirical data, thereby increasing our knowledge of the approach and its applicability. As a means of presenting the benefits of the method for PLS path modeling in marketing research, we focus on customer satisfaction to identify and treat heterogeneity in consumers through segmentation. However, the general approach of this analysis can be applied to any PLS application such as the various TAM model estimations in MIS.

Customer satisfaction has become a fundamental and well-documented construct in marketing that is critical with respect to demand and for any business's success given its importance and established relation with customer retention and corporate profitability [2, 52, 53]. Although it is often acknowledged that there are no truly homogeneous segments of consumers, recent studies report that there is indeed substantial unobserved customer heterogeneity within a given product or service class [81]. Dealing with this unobserved heterogeneity in the overall sample is critical for forming groups of consumers that are homogeneous in terms of the benefits that 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.

2.4.2 Data and Measures

We applied FIMIX-PLS to the ACSI model to measure customer satisfaction as presented by Fornell et al. [21] in the *Journal of Marketing* but used empirical data from their subsequent survey in 1999.[2] These data are collected quarterly to assess customers' overall satisfaction with the services and products that they buy from a number of organizations. The ACSI study has been conducted since 1994 for consumers of 200 publicly traded Fortune 500 firms as well as several US public administration and government departments. These firms and departments comprise more than 40% of the US gross domestic product. The sample selection mechanism ensures that all

[2] The data were provided by Fornell, Claes. AMERICAN CUSTOMER SATISFACTION INDEX, 1999 [Computer file]. ICPSR04436-v1. Ann Arbor, MI: University of Michigan. Ross School of Business, National Quality Research Center/Reston, VA: Wirthlin Worldwide [producers], 1999. Ann Arbor, MI: Inter-University Consortium for Political and Social Research [distributor], 2006-06-09. We would like to thank Claes Fornell and the ICPSR for making the data available.

types of organizations are included across all economic sectors considered. For the 1999 survey, about 250 consumers of each organization's products/services were selected via telephone. Each call identified the person in the household (for household sizes >1) whose birthday was closest, after which this person (if older than 18 years) was asked about the durables he or she had purchased during the last 3 years and about the nondurables purchased during the last month. If the products or services mentioned originated from one of the 200 organizations, a short questionnaire was administered that contained the measures described in Table 2.4.

The data-gathering process was carried out in such a manner that the final data were comparable across industries [21]. The ACSI data set has frequently been used in diverse areas in the marketing field, using substantially different methodologies such as event history modeling or simultaneous equations modeling. However, past research has not yet accounted for unobserved heterogeneity.

Table 2.4 Measurement scales, items, and descriptive statistics

Construct	Items
Overall Customer Satisfaction	Overall satisfaction Expectancy disconfirmation (performance falls short of or exceeds expectations) Performance versus the customer's ideal product or service in the category
Customer Expectations of Quality	Overall expectations of quality (prior to purchase) Expectation regarding customization, or how well the product fits the customer's personal requirements (prior to purchase) Expectation regarding reliability, or how often things would go wrong (prior to purchase)
Perceived Quality	Overall evaluation of quality experience (after purchase) Evaluation of customization experience, or how well the product fits the customer's personal requirements (after purchase) Evaluation of reliability experience, or how often things have gone wrong (after purchase)
Perceived Value	Rating of quality given price Rating of price given quality
Customer Complaints	Has the customer complained either formally or informally about the product or service?
Customer Loyalty	Likelihood rating prior to purchase
Covariates	
Age	Average = 43, Standard deviation = 15, minimum = 18, maximum = 84
Gender	42% male, 58% female
Education	Less than high school = 4.8%, high school graduate = 21.9%, some college = 34.6%, college graduate = 23.1%, post graduate = 15.5%
Race	White = 82.4%, Black/African American = 7.2%, American Indian = 1.1%, Asian or Pacific Islander = 1.8%, other race = 3.7%
Total Annual Family Income	Under $20.000 = 13.5%, $20.000–$30.000 = 13.9%, $30.000– $40.000 = 14.9%, $40.000–$60.000 = 22.3%, $60.000–$80.000 = 15.1%, $80.000–$100.000 = 8.4%, Over $100.000 = 11.9%

To illustrate the capabilities of FIMIX-PLS, we used data from the first quarter of 1999 ($N = 17,265$). To ensure the validity of our analysis, we adjusted the data set by carrying out a missing value analysis. In standard PLS estimations, researchers frequently revert to mean replacement algorithms. However, when replacing relatively high numbers by missing values per variable and case by mean values, FIMIX-PLS will most likely form its own segment of these observations. Consequently, we applied case-wise replacement. As this procedure would have led to the exclusion of a vast number of observations, we decided to reduce the original ACSI model as presented by Fornell et al. [21]. Consequently, we excluded two items from the "Customer Loyalty" construct, as they had a high number of missing values. Furthermore, we omitted the construct "Customer Complaints," measured by a binary single item, because we wanted to use this variable as an explanatory variable in the ex post analysis (step 3 in Fig. 2.3).

As our goal is to demonstrate the applicability of FIMIX-PLS regarding empirical data and to illustrate a cause–effect relationship model with respect to customer satisfaction, we do not regard the slight change in the model setup as a debilitating factor. Consequently, the final sample comprised $N = 10,417$ observations. Figure 2.1 illustrates the path model under consideration.

Fornell et al. [21] identified the three driver constructs "Perceived Quality," "Customer Expectations of Quality," and "Perceived Value," which are measured by three and two reflective indicators, with respect to "Overall Customer Satisfaction." The ACSI construct itself directly relates to the "Customer Loyalty" construct. Both latent variables also employ a reflective measurement operationalization. Table 2.4 provides the measurement scales and the items used in our study plus various descriptive statistics of the full sample.

