Identifying Hidden Structures in Marketing's Structural Models Through Universal Structure Modeling

An Explorative Bayesian Neural Network Complement to LISREL and PLS

by Frank Buckler and Thorsten Hennig-Thurau

Universal Structure Modeling (USM), introduced herein, offers an exploratory complement to confirmatory structural equation modeling methods such as covariance-based structural equation modeling (e.g., LISREL) and partial least squares. Because USM combines the iterative methodology of partial least squares with a Bayesian neural network approach involving a multilayer perceptron architecture, it enables researchers to identify "hidden" structures within their models and highlights theoretically unproposed model paths, nonlinear relations among model variables, and interactive effects. Using synthetic data, the authors demonstrate USM's ability to identify linear and nonlinear relationships and provide evidence that the method does not overfit the original data. They also find hidden paths, nonlinearity, and interactions in two structural models published in the *Journal of Marketing*, which illustrates the practical relevance of USM. They provide recommendations for researchers regarding in which conditions and how USM should be used.

Frank Buckler, Jungbergerstr. 7, 51105 Cologne, Germany. E-Mail: buckler @usm-analysis.com

Thorsten Hennig-Thurau, Department of Marketing and Media Research, School of Media, Bauhaus-University of Weimar 99423 Weimar, Germany. E-Mail: tht@medien.uni-weimar.de

1. A New Perspective on Structural Modeling in Marketing

A large body of research in leading marketing journals uses structural equation modeling (SEM) to estimate structural models with three or more latent variables simultaneously. The two most frequently applied SEM methods are covariance-based structural equation modeling (CVSEM), made popular through Jöreskog and Sörbom's (1999) LISREL program, and the component-based partial least squares (PLS) approach originated by Wold (1989). More than 180 articles published in the *Journal of Marketing*, *Journal of Marketing Research*, and *Journal of the Academy of Marketing Science* applied SEM between 1995 and 2005, with 89% of these publications using CVSEM and 11% PLS. Today, SEM can be considered a methodological paradigm in its own right within the marketing discipline–a dominant logic for defining and addressing complex research problems.

Although both CVSEM and PLS offer widely recognized, powerful methods for testing a specific model, the early stage of theory development in marketing often prevents researchers from excluding the possibility that alternative models might represent the true relations among model constructs more effectively (Rust and Schmittlein 1985). Taking a philosophy of science perspective, the empirical ability to support (i.e., to not falsify) a certain model structure always requires the elimination of alternative explanations. While SEM researchers are recommended to compare the proposed model structure with alternative models (Bollen 1989; Cudeck and Browne 1983), in most empirical applications this heuristic approach does not rule out the existence of other models which are equally (or even more) powerful than the proposed one. As Rust and Schmittlein (1985, p. 20) state, "it is generally the case that two, three, or several such models may be constructed." In practical

applications, alternative models often seem to be constructed primarily to demonstrate the superiority of the proposed model instead of constituting serious alternative approaches (e.g., De Wulf, Odekerken-Schröder, and Iacobucci 2001; Morgan and Hunt 1994). In other words, while comparing a proposed model with certain alternative models is certainly helpful (Bollen 1989; Cudeck and Browne 1983), philosophy of science requires researchers to identify *all* possible model structures and to demonstrate the superiority of the theoretically proposed model over its alternatives, something that can hardly be achieved by CVSEM. Similarly, the widely available software for CVSEM (e.g., LISREL, AMOS, EQS) and PLS (e.g., PLS Graph, SmartPLS) remains limited to linear relations among constructs and does not test for interactions among model variables that have not been theoretically proposed by the researchers. Accordingly, alternative models with theoretically unproposed nonlinear paths and interactions systematically get overlooked by CVSEM and PLS methods.[1] This exclusion is important because both nonlinear effects (Agustin and Singh 2005; Oliva, Oliver, and MacMillan 1992) and interactions (Chandrashekaran et al. 1999; Kohli, Shervani, and Challagalla 1998; Nowlis and Simonson 1996; Rao, Qu, and Rueckert 1999) are common phenomena in marketing. Philosophy of science would demand a model testing approach that points researchers to the existence of such interaction effects and helps them to gain undistorted path coefficients.

Overcoming these limitations of traditional SEM methods requires applying a more exploratory approach that is not limited to testing a small (and often arbitrarily chosen) number of structural models but rather provides insight into any possible relationship among the variables of a structural model. Ideally, such an exploratory approach takes into account the potential existence of theoretically unproposed nonlinear relations and interactions among model constructs, in addition to unhypothesized model paths. This manuscript introduces Universal Structure Modeling (USM) as a method that enables researchers to apply such an exploratory approach to SEM and thus helps them identify different kinds of "hidden" structures instead of testing a limited set of rival model structures. Specifically, the USM approach combines the iterative component-based approach of PLS with a Bayesian neural network involving a multilayer perceptron architecture and points researchers toward theoretically unproposed (1) paths among model constructs, (2) nonlinear relations between model constructs, and (3) interactions among model constructs. As a result, USM enables researchers to improve their theoretical models and rule out the existence of superior alternatives.

The remainder of this manuscript is structured as follows: After presenting the USM algorithm and its assumptions, we explore the power of USM with two sets of synthetic data (one involving nonlinear relations and interactions, the other linear relations only). We then apply USM to two models from *Journal of Marketing* articles and compare the results with CVSEM and PLS to demonstrate the method's practical relevance for marketing phenomena. The findings suggest recommendations for researchers regarding in which conditions and how USM should be used to test structural models in a marketing context.

2. The universal structure modeling approach

Universal Structure Modeling builds on the iterative PLS approach for testing structural models but substitutes its linear least squares regression element with a universal regression method, namely, a Bayesian neural network.[2] Thus, USM solves the black box problem inherent to universal regression through its combined use of methods that measure the strength of model paths and procedures that quantify and visualize nonlinear and interactive effects among model constructs. Whereas PLS and CVSEM both limit model estimation to *a priori* hypothesized paths, USM represents a more exploratory approach that also tests for hidden model structures, namely, theoretically unproposed paths, nonlinearity, and interaction effects. In Figure 1, we overview the different phases and steps of the USM parameter estimation process, each of which we discuss in detail.

Step 1: Model Specification

As with CVSEM and PLS, a USM model consists of a structural (or inner) model that contains several latent variables and their interrelations, as well as a measurement (or outer) model that links each latent variable to a set of manifest measurement variables. The initial step of a USM analysis involves creating a structural model specification matrix S that indicates the relations among the latent variables of the structural model to be excluded from the estimation process. Generally, because USM represents an exploratory approach to structural model estimation, the model includes all possible relationships between model variables. Only those relationships that are *known* to be wrong (e.g., a path from phenomenon B to phenomenon A when A took place before B) should be excluded by assigning values of 0 in the model specification matrix. If cross-sectional data appear in the model, researchers must decide *a*

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[1] We use the term "theoretically unproposed" to acknowledge that nonlinear relations and interactions that are known in advance could be considered when testing a structural marketing model with CVSEM and PLS. We focus on those interactions and nonlinear relations that are *not* hypothesized by a researcher and, therefore, are not part of the theoretical model.

[2] Universal regression methods, given sufficient parameterization, can model any kind of function (Rojas 1996). Examples of these regression algorithms include, in addition to neural networks, projection pursuit regression, Gaussian processes, and multivariate adaptive regression splines. We have chosen neural networks because of their high flexibility and appropriateness for marketing issues demonstrated in earlier work (e.g., West, Brockett, and Golden 1997).

priori about the direction of model paths and exclude reverse effects.[3]

In USM, the endogenous latent variables *y* are defined as functions of one or more other latent variables *y* that can be exogenous or endogenous in the structural model. Formally, the estimator $\hat{y}^j$ of the endogenous latent variable y^j is defined as the output of a multilayer perceptron (MLP) architecture, as shown in Equation 1:[4]

$$\hat{y}^j = f_{Act2}\left(\sum_{h=1}^{H} w_h \cdot f_{Act1}\left(\sum_{i=1}^{I} w_{ih} \cdot S_i^j \cdot y^i + b_{1h}\right) + b_2\right), \quad (1)$$

where f_{Act1} is the logistic sigmoid activation function $f_{Act1}(Term) = \dfrac{1}{1 + e^{-Term}}$ of the hidden neural units, and f_{Act2} is the linear activation function of the output neural unit. Specifically, f_{Act2} is a unity function required in MLP networks if the dependent variable is metric (Bishop 1995). In turn, *H* is the number of hidden neural units, *I* is the number of latent input variables *y*, *w* are the weights, and *b* are the bias weights. In addition, S_i^j is the *a priori* likelihood that a variable *i* influences another variable *j*.[5] S_i^j is set to 1 for all variables that affect *j* in the model specification matrix and 0 for other variables. The sigmoid activation function f_{Act1} is approximately linear for a certain range of values, namely, very small weight parameters w_{ih} in Equation 1 (Ripley 1996).