2.4.3 Data Analysis and Results

Methodological considerations that are relevant to the analysis include the assessment of the measures' reliability, their discriminant validity. As the primary concern of the FIMIX-PLS algorithm is to capture heterogeneity in the inner model, the focus of the comparison lies on the evaluation of the overall goodness-of-fit of the models. Nevertheless, as the existence of reliable and valid measures is a prerequisite for deriving meaningful solutions, we also deal with these aspects.

As depicted in Fig. 2.3, the basic PLS algorithm [43] is applied to estimate the overall model by using the SmartPLS 2.0 [64] in step 1. To evaluate the PLS estimates, we follow the suggestions by Chin [8] and Henseler et al. [32]. On assessing the empirical results, almost all factor loadings exhibit very high values of above 0.8. The smallest loading of 0.629 still ranges well above the commonly suggested threshold value of 0.5 [35], thus supporting item reliability. Composite reliability is assessed by means of composite reliability ρ_c and Cronbach's α. Both measures' values are uniformly high around 0.8, thus meeting the stipulated thresholds [56]. To assess the discriminant validity of the reflective measures, two approaches are applied. First, the indicators' cross loadings are examined, which reveals that no indicator loads higher on the opposing endogenous constructs. Second, the Fornell and Larcker [22] criterion is applied, in which the square root of each endogenous construct's average variance extracted (AVE) is compared with its bivariate correlations with all opposing endogenous constructs [cp. 28, 32]. The results show that in all cases, the square root of AVE is greater than the variance shared by each construct and its opposing constructs. Consequently, we can also presume a high degree of discriminant validity with respect to all constructs in this study.

The central criterion for the evaluation of the inner model is the R^2. Whereas ACSI exhibits a highly satisfactory R^2 value of 0.777, all other constructs show only moderate values of below 0.5 (Table 2.8).

In addition to the evaluation of R^2 values, researchers frequently revert to the cross-validated redundancy measure Q^2 (Stone–Geisser test), which has been developed to assess the predictive validity of the exogenous latent variables and can be computed using the blindfolding procedure. Values greater than zero imply that the exogenous constructs have predictive relevance for the endogenous construct under consideration, whereas values below zero reveal a lack of predictive relevance [8]. All Q^2 values range significantly above zero, thus indicating the exogenous constructs' high predictive power. Another important analysis concerns the significance of hypothized relationships between the latent constructs. For example, "Perceived Quality" as well as "Perceived Value" exert a strong positive influence on the endogenous variable "Overall Customer Satisfaction," whereas the effect of "Customer Expectations of Quality" is close to zero. To test whether path coefficients differ significantly from zero, t values were calculated using bootstrapping with 10,417 cases and 5000 subsamples [32]. The analysis reveals that all relationships in the inner path model exhibit statistically significant estimates (Table 2.8).

In the next analytical step, the FIMIX-PLS module of SmartPLS was applied to segment observations based on the estimated latent variable scores (step 2 in Fig. 2.3). Initially, FIMIX-PLS results are computed for two segments (see settings in Fig. 2.4). Thereafter, the number of segments is increased sequentially. A comparison of the segment-specific information and classification criteria, as presented in Table 2.5, reveals that the choice of two groups is appropriate for customer segmentation purposes. All relevant evaluation criteria increase considerably in the ensuing numbers of classes.

The choice of two segments is additionally supported by the EN value of 0.504. As illustrated in Table 2.6, more than 80% of all our observations are assigned to one of the two segments with a probability P_{ik} of more than 0.7. These probabilities decline considerably with respect to higher numbers of K classes, which indicates an increased segmentation fuzziness that is also depicted by the lower EN. An EN of 0.5 or higher for a certain number of segments allows the unambiguous segmentation of data.

Next, observations are assigned to each segment according to their segment membership's maximum probability. Table 2.7 shows the segment sizes with respect to the different segment solutions, which allows the heterogeneity that affects the analysis to be specified: (a) As the number of segments increases, the smaller seg-

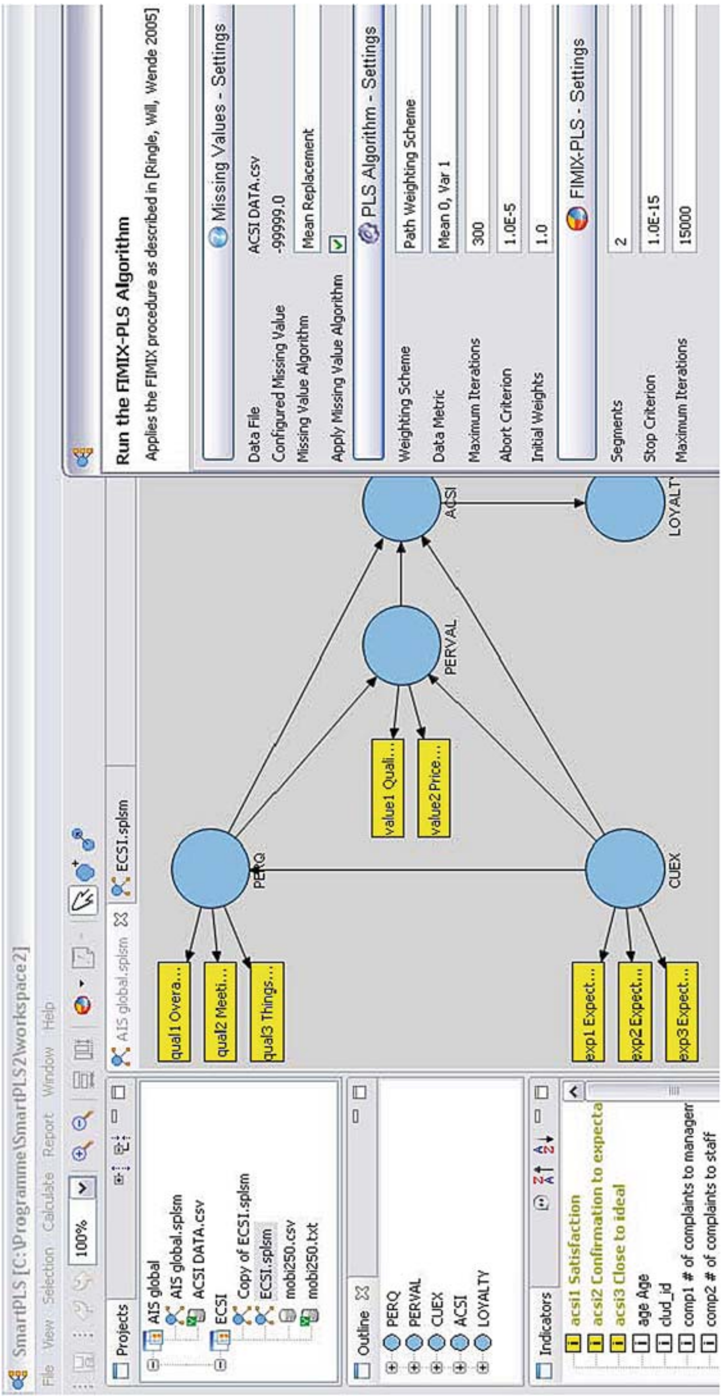

Fig. 2.4 PLS path modeling and FIMIX-PLS settings in SmartPLS

Table 2.5 Information and classification criteria for varying K

K	1nL	AIC	BIC	CAIC	EN
2	$-44,116.354$	88,278.708	88,445.486	88,468.486	0.504
3	$-46,735.906$	93,541.811	93,795.563	93,830.563	0.431
4	$-47,276.720$	94,647.440	94,988.246	95,035.246	0.494
5	$-49,061.353$	98,240.706	98,668.527	98,727.527	0.447
6	$-50,058.503$	100,259.006	100,773.840	100,844.840	0.443

Table 2.6 Overview of observations' highest probability of segment membership

P_{ik}	K = 2	K = 3	K = 4	K = 5	K = 6
[0.9, 1.0]	0.510	0.158	0.134	0.054	0.046
[0.8, 0.9)	0.211	0.279	0.237	0.093	0.061
[0.7, 0.8)	0.118	0.182	0.195	0.253	0.171
[0.6, 0.7)	0.090	0.153	0.173	0.225	0.198
[0.5, 0.6)	0.071	0.142	0.151	0.198	0.236
[0.4, 0.5)		0.076	0.087	0.147	0.225
[0.3, 0.4)		0.009	0.022	0.030	0.061
[0.2, 0.3)			0.001		0.002
[0.1, 0.2)					
[0, 0.1)					
Sum	1.000	1.000	1.000	1.000	1.000

Table 2.7 Segment sizes for different numbers of segments

K	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	$\sum_k \rho_k$
2	0.673	0.327					1.000
3	0.179	0.219	0.602				1.000
4	0.592	0.075	0.075	0.258			1.000
5	0.534	0.036	0.245	0.096	0.089		1.000
6	0.079	0.313	0.449	0.037	0.081	0.041	1.000

ment is gradually split up to create additional segments, while the size of the larger segment remains relatively stable (about 0.6 for $K \in \{2,3,4\}$ and 0.5 for $K \in \{5,6\}$). (b) The decline in the outcomes of additional numbers of classes based on the EN criterion allows us to conclude that the overall set of observations regarding this particular analysis of the ACSI consists of a large, stable segment and a small fuzzy one. (c) FIMIX-PLS cannot further reduce the fuzziness of the smaller segment.

In the process of increasing the number of segments, FIMIX-PLS can still identify the larger segment with comparably high probabilities of membership but is ambivalent when processing the small group with heterogeneous observations. Consequently, the probability of membership P_{ik} declines, resulting in decreasing

EN values. This indicates methodological complexity in the process of assigning the observations in this data set to additional segments. FIMIX-PLS computation forces observations to fit within a given number of K classes. As a result, FIMIX-PLS generates outcomes that are statistically problematic for the segment-specific estimates B_k and for Γ_k, i.e., regarding the inner relationships of the path model, and for Ψ_k, i.e., regarding the regression variances of endogenous latent variables. In this example, results exhibiting inner path model relationships and/or regression variances above one are obtained with respect to $K = 7$ classes. Consequently, the analysis of additional numbers of classes can stop at this juncture in accordance with the development of segment sizes in Table 2.7.

Table 2.8 presents the global model and FIMIX-PLS results of two latent segments. Before evaluating goodness-of-fit measures and inner model relationships, all outcomes with respect to segment-specific path model estimations were tested with regard to reliability and discriminant validity. The analysis showed that all measures satisfy the relevant criteria for model evaluation [32]. As in the global model, all paths are significant at a level of 0.01.

When comparing the global model with the results derived from FIMIX-PLS, one finds that the relative importance of the driver constructs "Overall Customer Satisfaction" differs quite substantially within the two segments. For example, the global model suggests that the perceived quality is the most important driver construct with

Table 2.8 Global model and FIMIX-PLS results of two latent segments

		FIMIX-PLS		
	Global	k = 1	k = 2	t[mgp]
Customer Expectations of Quality	0.556***	0.807***	0.258***	26.790***
→ Perceived Quality	(56.755)	(168.463)	(13.643)	
Customer Expectations of Quality	0.072***	0.218***	−0.107***	15.571***
→ Perceived Value	(7.101)	(16.619)	(6.982)	
Customer Expectations of Quality	0.021***	0.117***	−0.068***	14.088***
→ Overall Customer Satisfaction	(3.294)	(14.974)	(6.726)	
Perceived Quality	0.557***	0.425***	0.633***	10.667***
→ Overall Customer Satisfaction	(63.433)	(50.307)	(49.038)	
Perceived Quality	0.619***	0.582***	0.544***	1.899**
→ Perceived Value	(62.943)	(46.793)	(42.394)	
Perceived Value	0.394***	0.455***	0.308***	7.922***
→ Overall Customer Satisfaction	(44.846)	(62.425)	(21.495)	
Overall Customer Satisfaction	0.687***	0.839***	0.481***	19.834***
→ Customer Loyalty	(93.895)	(208.649)	(31.794)	
ρ_k	1.000	0.673	0.327	
$R^2_{\text{Perceived Quality}}$	0.309	0.651	0.067	
$R^2_{\text{Perceived Value}}$	0.439	0.591	0.277	
$R^2_{\text{Overall Customer Satisfaction}}$	0.777	0.848	0.679	
$R^2_{\text{Customer Loyalty}}$	0.471	0.704	0.231	