In USM, the measurement model defines a latent variable y^i (or, more precisely, its estimator $\hat{y}^i$) as a linear combination of its indicators:

$$\hat{y}^i = \sum_{m=1}^{M_i} f_m \cdot x_m + f_0, \quad (2)$$

where *x* are the values of M_i measurement variables that determine $\hat{y}^i$, f_m are factor loadings, and f_0 is the constant term of the function. Although the USM approach in general allows measurement model relations to be nonlinear, the nonlinear representation of constructs by a set of items further would increase the method's complexity and impede comparisons of the USM structural model results with other methods. Accordingly, we limit nonlinear relations to the structural model in USM in this manuscript.

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[3] Please note that this in some ways limits USM to explore only those relationships which are consistent with the assumed path direction.

[4] Regarding parameterization, we started all calculations in this research with ten hidden units and one hidden unit layer. This is an arbitrary choice which we chose based on our experience with the method. Please note that the choice of the number of hidden units is not a crucial question in the Bayesian framework, as the ASP mechanism automatically decreases the number of hidden units to the required level. Consequentially, in our empirical studies reported in this paper, ten units led to literally the same results as 20 units, so we chose 10 units to save calculation time.

[5] Our discussion of USM focuses on metric output units, which is the traditional scale format for structural models. Although it is possible to run USM with nonmetric (i.e., dichotomous) output units, this application is beyond the scope of this manuscript.
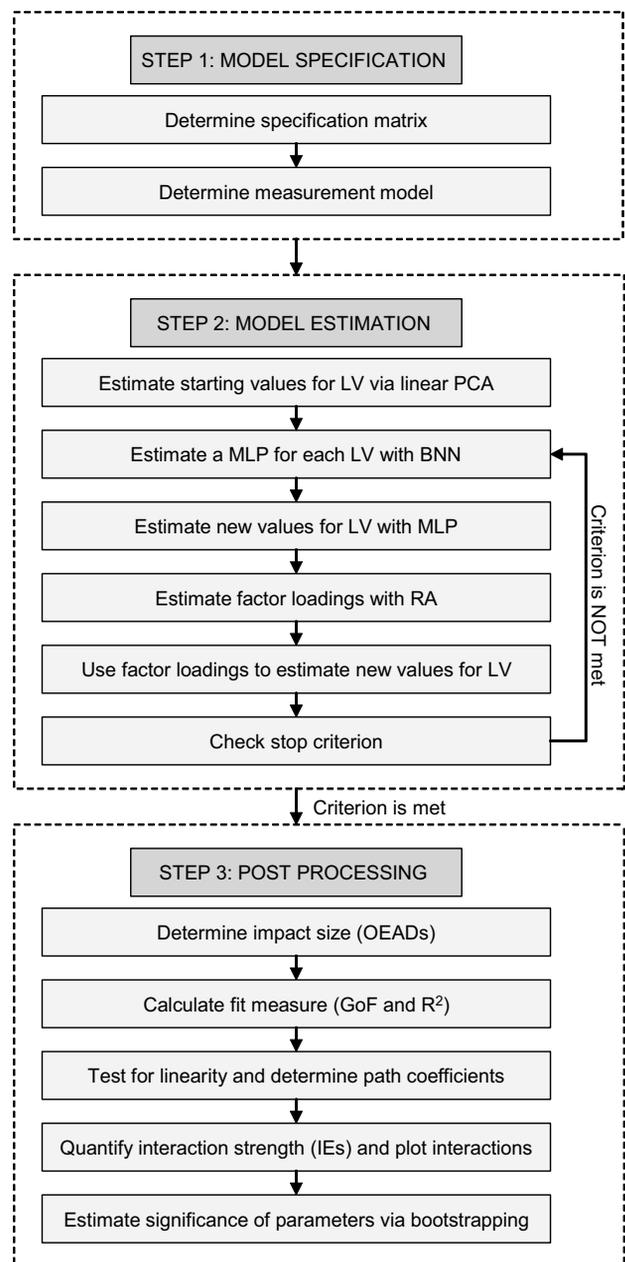

Figure 1: Phases and Steps of a USM Analysis

Note: LV = Latent Variables; PCA = Principal Component Analysis; MLP = MultiLayer Perceptron; BNN = Bayesian neural networks; RA = regression analysis; OEAD = Overall Explained Absolute Deviation; GoF = Goodness of Fit; IE = Interactive Effect.

Step 2: Model Estimation

As with PLS, structural and measurement models get estimated simultaneously in USM through an iterative estimation process. For USM, the estimation process starts with values for the latent variables derived from linear principal component analysis (instead of arbitrary values, as in PLS, mainly to save time) and estimates the paths between the latent variables using a Bayesian neural network involving the MLP architecture (Minsky and Papert 1988; Ripley 1996). We use the evidence framework for MLP architectures introduced by MacKay (1992) for parameter estimation, which ensures effective

weights and input pruning to detect irrelevant paths and prevent overfitting. Specifically, USM estimates the neural network by minimizing the error function E for each endogenous variable i of the structural model, with E being the overall error of the respective variable's neural network:

$$E_i = \beta \cdot \sum_{n=1}^{N} (\hat{y}_{t-1,n}^i - \hat{y}_{t,n}^i)^2 + \sum_{h=1}^{H} \alpha_{t,h} \cdot \sum_{p=1}^{P} w_{ph}^2, \qquad (3)$$

where n is an index for the individual cases, N is the number of cases included in the estimation, and p is an index for the weights w. In addition, $\hat{y}_t^i$ is the conditional estimate of the latent variable i in the current estimation round t, as calculated from the structural model by the Bayesian neural network, and $\hat{y}_{t-1}^i$ is the estimate of the previous iteration for this latent variable, derived from the measurement model. Finally, α_h and β are hyperparameters that limit the space of possible solutions (i.e., degrees of freedom) and prevent overfitting of the model. Practically, parameters that do not contribute substantially to explaining the dependent variable's variance are removed from the estimation process (MacKay 1995). The hyperparameters α_h and β get computed in every learning iteration, as described in Equations 4 and 5:

$$\alpha_h = \frac{\gamma}{2\sum_{n=1}^{N} w_{nh}^2}, \text{ and} \qquad (4)$$

$$\beta = \frac{N - \gamma}{2\sum_{n=1}^{N} (y_n^i - \hat{y}_n^i)^2}, \qquad (5)$$

where N is the number of cases and $\gamma = \sum_{p=1}^{P} \frac{\lambda_p}{\lambda_p + \alpha_{LI-1}}$. Finally, λ_p are the eigenvalues of the Hessian matrix of the error function (see equation 3), and α_{LI-1} is the hyperparameter α from the previous learning iteration (*LI*).

In contrast to weighted decay and ridge regression, the evidence framework is not based on heuristics but on a systematic statistical approach with an inherent logic (for a detailed discussion, see Bishop 1995, p. 385 ff.). We use the RPROP algorithm, suggested by Riedmiller and Braun (1993), to minimize the overall error E. RPROP is a variation of the basic back-propagation algorithm that changes the network parameters in the direction in which the overall error E declines (also referred to as "negative gradient"). We employ a boosting (i.e., Committee-of-Networks) approach to generate stable results with 30 replications (Bishop 1995)[6] by averaging 30 estimates of $\hat{y}^i$.[7]

The output of the neural network results in improved scores for the latent variables. These new scores then provide input for calculating the weights of the measurement model, which we need to generate the next round of latent variable scores. The concrete procedure in this step differs between reflective and formative measurement scales (Fornell and Cha 1994; Jarvis, MacKenzie, and Podsakoff 2003). In the case of reflective items, the new latent construct estimates emerge from a series of bivariate regression analyses (with observed scores as dependent variables), whereas we use multivariate regression analysis for formative scales (with the latent construct score as dependent variable). In both cases, the weighted regression coefficients transform into new estimates for the latent variable $\hat{y}_t^i$, which substitute for the previous latent variable estimations $\hat{y}_{t-1}^i$. The process of iteratively calculating inner and outer model estimates continues until the differences between the latent variable scores calculated by the inner model and those by the outer model are minimal. Specifically, we stop the estimation process when the divisor of the absolute change in the latent variable scores summed across all model constructs and the sum of latent variable scores falls below 1%.