t[mgp] = t-value for multi-group comparison test
*** sig. at 0.01, **sig. at 0.05, *sig. at 0.1

respect to customer overall satisfaction. As "Perceived Quality" describes an ex post evaluation of quality, companies should emphasize product and service quality and their fit with use, which can be achieved through informative advertising. However, in the first segment of FIMIX-PLS, the most important driver construct with respect to customer satisfaction is "Perceived Value." In addition, also "Customer Expectations of Quality" exerts an increased positive influence on customer satisfaction. Likewise, both segments differ considerably with regard to the relationships between the three driver constructs "Perceived Quality," "Customer Expectations of Quality," and "Perceived Value."

However, only significant differences between the segments offer valuable interpretations for marketing practice. Consequently, we performed a multigroup comparison to assess whether segment-specific path coefficients differ significantly. The PLS path modeling multigroup analysis (PLS-MGA) applies the permutation test (5000 permutations) as described by [13] and which has recently been implemented as an experimental module in the SmartPLS software.

Multigroup comparison results show that all paths differ significantly between $k = 1$ and $k = 2$. Thus, consumers in each segment exhibit significantly different drivers with respect to their overall satisfaction, which allows differentiated marketing activities to satisfy customers' varying wants better. At the same time, all endogenous constructs have increased R^2 values, ranging between 2% ("Overall Customer Satisfaction") and 49% ("Perceived Quality") higher than in the global model. These were calculated as the sum of each endogenous construct's R^2 values across the two segments, weighted by the relative segment size.

The next step involves the identification of explanatory variables that best characterize the two uncovered customer segments. We consequently applied the QUEST [42] and Exhaustive CHAID [6] algorithm, using SPSS Answer Tree 3.1 on the covariates to assess if splitting the sample according to the sociodemographic variables' modalities leads to a statistically significant discrimination in the dependent measure. In the latter, continuous covariates were first transformed into ordinal predictors. In both approaches, "age" and "total annual family income" showed the greatest potential for meaningful a priori segmentation, with Exhaustive CHAID producing more accurate results. The result is shown in Fig. 2.5. The percentages in the nodes denote the share of total observations (as described in the root node) with respect to each segment. These mark the basis of the a priori segmentation of observations based on the maximum percentages for each node.

Segment one ($n_{k1} = 6,314$) comprises middle-aged customers ($age \in (28, 44]$) with a total annual family income between $40,000 and less than $100,000. Furthermore, customers aged 44 and above belong to this segment. Segment two ($n_{k2} =$ 4,103) consists of young customers (age ≤ 28) as well as middle-aged customers with a total annual family income of less than $40,000 or more than $100,000. The resulting classification corresponds to 56.878% of the FIMIX-PLS classification. In addition to this clustering according to sociodemographic variables, we used the behavioral variable "Customer Complaints" (Table 2.4) to segment the data. Segment one ($n_{k1} = 7,393$) represents customers that have not yet complained about a product or service, whereas segment two ($n_{k2} = 3,023$) contains customers who

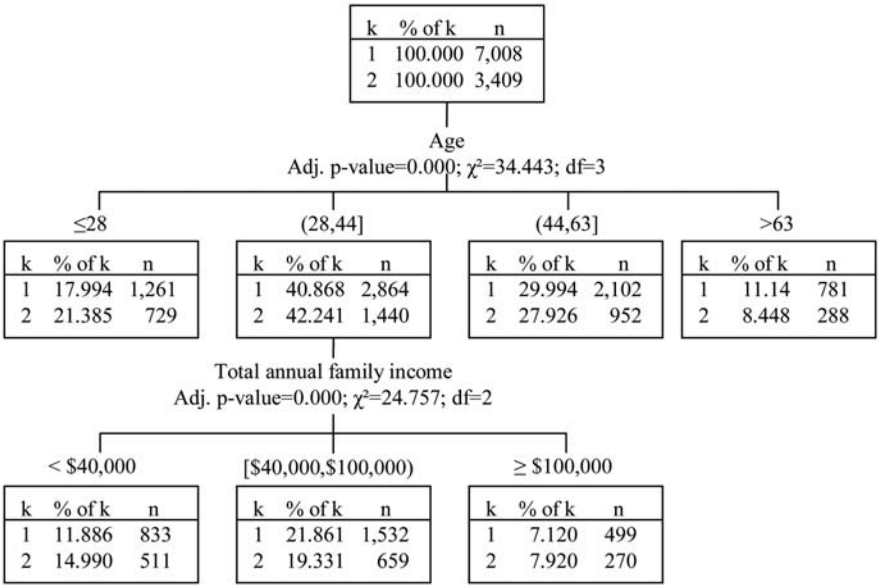

Fig. 2.5 Segmentation tree results of the exhaustive CHAID analysis

have complained in the past (consistency with FIMIX-PLS classification: 62.811%). Table 2.9 documents the results of the ex post analysis. The evaluation of the PLS path modeling estimates [8] with respect to these four a priori segmented data sets confirms that the results are satisfactory.

Similar results as those with the FIMIX-PLS analysis were obtained with regard to the ex post analysis using the Exhaustive CHAID algorithm. Again, the goodness-of-fit measures of the first segment exhibit increased values. Furthermore, the path coefficients differ significantly between the two segments. For example, the large segment exhibits a substantial relationship between "Customer Expectations of Quality" and "Overall Customer Satisfaction," which is highly relevant from a marketing perspective. With respect to this group of mostly older consumers, satisfaction is also explained by expected quality, which can potentially be controlled by marketing activities. For example, non-informative advertising (e.g., sponsorship programs) can primarily be used as a signal of expected product quality [39, 51]. However, it must be noted that with respect to the global model, the differences are less pronounced than those in the FIMIX-PLS analysis. Even though there are several differences observable, the path coefficient estimates are more balanced across the two segments, thus diluting response-based segmentation results. Similar figures result with respect to the ex post analysis based on the variable "customer complaints."

Despite the encouraging results of the ex post analysis, the analysis showed that the covariates available in the ACSI data set only offer a limited potential for meaningful a priori segmentation. Even though one segment's results improved, the dif-

Table 2.9 Inner model path coefficients with *t* values and goodness-of-fit measures

		Ex Post CHAID			Ex Post Cust. Compl.		
	Global	k = 1	k = 2	t[mgp]	k = 1	K = 2	t[mgp]
Customer Expectations of Quality	0.556***	0.575***	0.526***	2.599***	0.589***	0.511***	3.457***
→ Perceived Quality	(56.755)	(45.184)	(29.956)		(50.844)	(29.224)	
Customer Expectations of Quality	0.072***	0.072***	0.067***	0.246	0.089***	0.071***	0.825
→ Perceived Value	(7.101)	(5.511)	(3.581)		(6.169)	(4.025)	
Customer Expectations of Quality	0.021***	0.036***	−0.002	2.761***	0.047***	−0.001	3.252***
→ Overall Customer Satisfaction	(3.294)	(4.334)	(0.252)		(5.336)	(0.094)	
Perceived Quality	0.557***	0.548***	0.572***	1.283*	0.517***	0.578***	3.179***
→ Overall Customer Satisfaction	(63.433)	(45.653)	(35.861)		(45.217)	(35,806)	
Perceived Quality	0.619***	0.635***	0.599***	1.716**	0.519***	0.659***	6.518***
→ Perceived Value	(62.943)	(50.417)	(36.269)		(35.082)	(43,397)	
Perceived Value	0.394***	0.400***	0.384***	0.819	0.402***	0.390***	0.608
→ Overall Customer Satisfaction	(44.846)	(34.377)	(24.571)		(35.728)	(23,599)	
Overall Customer Satisfaction	0.687***	0.677***	0.698***	1.440*	0.616***	0.705***	6.237***
→ Customer Loyalty	(93.895)	(68.975)	(57.207)		(58.929)	(57.805)	
ρ_k	1	0.606	0.394	0.710	0.290		
$R^2_{\text{Perceived Quality}}$	0.309	0.331	0.277	0.347	0.261		
$R^2_{\text{Perceived Value}}$	0.439	0.461	0.406	0.332	0.488		
$R^2_{\text{Overall Customer Satisfaction}}$	0.777	0.793	0.752	0.713	0.798		
$R^2_{\text{Customer Loyalty}}$	0.471	0.459	0.488	0.380	0.497		

t[mgp] = t-value for multi-group comparison test
*** sig. at 0.01, ** sig. at 0.05, * sig. at 0.1

ferences between the segments were considerably smaller when compared to those of the FIMIX-PLS results.

2.5 Summary and Conclusion

Unobserved heterogeneity and measurement errors are common problems in social sciences. Jedidi et al. [37] have addressed these problems with respect to CBSEM. Hahn et al. [31] have further developed their finite mixture SEM methodology for PLS path modeling, which is an important alternative to CBSEM for researchers and practitioners. This chapter introduced and discussed the FIMIX-PLS approach, as it has recently been implemented in the software application SmartPLS. Consequently, researchers from marketing and other disciplines can exploit this approach to response-based segmentation by identifying certain groups of customers. We demonstrate the potentials of FIMIX-PLS by applying the procedure on data from the ACSI model. We thus extend prior research work on this important model by explaining unobserved heterogeneity in the inner model path estimates. Moreover, we show that, contrary to existing work on the same data set, there are different segments, which has significant implications.

Our example application demonstrates how FIMIX-PLS reliably identifies an appropriate number of customer segments, provided that unobserved moderating factors account for consumer heterogeneity within inner model path relationships. In this kind of very likely situation, FIMIX-PLS enables us to identify two segments with distinct inner model path estimates that differ substantially from the aggregate-level analysis. For example, unlike in the global model, “Customer Expectations of Quality” exerts a pronounced influence on the customers’ perceived value. Furthermore, the FIMIX-PLS analysis achieved a considerably increased model fit in the larger segment.

In the course of an ex post analysis, two explanatory variables (“Age” and “Total Annual Family Income”) were uncovered. An a priori segmentation based on the exhaustive CHAID analysis results, followed by segment-specific path analyses yielded similar findings as the FIMIX-PLS procedure. The same holds for segmenting along the modalities of the behavioral variable “Customer Complaints.” These findings allow marketers to formulate differentiated, segment-specific marketing activities to better satisfy customers’ varying wants. Researchers can exploit these additional analytic potentials where theory essentially supports path modeling in situations with heterogeneous data. We expect that these conditions will hold true in many marketing-related path modeling applications.

Future research will require the extensive use of FIMIX-PLS on marketing examples with heterogeneous data to illustrate the applicability and the problematic aspects of the approach from a practical point of view. Researchers will also need to test the FIMIX-PLS methodology by means of simulated data with a wide range of statistical distributions and a large variety of path model setups to gain additional implications. Finally, theoretical research should provide satisfactory improvements of problematic areas such as convergence to local optimum solutions, computation of improper segment-specific FIMIX-PLS results, and identification of suitable explanatory variables for a priori segmentation. These critical aspects have been discussed, for example, by Ringle [61] and Sarstedt [74]. By addressing these deficiencies, the effectiveness and precision of the approach could be extended, thus further extending the analytical ground of PLS path modeling.