The iteration process aims to minimize residual variance (instead of maximizing a theoretically derived function, as is the case with CVSEM), and the different kinds of residual variables to be minimized (for endogenous latent and measurement variables) are partitioned into estimable subsets. In other words, one part of the parameters is held fixed (and is assumed to be known), whereas the other part gets estimated. This step describes basically the same procedure as PLS, so we can assume the iterative process converges, though convergence has not been formally proven (Fornell and Cha 1994).

Step 3: Post-Processing

After determining the final estimates for the latent variables, the next step is to investigate the strength, significance, and shape of the relations among the latent constructs of the inner model. Therefore, we calculate variance explanation parameters, coefficients of determination, the model's goodness of fit, path coefficients (for linear relations), and interaction effects.

Overall Explained Absolute Deviation. Path coefficients (measures of the strength of the relation between two latent variables) can be calculated only when the relationship between two variables is linear (note that path coefficients describe the additive influence of one variable on another). Therefore, we require a more general criterion for the strength of construct interrelations.[8] We draw on Zimmermann (1994) and introduce the Overall

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[6] A weighted mean of the output of all Committee-of-Network solutions performs well on validation data (Bishop 1995, p. 364). We employ boosting since backpropagating MLPs start with random weights and never stop with exactly the same solution, as they perform a search on an error surface with many local optima. This issue may be of theoretical, but hardly of practical importance.

[7] Please note that, conceptually, USM is not limited to the use of the MLP architecture; it also could run with alternative approaches such as Gaussian processes.

[8] Another way to compare the results would be to use measures of prediction accuracy (e.g., MAE, hit rates). However, as both USM and CVSEM/PLS aim at testing, not prediction, we consider these measures as inappropriate.

Explained Absolute Deviation (OEAD) as a measure of latent variable i's share of variance which is explained by latent variable j in the structural model. We formally define OEAD in Equation 6:

$$OEAD_j^i = \frac{\sum_{n=1}^{N} \left| \frac{\hat{y}_n^i - f_n^i(y^1,...,\overline{y}^j,...,y^I)}{\hat{y}_n^i - \overline{\hat{y}}_n^i} \right|}{N},$$ (6)

where $f^i(y^1,...,\overline{y}^j,...,y^I)$ is the outcome of the neural network function (Equation 1) when the mean of y^j (termed $\overline{y}^j$) serves as an input variable. In other words, as the numerator of Equation 6 shows, we calculate for each case how the estimates of a latent variable i change if we exclude the latent variable j from the model. This is done by fixing the input of variable j to its mean value, or $\overline{y}^j$. We normalize the effect by dividing it by the number of cases. Because the effect size of a latent variable for any other variable does not depend on the direction of this effect, we use the absolute value (the direction must be taken from the graphic depiction of the respective effect). We calculate effect sizes for each case, and OEAD represents the mean of the case-specific values. Because we can calculate OEAD for all kinds of relationships in structural models, including linear ones, we are able to compare USM structural model results with results from CVSEM and PLS. If a relationship between two latent variables is linear, USM also reports path coefficients by isolating the additive portion of a relationship. We discuss this feature formally in the context of interaction effects.

Coefficient of determination and goodness of fit. In addition to OEAD as a measure of relationship strength between two latent variables, USM provides R^2 as the total variance of an endogenous latent variable explained by all other model constructs. Furthermore, because USM does not aim to fit empirical and theoretical covariance matrices and therefore does not allow for a formal test of the "appropriateness" of a proposed model, we draw on the goodness-of-fit (GoF) criterion suggested by Tenenhaus and colleagues (2005) to compare the overall model fit of USM with CVSEM and PLS:

$$GoF = \sqrt{\left(\frac{1}{M} \sum_{i=1}^{I} M_i \cdot communality_i \right) \cdot \overline{R^2}},$$ (7)

where I is the number of latent constructs in the model, M is the total number of measurement variables in the model, and M_i is the number of measurement variables for the construct i. Communality refers to the regression coefficient between an item and its latent variable, and $\overline{R^2}$ is the mean explained variance of all endogenous latent variables of the structural model.

Nonlinear shapes, path coefficients, and interaction effects. To identify an additive (and potentially nonlinear) effect of the latent variable j on y^i, we calculate an a-score for each individual case n (Plate 1998):[9]

$$a_j^i = f^i(y^1,...y^j,...,y^n) - f^i(y^1,...\overline{y}^j,...,y^I),$$ (8)

where a_j^i is the change in y^i caused by the additive effect of y^j, f_{NN} again is the neural network function (see Equation 1), and y^1 to y^n are the latent input variables of the structural model. The second term on the right side of Equation 8 represents the network output (i.e., $\hat{y}^i$) when variable j is absent (we use the mean value over all cases, $\overline{y}^j$, to fix j at an arbitrary value). The difference between the first and second terms on the right side represents the change in y^i that y^j provides in an additive manner.

We test the linearity of this additive effect of y^j on y^i for each relationship by estimating a series of polynomial regressions of y^j on a_j^i (Hastie and Tibshirani 1990). When doing that, we increase the number of parameters of the polynomial regression stepwise, an approach referred to as a "growing algorithm" (Bishop 1995, p. 353). If only linear effects are considered (i.e., one degree of freedom), polynomial regression is equivalent to linear regression. We assume that a relationship between two latent constructs is linear if a regression model with two degrees of freedom (i.e., quadratic model) shows lower prediction performance for validation data than does the linear model. This comparison relies on a jack-knifing cross-validation procedure (Bishop 1995). If we find a linear relationship, we take the standardized regression parameter β from the polynomial regression with one degree of freedom and interpret it as a path coefficient, similar to PLS and CVSEM.[10]

To measure the interaction effect of two independent latent variables y^j and y^k on y^i, we calculate a z-score for each individual case n (Plate 1998):

$$z_{jk}^i = f^i(y^1,...y^j,...,y^k,...,y^I) - f^i(y^1,...\overline{y}^j,...,\overline{y}^k,...,y^I),$$ (9)

where z is the change in y^i for an individual case caused by the additive and the interactive effect of y^j and y^k, and $\overline{y}^j$ and $\overline{y}^k$ represent the mean values of y^j and y^k, respectively. The idea behind this equation is that the difference in latent variable i when both latent variables j and k simultaneously are fixed to the mean value represents the interactive effect (Plate 1998). The strength of the interactive effect IE_{jk}^i then can be calculated according to Equation 10:

$$IE_{jk}^i = \frac{\sum_{n=1}^{N} \left| \frac{\hat{z}_{jk}^i - \hat{a}_j - \hat{a}_k}{\hat{y} - \overline{y}} \right|}{N},$$ (10)

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[9] As it is not possible to interpret the weights from neural network estimations directly (e.g., Kumar, Rao, and Soni 1995, p. 262), additional techniques have to be used.

[10] Because USM uses standardized raw data for its calculations, the USM path coefficients are, by definition, standardized parameters ranging from +1 to –1. Please note that an effect found to be linear through the described procedure could also be the result of interaction effects; something which can be ruled out by looking at the respective *IE* parameters or the graphical representation of the relationship under scrutiny. Specifically, if an *IE* parameter is significant, the β parameter can not be interpreted similar to CVSEM/PLS path coefficients. In this case, the detailed characteristics of the relationship can be taken from the y^j-y_j^i plot as well as the y^j-y^k-y_j^i plots. All linear paths reported in the empirical section of this paper are "true" linear effects and do not result from interactions.

where $\hat{a}$ are the additive scores of a polynomial regression of y on a (as introduced in equation 8), and $\hat{z}$ is the outcome of a universal regression with the two latent variables j and k as regressors on z_{jk}^i. In other words, the interaction effect IE_{jk}^i is expressed as the portion of variable i's explained variance that can be attributed to the interaction between y^j and y^k, with $IE_{jk}^i = 1$ meaning that the explained variance of i is caused fully by this interaction. Because IE only provides a measure of interaction strength, not the kind of interaction effect at work, we visualize the interaction effect by creating a three-dimensional scatter plot, in which y^j and y^k plot on the x-axis and the y-axis, respectively, and z_{jk}^i on the z-axis. The data points are complemented by the surface derived from the $\hat{z}_{jk}^i$ estimates. We limit our discussion to two-way interactions in this manuscript, but in principle, USM can also handle interactions among more than two variables. The main challenge for such multivariate interactions would be the higher-dimensional graphical representation that is needed to interpret the interaction effect (Soukup and Davidson 2002).