References

1. Ritu Agarwal and Elena Karahanna. Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS Quarterly*, 24(4):665–694, 2000.
2. Eugene W. Anderson, Claes Fornell, and Donald. R. Lehmann. Customer satisfaction, market share and profitability: Findings from Sweden. *Journal of Marketing*, 58(3):53–66, 1994.
3. Richard P. Bagozzi. On the meaning of formative measurement and how it differs from reflective measurement: Comment on Howell, Breivik, and Wilcox (2007). *Psychological Methods*, 12(2):229–237, 2007.
4. Richard P. Bagozzi and Youjae Yi. Advanced topics in structural equation models. In Richard P. Bagozzi, editor, *Principles of Marketing Research*, pages 1–52. Blackwell, Oxford, 1994.
5. Thomas Bayes. 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. *Biometrika*, 45:296–315, 1763/1958.
6. David Biggs, Barry de Ville, and Ed Suen. A method of choosing multiway partitions for classification and decision trees. *Journal of Applied Statistics*, 18(1):49–62, 1991.
7. Kenneth A. Bollen. Interpretational confounding is due to misspecification, not to type of indicator: Comment on Howell, Breivik, and Wilcox (2007). *Psychological Methods*, 12(2):219–228, 2007.
8. Wynne W. Chin. The partial least squares approach to structural equation modeling. In George A. Marcoulides, editor, *Modern Methods for Business Research*, pages 295–358. Lawrence Erlbaum, Mahwah, NJ, 1998.
9. Sven F. Crone, Stefan Lessmann, and Robert Stahlbock. The impact of preprocessing on data mining: An evaluation of classifier sensitivity in direct marketing. *European Journal of Operational Research*, 173(3):781–800, 2006.
10. Fred D. Davis. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3):319–340, 1989.
11. Adamantios Diamantopoulos. The C-OAR-SE procedure for scale development in marketing: A comment. *International Journal of Research in Marketing*, 22(1):1–10, 2005.
12. Adamantios Diamantopoulos, Petra Riefler, and Katharina P. Roth. Advancing formative measurement models. *Journal of Business Research*, 61(12):1203–1218, 2008.
13. Jens Dibbern and Wynne W. Chin. Multi-group comparison: Testing a PLS model on the sourcing of application software services across germany and the usa using a permutation based algorithm. In Friedhelm W. Bliemel, Andreas Eggert, Georg Fassott, and Jörg Henseler, editors, *Handbuch PLS-Pfadmodellierung. Methode, Anwendung, Praxisbeispiele*, pages 135–160. Schäffer-Poeschel, Stuttgart, 2005.
14. William Dumouchel, Chris Volinsky, Theodore Johnson, Corinna Cortes, and Daryl Pregibon. Squashing flat files flatter. In *Proceedings of the 5th ACM SIGKDD International Conferennce on Knowledge Discovery in Data Mining*, pages 6–15, San Diego, CA, 1999. ACM Press.
15. Jacob Eskildsen, Kai Kristensen, Hans J. Juhl, and Peder Østergaard. The drivers of customer satisfaction and loyalty: The case of Denmark 2000–2002. *Total Quality Management*, 15(5-6):859–868, 2004.

16. Vincenzo Esposito Vinzi, Christian M. Ringle, Silvia Squillacciotti, and Laura Trinchera. Capturing and treating unobserved heterogeneity by response based segmentation in PLS path modeling: A comparison of alternative methods by computational experiments. Working Paper No. 07019, ESSEC Business School Paris-Singapore, 2007.
17. Vincenzo Esposito Vinzi, Laura Trinchera, Silvia Squillacciotti, and Michel Tenenhaus. REBUS-PLS: A response-based procedure for detecting unit segments in PLS path modeling. *Applied Stochastic Models in Business and Industry*, 24(5):439–458, 2008.
18. Fabian Festge and Manfred Schwaiger. The drivers of customer satisfaction with industrial goods: An international study. In Charles R. Taylor and Doo-Hee Lee, editors, *Advances in International Marketing – Cross-Cultural Buyer Behavior*, volume 18, pages 179–207. Elsevier, Amsterdam, 2007.
19. Adam Finn and Ujwal Kayande. How fine is C-OAR-SE? a generalizability theory perspective on rossiter's procedure. *International Journal of Research in Marketing*, 22(1):11–22, 2005.
20. Claes Fornell and Fred L. Bookstein. Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *Journal of Marketing Research*, 19(4):440–452, 1982.
21. Claes Fornell, Michael D. Johnson, Eugene W. Anderson, Jaesung Cha, and Barbara Everitt Johnson. The American customer satisfaction index: Nature, purpose, and findings. *Journal of Marketing*, 60(4):7–18, 1996.
22. Claes Fornell and David F. Larcker. Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1):39–50, 1981.
23. Claes Fornell, Peter Lorange, and Johan Roos. The cooperative venture formation process: A latent variable structural modeling approach. *Management Science*, 36(10):1246–1255, 1990.
24. Claes Fornell, William T. Robinson, and Birger Wernerfelt. Consumption experience and sales promotion expenditure. *Management Science*, 31(9):1084–1105, 1985.
25. David Gefen and Detmar W. Straub. Gender differences in the perception and use of e-mail: An extension to the technology acceptance model. *MIS Quarterly*, 21(4):389–400, 1997.
26. Oliver Götz, Kerstin Liehr-Göbbers, and Manfred Krafft. Evaluation of structural equation models using the partial least squares (PLS-) approach. In Vincenzo Esposito Vinzi, Wynne W. Chin, Jörg Henseler, and Huiwen Wang, editors, *Handbook of Partial Least Squares: Concepts, Methods and Applications in Marketing and Related Fields*, forthcoming. Springer, Berlin-Heidelberg, 2009.
27. Peter H. Gray and Darren B. Meister. Knowledge sourcing effectiveness. *Management Science*, 50(6):821–834, 2004.
28. Yany Grégoire and Robert J. Fisher. The effects of relationship quality on customer retaliation. *Marketing Letters*, 17(1):31–46, 2006.
29. Siegfried P. Gudergan, Christian M. Ringle, Sven Wende, and Alexander Will. Confirmatory tetrad analysis in PLS path modeling. *Journal of Business Research*, 61(12):1238–1249, 2008.
30. Peter Hackl and Anders H. Westlund. On structural equation modeling for customer satisfaction measurement. *Total Quality Management*, 11:820–825, 2000.
31. Carsten Hahn, Michael D. Johnson, Andreas Herrmann, and Frank Huber. Capturing customer heterogeneity using a finite mixture PLS approach. *Schmalenbach Business Review*, 54(3):243–269, 2002.
32. Jörg Henseler, Christian M. Ringle, and Rudolf R. Sinkovics. The use of partial least squares path modeling in international marketing. In Rudolf R. Sinkovics and Pervez N. Ghauri, editors, *Advances in International Marketing*, volume 20, pages 277–320. Emerald, Bingley, 2009.
33. Roy D. Howell, Einar Breivik, and James B. Wilcox. Is formative measurement really measurement? reply to Bollen (2007) and Bagozzi (2007). *Psychological Methods*, 12(2): 238–245, 2007.
34. Roy D. Howell, Einar Breivik, and James B. Wilcox. Reconsidering formative measurement. *Psychological Methods*, 12(2):205–218, 2007.