Significance of parameters. Finally, as with PLS and in contrast to CVSEM, USM does not pose any distributional assumptions on the data, which prevents us from testing the significance of its parameters against any kind of statistical distribution. We therefore test the model parameters' statistical significance through a bootstrapping routine (Mooney and Duval 1993). Specifically, we conduct such tests for all OEADs and IEs, as well as for the path coefficients and the factor loadings of the measurement model.

3. Comparing USM with CVSEM and PLS: Similarities and Differences

3.1. Theory Testing vs. Identification of Hidden Structures

Although in USM the researcher has to, like with CVSEM and PLS, determine the paths of a structural model to be included in the estimation process (by fixing a path to 0), USM is based on a different theoretical perspective than traditional SEM methods. While CVSEM and PLS are basically confirmatory methods in that, from a philosophy of science perspective, they are intended to test the "truth" of a structural model (Jöreskog 1973), USM is based on the assumption that such a theory-testing approach is inappropriate for most marketing models and that an approach is needed which combines model testing with the identification of structures and elements that are not theoretically proposed by researchers. As a consequence, USM requires the researcher to exclude only illogical paths and therefore includes all other paths in the estimation. Instead of testing a single model, the proposed model inherently has to compete with an array of alternative model specifications. In addition, USM helps researchers to locate other hidden structures and elements in structural models,

namely nonlinear relations among model variables and interactions between two or more variables with regard to another model variable. We believe that gaining knowledge with regard to these aspects of a structural model facilitates marketing's striving towards new knowledge and the development of general theories.

Hidden paths. While PLS is an exclusively confirmatory method, as it provides literally no information on the existence of alternative relations among model elements, CVSEM software usually reports "modification indices" which generally describe the effect of deleting or adding constraints on a model's chi-square and might be used for model refinement (Jöreskog and Sörbom 1993). However, in practice, these indices do provide only limited insight into the underlying structures and have to be treated cautiously (Fornell 1987; MacCallum 1986). USM, in contrast, encourages the researcher to add only a minimum number of constraints to his/her model. This procedure simultaneously tests the proposed relations (i.e., hypotheses), while at the same time searching for not theoretically proposed relations, which can then be used for theory development.

Hidden nonlinearity. CVSEM and PLS software test for linear model paths only. The inclusion of nonlinear effects can be achieved in these methods by rescaling certain parts of the raw data (e.g., exponential transformations), which requires the researcher to know the "true" course of the nonlinear function in advance (which is usually not the case). In contrast, USM provides insight on potential nonlinear structures among the model variables due to its Bayesian neural network estimation technique. As several relationships of key interest for marketing have been shown to be of a nonlinear kind (e.g., Agustin and Singh 2005), USM does integrate such effects into structural models and, as a consequence, can help to prevent marketing scholars from drawing wrong conclusions on the phenomena under scrutiny caused by otherwise undetected nonlinear relations between these phenomena.

Hidden interactions. With regard to interactions between the elements of a structural model, CVSEM and PLS require the use of multi-group structural equation modeling (MGSEM; Jöreskog 1971; Chin 2004) or the inclusion of interaction-term variables generated by the multiplication of construct items (Baron and Kenny 1986; Kenny and Judd 1984). While these approaches can be powerful for quantifying theoretically hypothesized interactions, they imply that the decision to test for a potential interaction among model variables remains with the researcher. Even if a researcher successfully identifies an interaction (or moderator) effect, other interactions might remain untapped. As USM calculates *IE* scores for each model construct accounting for the potential interaction effect of any pair of model constructs on this construct, interaction effects within a proposed structural model are *systematically* detected by USM. In addition, once an interaction effect has been

located, neither CVSEM nor PLS provide insights into *how* this effect influences the dependent variable. However, the provision of surface graphics by USM informs the researcher not only about the strengths of the interaction effect, but also about how the two 'independent' variables interact with regard to the 'dependent' variable. It should be noted that potential moderating effects of other variables not included in the model have to be tested with USM using the same approaches as in PLS (Chin 2004).

3.2. Other Issues

Measurement error. A major difference between PLS and CVSEM lies in the role assigned to theory versus data and their respective role for the estimation results. As Fornell (1989) illustrates, CVSEM favors the specified model over empirical correlations, "almost to the point that it 'overrides' the data" (Fornell 1989, p. 165). With CVSEM, observed data can be 'explained away' as random noise, discrediting the observations to support the theory (Fornell and Bookstein 1982). Using CVSEM, Fornell (1989) finds for a model with two latent constructs each with two items which have pairwise correlations between .11 and .26, a path coefficient between the latent constructs of .87. Using the same data, he shows that PLS calculates a path coefficient of .29, as the method limits the distance of the results from the data, preventing the analysis to go 'beyond the data' (Fornell and Bookstein 1982). Related, PLS requires the latent constructs to be constructed out of nothing else than their measurement variables, while CVSEM draws data from *all* measurement variables, generating "indeterminate" latent measures (Chin and Newsted 1999; Tenenhaus et al. 2005). As Fornell (1989, p. 165) states, "each researcher must make a decision about the relative weight that should be given to data vs. theory". Consistent with the approach of not testing a single 'final' model or theory, USM does not "defend" the structural model suggested by the researcher as is the case with CVSEM, but uses a similar data-driven approach to PLS. Consequently, USM puts equal weight on theory and data, preventing the results from being "overly far" from the underlying correlations.

Distributional assumptions. While the maximum likelihood optimization approach of CVSEM requires the data to follow a multivariate normal distribution and independence of the observations (although the method has been shown to be relatively robust against violations of these assumptions; Bollen 1989), no such requirements exist for PLS as well as USM (see Fornell and Cha 1994). As is the case with PLS, USM does not impose any distributional restrictions on the data except for predictor specification, as the arguments on the distribution-free character of PLS (Fornell and Cha 1994) can be applied equally to USM.

Reflective vs. formative scales. Although CVSEM offers researchers ways to include formative scales in a measurement model by treating formative items as exoge-

nous manifest constructs, this procedure comes with several limitations (MacCallum and Browne 1993). PLS, in contrast, allows researchers to freely choose between reflective and formative scales for each construct (Chin and Newsted 1999). This is also true for USM which uses the same approach as PLS with regard to formative scales, namely running a multiple regression with the measured data of the formative items as regressors and the provisional latent variable score as regressand. The only difference between PLS and UMS in the case of formative constructs is the way the latent variable scores are calculated (through Bayesian neural network estimation instead of linear regression).

Sample size requirements. CVSEM requires a relatively large sample to obtain stable results; absolute minimal recommendations range from 200 to 800 (Chin and Newsted 1999). PLS has less restrictive sample size requirements, which are often considered a major argument for its use (Fornell and Bookstein 1982). As PLS considers only a part of the available information for parameter estimation, the minimum sample size for PLS is equal to the largest number of parameters to be estimated in each structural equation for reflective indicators (i.e., the largest number of incoming paths for a model variable) or each measurement equation and structural equation for formative scales (i.e., the largest number of incoming paths for a latent model variable or of formative items for a construct). Applying the Bentler and Chou (1987) rule, the sample size of a PLS model should be 5 to 10 times that number to assure stable results (absolute minimal recommendations range from 30 to 100 cases; Chin and Newsted 1999). As USM also uses a "partial" optimization approach and draws on the Bayesian framework, its minimum sample size requirements are the same as for PLS when the true relations are linear and additive. Although nonlinearity and interactive effects always require larger sample sizes, our experimentations give us confidence to say that USM is able to model significant levels of nonlinearity and interactions with sample sizes of less than 250 cases.