35. John Hulland. Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic Management Journal*, 20(2):195–204, 1999.
36. Magid Igbaria, Nancy Zinatelli, Paul Cragg, and Angele L. M. Cavaye. Personal computing acceptance factors in small firms: A structural equation model. *MIS Quarterly*, 21(3): 279–305, 1997.
37. Kamel Jedidi, Harsharanjeet S. Jagpal, and Wayne S. DeSarbo. Finite-fixture structural equation models for response-based segmentation and unobserved heterogeneity. *Marketing Science*, 16(1):39–59, 1997.
38. Karl G. Jöreskog. Structural analysis of covariance and correlation matrices. *Psychometrika*, 43(4):443–477, 1978.
39. Richard E. Kihlstrom and Michael H. Riordan. Advertising as a signal. *Journal of Political Economy*, 92(3):427–450, 1984.
40. Philip Kotler and Kevin Lane Keller. *Marketing Management*. Prentice Hall, Upper Saddle River, NJ, 12 edition, 2006.
41. Kai Kristensen, Anne Martensen, and Lars Grønholdt. Customer satisfaction measurement at post denmark: Results of application of the European customer satisfaction index methodology. *Total Quality Management*, 11(7):1007–1015, 2000.
42. Wei-Yin Loh and Yu-Shan Shih. Split selection methods for classification trees. *Statistica Sinica*, 7(4):815–840, 1997.
43. Jan-Bernd Lohmöller. *Latent Variable Path Modeling with Partial Least Squares*. Physica, Heidelberg, 1989.
44. Scott B. MacKenzie, Philip M. Podsakoff, and Cheryl B. Jarvis. The problem of measurement model misspecification in behavioral and organizational research and some recommended solutions. *Journal of Applied Psychology*, 90(4):710–730, 2005.
45. Ranjan Maitra. Clustering massive data sets with applications in software metrics and tomography. *Technometrics*, 43(3):336–346, 2001.
46. Geoffrey J. McLachlan and Kaye E. Basford. *Mixture Models: Inference and Applications to Clustering*. Dekker, New York, NY, 1988.
47. Geoffrey J. McLachlan and Thriyambakam Krishnan. *The EM Algorithm and Extensions*. Wiley, Chichester, 2004.
48. Geoffrey J. McLachlan and David Peel. *Finite Mixture Models*. Wiley, New York, NY, 2000.
49. Christopher Meek, Bo Thiesson, and David Heckerman. Staged mixture modeling and boosting. In *In Proceedings of the 18th Annual Conference on Uncertainty in Artificial Intelligence*, pages 335–343, San Francisco, CA, 2002. Morgan Kaufmann.
50. Marina Meilă and David Heckerman. An experimental comparison of model-based clustering methods. *Machine Learning*, 40(1/2):9–29, 2001.
51. Paul Milgrom and John Roberts. Price and advertising signals of product quality. *Journal of Political Economy*, 94(4):796–821, 1986.
52. Vikas Mittal, Eugene W. Anderson, Akin Sayrak, and Pandu Tadikamalla. Dual emphasis and the long-term financial impact of customer satisfaction. *Marketing Science*, 24(4): 531–543, 2005.
53. Neil Morgan, Eugene W. Anderson, and Vikas Mittal. Understanding firms' customer satisfaction information usage. *Journal of Marketing*, 69(3):121–135, 2005.
54. Bengt O. Muthén. Latent variable modeling in heterogeneous populations. *Psychometrika*, 54(4):557–585, 1989.
55. Linda K. Muthén and Bengt O. Muthén. *Mplus User's Guide*. Muthén & Muthén, Los Angeles, CA, 4th edition, 1998.
56. Jum C. Nunnally and Ira Bernstein. *Psychometric Theory*. McGraw Hill, New York, NY, 3rd edition, 1994.
57. Francesco Palumbo, Rosaria Romano, and Vincenzo Esposito Vinzi. Fuzzy PLS path modeling: A new tool for handling sensory data. In Christine Preisach, Hans Burkhardt, Lars Schmidt-Thieme, and Reinhold Decker, editors, *Data Analysis, Machine Learning and Applications – Proceedings of the 31st Annual Conference of the Gesellschaft für Klassifika-*