Model complexity requirements. The CVSEM approach is known to work best for models of low to moderate complexity. For example, Chin and Newsted (1999) suggest that CVSEM models should have less than 100 measurement variables. If the complexity of a structural model exceeds this level, CVSEM often produces illogical results such as negative variance estimates and loadings above one and encounters matrix inversion problems due to the method's "overall" optimization approach (Fornell and Bookstein 1982). In contrast, PLS can also handle models with large complexity (up to 100 latent constructs and 1,000 items; Chin and Newsted 1999). The same can be said for USM, which can be used to test equally complex models, but also works for models of small or medium complexity. In the case of USM, the time required for model estimation is actually a more restrictive bottleneck than the number of constructs and items of a model because of the employed

boosting approach (i.e., 30 replications). This is particularly relevant when bootstrapping is employed, as this requires a multiplication of each bootstrap run with the number of replications (e.g., in the case of 200 bootstrap samples, a total of 6,000 replications is needed).[11]

4. Exploring Universal Structure Modeling with synthetic data

To investigate how USM performs empirically, we apply USM to different synthetic data sets and compare the results with the confirmatory methods of CVSEM and PLS. The objectives of this procedure are threefold. First, we test whether USM can discover "true" nonlinear structures and interactions among variables or if it overfits the data. We address this issue with a data set that contains different kinds of nonlinear relations and interaction effects between latent variables. Second, we test whether USM can discover linear relationships among model constructs to a degree comparable to those of the standard techniques of CVSEM and PLS. The high flexibility of the method makes it particularly important that USM does not overfit the data and detects nonlinear courses when there are none. We address this issue by generating a set of data that contains only linear model paths. Third, we test whether the USM results fit a specific data set only or can be generalized (i.e., are valid) across samples. Specifically, we replicate the USM results for both the nonlinear and linear data sets with a second sample. Because of the complementary nature of

the USM approach to confirmatory SEM methods, our focus here is to demonstrate that USM generally is capable of providing stable and meaningful results rather than to compare its performance directly with CVSEM and PLS.

4.1. Estimating Nonlinear and Interactive Model Relations with USM

Data generation. We generate synthetic data with known parameter values and probability distributions for the exogenous latent variables from the model by De Wulf, Odekerken-Schröder, and Iacobucci (2001). The model proposes four relationship marketing instruments (i.e., direct mail, preferential treatment, interpersonal communication, and tangible rewards) that may influence perceived relationship investment, which in turn influences relationship quality, which itself exerts an impact on customer loyalty (see Figure 2; the USM specification matrix appears in the Appendix). We use this information to compute a set of data for the endogenous variables of the model that contains both nonlinear relationships between structural model variables and interaction effects among them (Gentle 2003). We then turn USM loose on the data to investigate how well the method discovers the true structure and parameters.

Specifically, the data for the exogenous latent variables follow a uniform distribution between 0 and 1; we rescale them to values between 1 and 7, as described in Equation 11:

$$MI = random(N) \cdot 6 + 1, \tag{11}$$

where *MI* is a relationship marketing instrument (i.e., direct mail, preferential treatment, interpersonal commu-

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[11] In the empirical applications described in this paper, the calculation time (including bootstrapping) was between one and three hours per model.
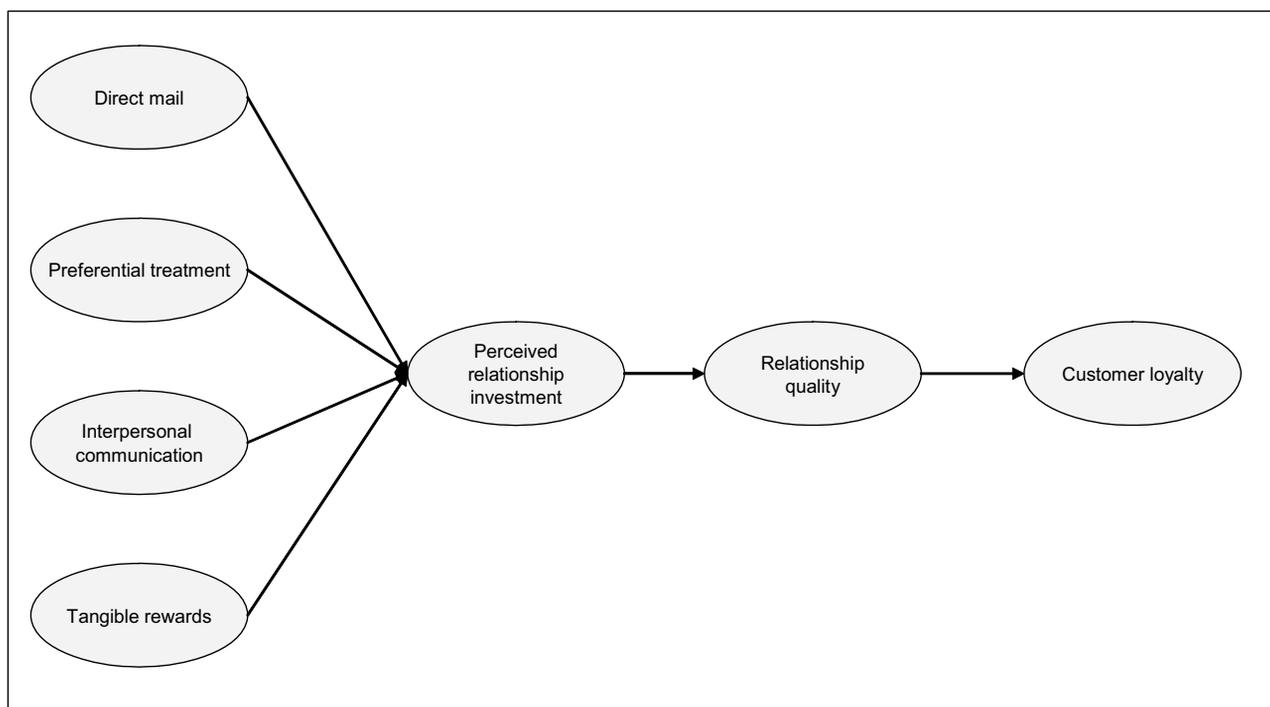
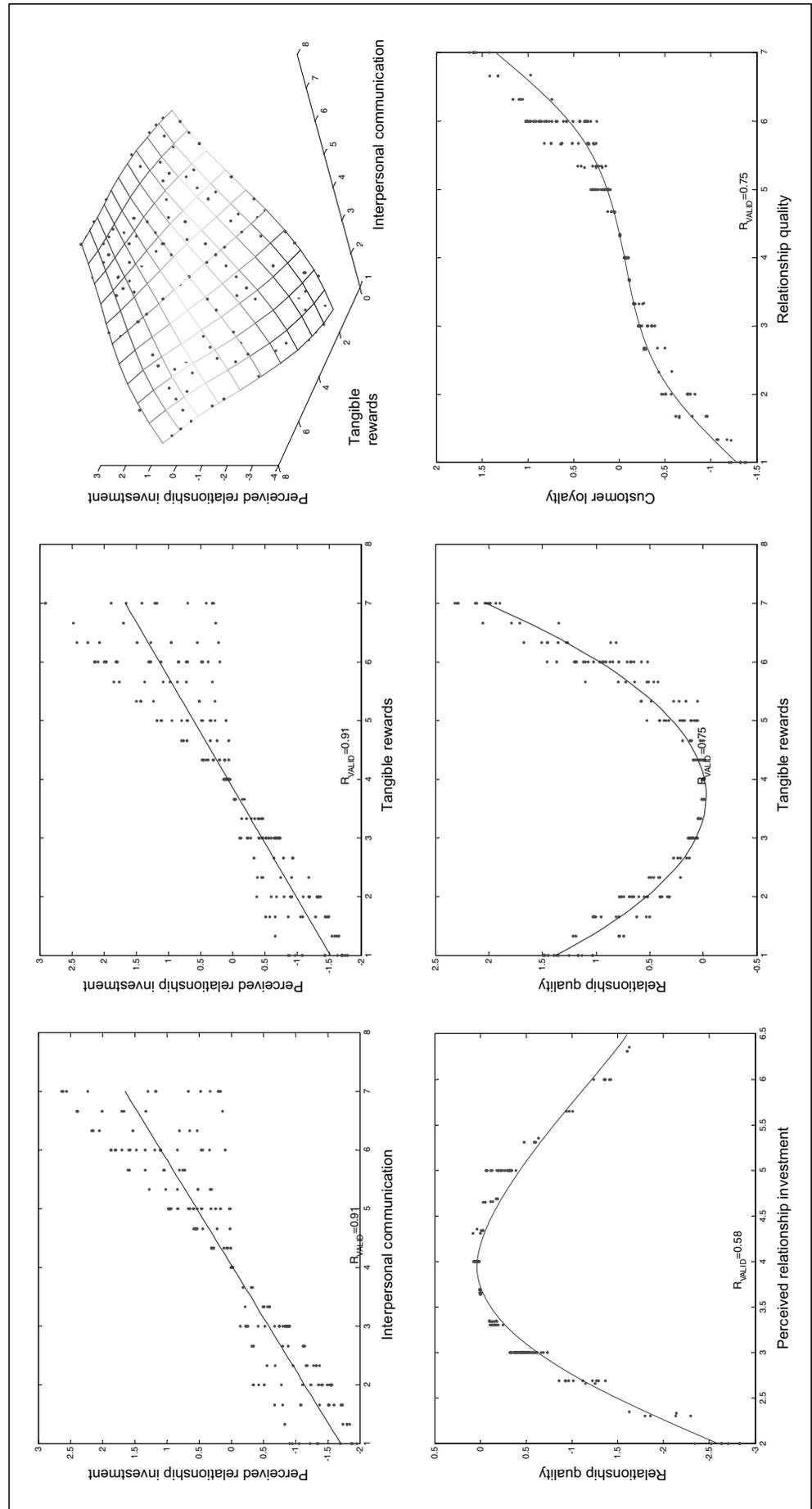

Figure 2: The De Wulf Model of Customer Loyalty

Figure 3: USM Results for Nonlinear Synthetic Data

Note: Only data points above the surface in the three-dimensional graphs appear.

nication, or tangible rewards), and N is the number of synthetic cases generated. We set N to 2,000 and use 240 of the cases for the model estimation task and the other 1,760 for cross-validation. We prefer 240 against a larger sample size because we consider it a realistic number for empirical applications in marketing and consumer research (it is also the mean of the two field samples used in the next section).

Among the variables of the structural model, we specify different kinds of nonlinear relationships and interactive effects (Equations 12–14). Specifically, we model the firm's relationship investment as perceived by the customer (PRI) as a function of the firm's level of interpersonal communication (IC) and the extent of tangible rewards offered to customers (TR):

$$PRI = \frac{(IC \cdot (14 - TR) + (14 - IC) \cdot TR)^2}{1500} + random(N) \cdot 0.3 \quad (12)$$

One independent variable (i.e., IC) has the strongest effect on the dependent variable PRI when the other independent variable (i.e., TR) is small, which represents an interactive effect. We square the impact of IC and TR on PRI to add a nonlinear element to the equation.

Next, we model the quality of the relationship as perceived by the customer (RQ) as a function of PRI, IC, and TR:

$$RQ = (PRI \cdot 2 - 8)^3 \cdot .01 + IC \cdot 0.005 + (TR - 4)^2 \cdot 0.2 + 3 + random(N) \cdot 0.3 \quad (13)$$

The impact of PRI on RQ is degressive up to the midpoint of the scale (i.e., 4) and then becomes progressive. Whereas IC has a weak linear effect on RQ, TR affects RQ in a quadratic way so that the relationship takes a U-shaped course.

Finally, we model customer loyalty (CL) as a function of relationship quality, with the relationship between RQ and CL taking an inverted U-shaped course:

$$CL = -(RQ - 4)^2 + 6 + random(N) \cdot 0.3 \quad (14)$$

We then derive the data for the measurement variables from the latent variables. We add normal distributed noise and round the resulting values to the next integral number that corresponds with the original 1–7 scale. Values less than 1 are set to 1 and values greater than 7 are set to 7.

Model estimation and results. The USM estimation uses a self-programmed software in the MATLAB environment and employs the 240 randomly drawn synthetic cases. As we show in Table 1, USM explains 62–92% of the variance of the three endogenous variables. The OEAD values reported in Table 2 demonstrate that in all cases, the variance explanation is caused by the "right" variables (i.e., those specified to have an impact on the respective outcome variable in Equations 12–14). Furthermore, a visual inspection of the functions estimated by USM (Figure 3) reveals that USM generally can identify the different kinds of nonlinear relationships in the synthetic data set. The only exception is the quadratic element of the PRI equation, which USM has difficulty locating. When applying a bootstrapping routine with 200 subsamples (240 cases per sample), the OEAD parameters of all specified effects are significant at $p < .05$ (see Table 2). In addition, USM discovers the interaction effect between IC and TR on PRI, as reflected in an IE value of .09 which is statistically significant at $p < .05$ ($t = 4.11$).[12]

To cross-validate our USM results, we apply the USM model functions to the 1,760 cases not used for the model estimation. For this purpose, we derive values for the latent variables (referred to as y_{true}^{1760}) from the measurement model parameters for each validation case and calculate estimates for each of the three endogenous latent variables (i.e., PRI, RQ, and CL) using the path coefficients derived from the original 240 cases; these estimates are named $\hat{y}^{240}$. We then calculate a validation coefficient R_{valid}^2 for each of the three endogenous variables. In other words, R_{valid}^2 represents the degree of variance of an endogenous variable in the validation sample ($n = 1,760$) explained by other latent variables when we use the model parameters from the original estimation ($n = 240$). As we show in Table 1, the R_{valid}^2 coefficients for the three endogenous constructs are only slightly below the degree of variance explained by the original data set for the respective variables. Specifically, the R_{valid}^2 parameter are only 1% (PRI) and 4% (both RQ and CL) lower than the original R^2 parameters. Therefore, USM

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[12] Here as well as in the other empirical studies, no interaction effect apart from those mentioned in the text is significant. For reasons of parsimony, we do not report *IE* values in the respective results tables.

Model Construct	Nonlinear Data				Linear Data				
	USM R^2	CVSEM R^{2*}	PLS R^2	USM R^2 valid	USM R^2	CVSEM R^{2*}	PLS R^2	USM R^2 valid	PLS R^2 valid
Perceived relationship investment	.92	-	.038	.91	.61	.62	.60	.57	.57
Relationship quality	.79	-	.409	.75	.75	.78	.75	.70	.70
Customer loyalty	.62	-	.176	.58	.80	.80	.78	.75	.76
		-							
Overall goodness of fit	.865	-	.448		.840	.839	.833		

*Model is empirically unidentified.

Table 1: Fit Measures for Nonlinear and Linear Synthetic Data Set

Impact of	on	Nonlinear Data						Linear Data		
		USM (OEAD/ t-value)	CV SEM (OEAD)†	PLS (OEAD)	USM (OEAD/ t-value)	CVSEM (OEAD)	PLS (OEAD)	USM (path coefficient/ t-value)	CVSEM (path coefficient/ t-value)	PLS (path coefficient/ t-value)
Direct mail	Perceived relationship investment	.000 (.01)	-	.000	.136** (2.14)	.198	.192	.397** (4.13)	.412** (9.01)	.409** (10.71)
Preferential treatment	Perceived relationship investment	.001 (.20)	-	.000	.403** (6.16)	.295	.292	.613** (8.89)	.625** (12.20)	.622** (15.32)
Interpersonal communication	Perceived relationship investment	.473** (7.26)	-	.011	.073** (1.97)	.118	.114	.245** (6.29)	.246** (5.64)	.244** (5.16)
Tangible rewards	Perceived relationship investment	.443** (9.34)	-	.012	.001 (.59)	.003	.001	.006 (.89)	.007 (.17)	.002 (.08)
Direct mail	Relationship quality	.000 (.03)	-	.058	.002 (.62)	.032	.042	.008 (1.42)	.042 (1.08)	.054 (1.54)
Preferential treatment	Relationship quality	.002 (.10)	-	.031	.003 (.94)	.019	.004	-.007 (.25)	-.025 (.53)	-.005 (.15)
Interpersonal communication	Relationship quality	.017 (1.03)	-	.036	.006 (1.28)	.014	.009	-.032 (1.32)	-.018 (.517)	-.011 (.57)
Tangible rewards	Relationship quality	.415** (3.76)	-	.255	.001 (.55)	.037	.036	-.053 (1.10)	-.048 (1.47)	-.047** (1.69)
Perceived relationship investment	Relationship quality	.358** (4.03)	-	-.030	.742** (11.58)	.668	.660	.874** (8.72)	.888** (16.35)	.857** (18.41)
Direct mail	Customer loyalty	.000 (.06)	-	.031	.001 (.54)	.024	.027	.003 (.73)	.034 (.89)	.036 (1.18)
Preferential treatment	Customer loyalty	.001 (.20)	-	.055	.004 (.81)	.051	.052	.011 (1.52)	.073 (1.63)	.070 (1.58)
Interpersonal communication	Customer loyalty	.006 (.36)	-	.011	.007 (1.20)	.014	.008	.000 (1.13)	-.020 (.602)	-.011 (.58)
Tangible rewards	Customer loyalty	.010 (.80)	-	.072	.012 (1.39)	.022	.028	.041 (1.04)	.032 (1.03)	.038 (1.40)
Perceived relationship investment	Customer loyalty	.071 (1.39)	-	.000	.013 (1.39)	.052	.025	.000 (1.25)	-.074 (.92)	-.034 (.71)
Relationship quality	Customer loyalty	.536** (8.03)	-	.000	.758** (8.29)	.637	.640	.872** (9.52)	.908** (13.13)	.861** (13.46)