tion e.V., Albert-Ludwigs-Universität Freiburg, March 7–9, 2007, pages 689–696, Berlin-Heidelberg, 2008. Springer.
58. Venkatram Ramaswamy, Wayne S. DeSarbo, David J. Reibstein, and William T. Robinson. An empirical pooling approach for estimating marketing mix elasticities with PIMS data. *Marketing Science*, 12(1):103–124, 1993.
59. Edward E. Rigdon. Structural equation modeling. In George A. Marcoulides, editor, *Modern methods for business research*, Quantitative Methodology Series, pages 251–294. Lawrence Erlbaum, Mahwah, 1998.
60. Edward E. Rigdon, Christian M. Ringle, and Marko Sarstedt. Structural modeling of heterogeneous data with partial least squares. *Review of Marketing Research*, forthcoming, 2010.
61. Christian M. Ringle. Segmentation for path models and unobserved heterogeneity: The finite mixture partial least squares approach. Research Papers on Marketing and Retailing No. 035, University of Hamburg, 2006.
62. Christian M. Ringle and Karl-Werner Hansmann. Enterprise-networks and strategic success: An empirical analysis. In Theresia Theurl and Eric C. Meyer, editors, *Strategies for Cooperation*, pages 133–152. Shaker, Aachen, 2005.
63. Christian M. Ringle and Rainer Schlittgen. A genetic segmentation approach for uncovering and separating groups of data in PLS path modeling. In Harald Martens, Tormod Næs, and Magni Martens, editors, *PLS'07 International Symposium on PLS and Related Methods – Causalities Explored by Indirect Observation*, pages 75–78, Ås, 2007. Matforsk.
64. Christian M. Ringle, Sven Wende, and Alexander Will. Customer segmentation with FIMIX-PLS. In Tomàs Aluja, Josep Casanovas, Vincenzo Esposito Vinzi, and Michel Tenenhaus, editors, *PLS'05 International Symposium on PLS and Related Methods – PLS and Marketing*, pages 507–514, Paris, 2005. Decisia.
65. Christian M. Ringle, Sven Wende, and Alexander Will. SmartPLS 2.0 (beta), 2005.
66. Christian M. Ringle, Sven Wende, and Alexander Will. The finite mixture partial least squares approach: Methodology and application. In Vincenzo Esposito Vinzi, Wynne W. Chin, Jörg Henseler, and Huiwen Wang, editors, *Handbook of Partial Least Squares: Concepts, Methods and Applications in Marketing and Related Fields*, forthcoming. Springer, Berlin-Heidelberg, 2009.
67. Christian M. Ringle, Marko Sarstedt, and Rainer Schlittgen. Finite mixture and genetic algorithm segmentation in partial least squares path modeling. In Andreas Fink, Berthold Lausen, Wilfried Seidel, and Alfred Ultsch, editors, *Advances in Data Analysis, Data Handling and Business Intelligence. Proceedings of the 32nd Annual Conference of the German Classification Society (GfKl)*, Springer, Heidelberg and Berlin, forthcoming.
68. John R. Rossiter. The C-OAR-SE procedure for scale development in marketing. *International Journal of Research in Marketing*, 19(4):305–335, 2002.
69. John R. Rossiter. Reminder: A horse is a horse. *International Journal of Research in Marketing*, 22(1):23–25, 2005.
70. Gastón Sánchez and Tomàs Aluja. A simulation study of PATHMOX (PLS path modeling segmentation tree) sensitivity. In Harald Martens, Tormod Næs, and Magni Martens, editors, *PLS'07 International Symposium on PLS and Related Methods – Causalities Explored by Indirect Observation*, pages 33–36, Ås, 2007. Matforsk.
71. Marko Sarstedt and Christian M. Ringle. Treating unobserved heterogeneity in PLS path modelling: A comparison of FIMIX-PLS with different data analysis strategies. *Journal of Applied Statistics*, forthcoming, 2010.
72. Marko Sarstedt, Christian M. Ringle, and Manfred Schwaiger. Do we fully understand the critical success factors of customer satisfaction with industrial goods? Extending Festge and Schwaiger's model to account for unobserved heterogeneity. *Journal of Business Market Management*, 3(3):185, 2009.
73. Marko Sarstedt. Market segmentation with mixture regression models. *Journal of Targeting, Measurement and Analysis for Marketing*, 16(3):228–246, 2008.
74. Marko Sarstedt. A review of recent approaches for capturing heterogeneity in partial least squares path modelling. *Journal of Modelling in Management*, 3(2):140–161, 2008.

75. Michel Tenenhaus, Vincenzo Esposito Vinzi, Yves-Marie Chatelin, and Carlo Lauro. PLS path modeling. *Computational Statistics & Data Analysis*, 48(1):159–205, 2005.
76. Viswanath Venkatesh and Ritu Agarwal. Turning visitors into customers: A usability-centric perspective on purchase behavior in electronic channels. *Management Science*, 52(3): 367–382, 2006.
77. Michel Wedel and Wagner Kamakura. *Market Segmentation: Conceptual and Methodological Foundations*. Kluwer, London, 2nd edition, 2000.
78. Ron Wehrens, Lutgarde M. C. Buydens, Chris Fraley, and Adrian E. Raftery. Model-based clustering for image segmentation and large datasets via sampling. *Journal of Classification*, 21(2):231–253, 2004.
79. John Williams, Dirk Temme, and Lutz Hildebrandt. A Monte Carlo study of structural equation models for finite mixtures. SFB 373 Discussion Paper No. 48, Humboldt University Berlin, 2002.
80. Herman Wold. Soft modeling: The basic design and some extensions. In Karl G. Jöreskog and Herman Wold, editors, *Systems Under Indirect Observations*, pages 1–54. North-Holland, Amsterdam, 1982.
81. Jianan Wu and Wayne S. DeSarbo. Market segmentation for customer satisfaction studies via a new latent structure multidimensional scaling model. *Applied Stochastic Models in Business and Industry*, 21(4/5):303–309, 2005.