†Model is empirically unidentified. ** $p < .05$. * $p < .10$.

Notes: OEAD = Overall Explained Absolute Deviation; the OEAD values for CVSEM and PLS are calculated by dividing a path coefficient by the sum of the path coefficients linked at the "dependent" construct and multiplying the outcome by the construct's R^2. The t-values for PLS and USM are calculated by a bootstrapping routine with 200 samples.

Table 2: Path Estimates for Nonlinear and Linear Synthetic Data Set

does not overfit the data, which warrants a generalization of parameter estimates to those elements of the population not used to estimate the model.

We also use the nonlinear synthetic data to estimate the structural model with CVSEM (i.e., LISREL 8.5; Jöreskog and Sörbom 1993) and PLS (i.e., SmartPLS 2.3; Ringle, Wende, and Will 2005). We acknowledge that these methods are intended to analyze linear relationships only, but we are interested in how the methods react when confronted with nonlinear data and interactions, because in practice, tests for linearity and interactions rarely are conducted prior to applying CVSEM and PLS to a data set. The results of our estimations also appear in Table 1, which shows that the methods have massive problems handling the data. In the case of PLS, coefficients of determination clearly are lower than for USM and the OEAD parameters appear arbitrary (Table 2). As a consequence, the overall model GoF of PLS is weaker than that of USM. In the case of CVSEM, empirical identification problems emerge, such that the full model produces path coefficients greater than 1 and a model that contains only the specified paths cannot be estimated as a result of matrix inversion problems.

4.2. Estimating Linear Model Relations with USM

Data generation. When generating the synthetic linear data set, we use the same structural model and apply the same procedure as in the case of the nonlinear data set. That is, the data for the exogenous variables again follow a uniform distribution between 0 and 1, rescaled to values between 1 and 7 according to Equation 11. We also randomly draw 240 cases from a synthetic data set of 2,000 cases and use them for model estimation. We derive the measurement variables from the latent variables. In this investigation, all relationships of the structural model follow a linear course. Specifically, we consider the following relationships for PRI, RQ, and CL:

$$PRI = 0.3 \cdot DM + 0.55 \cdot PT + 0.15 \cdot IC + 0.02 \cdot TR + random(N), \quad (15)$$

$$RQ = PRI + random(N), \text{ and} \quad (16)$$

$$CL = RQ + random(N). \quad (17)$$

Model estimation and results. In Table 1, we provide the degree of variance of the three endogenous variables explained by USM, and in Table 2, we list the OEAD values and path coefficients generated by USM. The results are consistent with the theoretical specifications reported in Equations 15–17. All specified effects are significant according to bootstrapping (200 subsamples), with the single exception of the OEAD of IC on PRI, which has a *t*-value slightly below 1.96. Similar to the nonlinear case, we use the additional 1,760 cases to calculate R^2_{valid} coefficients, which again are only slightly lower than the R^2s for the estimation data (4% for PRI; 5% for RQ and CL). Again, the USM results do not seem seriously affected by overfitting.

We also analyze the synthetic data with CVSEM (LISREL 8.5) and PLS (SmartPLS 2.3) and do not encounter any identification problems. The degree of explained variance of the endogenous variables is very similar among all three methods, with CVSEM explaining slightly more variance than USM and PLS. However, the GoF, which balances the variance explanation and measurement model fit, is slightly higher for USM than for either CVSEM or PLS. The path coefficients and OEAD parameters also are very similar (Table 2). All significant path coefficients in CVSEM and PLS also are significant in USM and no USM path is significant that is insignificant in the other methods (cf. path from TR to RQ, which is significant in PLS only; however, we do not specify that this effect differs systematically from 0 in Equation 16). Although the USM *t*-values are somewhat smaller than those of CVSEM and PLS (i.e., higher standard deviations in USM), the differences are limited in size and do not affect the significance of any parameter. Finally, we calculate R^2_{valid} coefficients for PLS to compare the cross-validation results and report them in Table 1 (LISREL does not allow for the calculation of R^2_{valid} coefficients, because it does not provide manifest values for latent constructs).[13] The PLS R^2_{valid} coefficients are almost identical to those calculated for USM, which suggests that USM results are generalizable to a similar extent as are PLS results.

5. Applying USM, PLS, and CVSEM To Field Data

We now apply USM to two field data sets and compare the results with PLS (SmartPLS 2.3) and CVSEM (LISREL 8.5). In addition to the model by De Wulf, Odekerken-Schröder, and Iacobucci (2001; hereafter, De Wulf model), which we use for our synthetic data analysis, we adapt a widely used model by Fornell and colleagues (1996; hereafter, Fornell model) that investigates the drivers of customer loyalty. For each model and data set, we summarize the main differences between USM and the two confirmatory methods.

5.1. The De Wulf Model

Data and scales. The data set consists of survey data collected from customers through mall-intercept personal interviews (De Wulf, Odekerken-Schröder, and Iacobucci 2001). We limit our analysis to one of six subsamples, namely, data for apparel retailers collected in the United States (n = 230). Originally, De Wulf et al. used LISREL to analyze the data and all construct measurements entail reflective multi-item scales. We retain all scales unchanged, except for one CL item that we drop to increase scale reliability. Alpha scores are greater than .70 in all cases.

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[13] We use PLSGraph 3.0 (Chin 2001) to calculate the cross-validation measures, because SmartPLS does not provide location parameters.

Comparison of results. In addition to testing the De Wulf model, we also apply CVSEM and SmartPLS to the "full" model (i.e., defined in the specification matrix *S*; see the Appendix). We encounter empirical identification problems when testing the full model with CVSEM. In Table 3, we list the OEAD values and path coefficients for USM, CVSEM, and PLS.

Significant paths in CVSEM and PLS generally also are significant in USM and the OEAD values are generally similar for all three estimation methods. However, the OEAD of the path from PRI to RQ is higher in CVSEM (.59) and PLS (.43) than in USM (.35), because USM identifies two additional substantial paths that link to RQ that are not included in the original model (i.e., "hidden"

Impact of	on	USM (OEAD/ t-Value)	USM (ß)	CVSEM (OEAD)	CVSEM (ß/t-value)	PLS[†] (OEAD)	PLS[†] (ß/t-value)
		Theoretically Proposed Relations					
Direct mail	Perceived relationship investment	.102 (1.58)	-	.105	.220 (1.57)	.137 / .135	.258** (2.94)/ .261** (2.88)
Preferential treatment	Perceived relationship investment	.007 (.36)	.007	.052	-.108 (.91)	.007/ .010	-.014 (.17) / -.020 (.25)
Interpersonal communication	Perceived relationship investment	.266** (2.81)	.351	.201	.419** (3.80)	.182 / .174	.344** (3.86) / .335** (3.64)
Tangible rewards	Perceived relationship investment	.093 (1.52)	-	.089	.185 (.94)	.063 / .064	.119 (.94) / .124 (.96)
Perceived relationship investment	Relationship quality	.352** (5.16)	-	.591	.769** (13.15)	.431 / .221	.656** (17.05) / .424** (6.08)
Relationship quality	Customer loyalty	.158** (4.78)	.496	.212	.461** (7.00)	.193 / .098	.439** (8.34) / .488** (4.88)
		Theoretically Unproposed Relations					
Direct mail	Relationship quality	.004 (.23)	-	n.i.	n.i.	n.i. / .055	n.i. / -.106 (1.39)
Preferential treatment	Relationship quality	.009 (.34)	.012	n.i.	n.i.	n.i. / .020	n.i. / .039 (.58)
Interpersonal communication	Relationship quality	.111** (3.16)	-	n.i.	n.i.	n.i. / .148	n.i. / .284** (3.80)
Tangible rewards	Relationship quality	.119* (1.75)	.155	n.i.	n.i.	n.i. / .114	n.i. / .219** (2.51)
Direct mail	Customer loyalty	.000 (.05)	-.002	n.i.	n.i.	n.i. / .006	n.i. / -.031 (.31)
Preferential treatment	Customer loyalty	.031 (1.59)	.161	n.i.	n.i.	n.i. / .048	n.i. / .237** (3.05)
Interpersonal communication	Customer loyalty	.011 (.09)	-.086	n.i.	n.i.	n.i. / .025	n.i. / -.122 (1.27)
Tangible rewards	Customer loyalty	.020** (2.10)	-.173	n.i.	n.i.	n.i. / .036	n.i. / -.180 (1.47)
Perceived relationship investment	Customer loyalty	.009 (.04)	.078	n.i.	n.i.	n.i. / .006	n.i. / .028 (.29)

[†] Numbers before the slash refer to the theoretically proposed model; numbers after the slash to the full model.
** $p < .05$. * $p < .10$.
Notes: OEAD = Overall Explained Absolute Deviation; the OEAD values for CVSEM and PLS are calculated by dividing a path coefficient by the sum of path coefficients linked at the "dependent" construct and multiplying the outcome with the construct's R^2. ß = standardized path coefficient. n.i. = path was not included in model estimation. The t-values for PLS and USM are calculated by a bootstrapping routine with 200 samples.

Table 3: Results for the De Wulf Model

The De Wulf Model
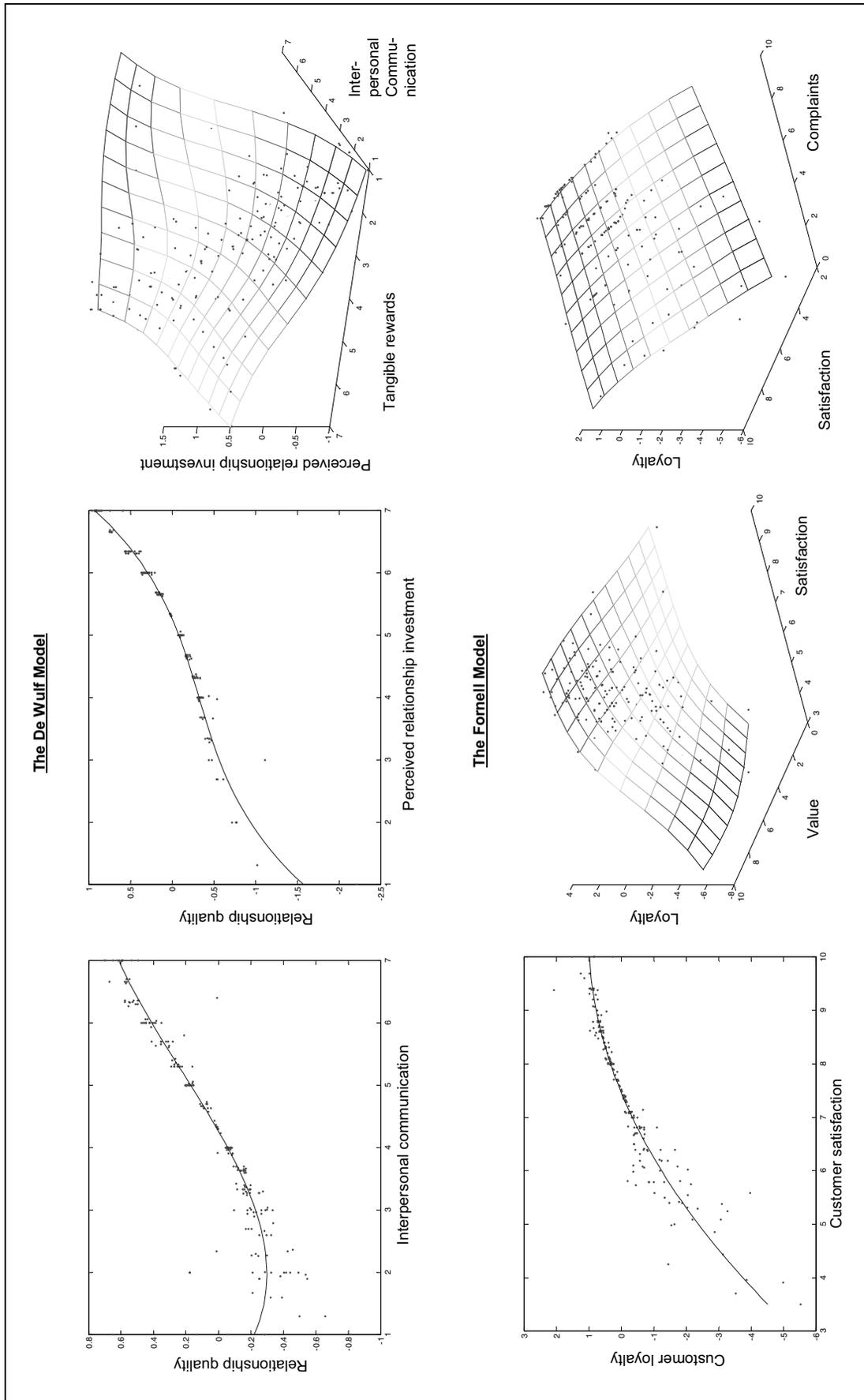
The Fornell Model

Notes: Only data points above the surface in the three-dimensional graphs appear.

Figure 4: Nonlinear and Interactive Effects for the De Wulf and Fornell Models

paths), namely, those from IC and TR to RQ. In other words, USM reveals that PRI does not serve as a full mediator of these two variables' impact on RQ, as suggested by the De Wulf model. Moreover, USM finds that TR exerts a direct impact on CL that is not mediated by PRI or RQ; thus, we learn that the original De Wulf model specification exaggerates the impact of PRI on RQ.

To address the small sample size, we employ bootstrapping as an alternative approach to cross-validation (Cooil, Winer, and Rados 1987). The results provide further evidence that USM does not overfit the data, in that overfitting would have resulted in high standard deviations and consequently a large number of insignificant model parameters.

The results in Table 1 also illustrate that most of the model relations are linear, consistent with the use of CVSEM (and PLS). However, substantial nonlinearity exists for two paths, namely, from IC to RQ (progressive growth function) and from PRI to RQ ("buckled" function that takes a progressive course at PRI = 4); both appear in the upper part of Figure 4. In addition, the USM results show that IC and TR exert a relatively strong interaction effect on PRI ($IE_{IC/TR}^{PRI}$ = .09; t = 10.05), which is also visible in the upper part of Figure 4. We thus learn that though PRI can increase through both IC and TR when applied in isolation, the combined usage of

these instruments does not result in similarly higher levels of PRI.

We offer the fit measures for all three methods in Table 4. As a result of the inclusion of hidden paths, nonlinearity, and interactive effects, the R^2 values for USM are the highest of all three endogenous constructs, followed by CVSEM and PLS. The higher variance explanation of USM compared with CVSEM has particular interest, because USM (cf. CVSEM; see Bagozzi and Yi 1994; Fornell 1989) does not "overwrite the data" and therefore can be viewed as a more conservative estimator in terms of inner-model variance explanations.[14] This greater closeness of USM to the raw data also appears in the average variance extracted (AVE) scores in Table 2, which reveal that the USM AVEs are consistently higher than the CVSEM AVEs (and as high as the PLS AVEs). The overall model fit (measured by GoF) is highest for USM.

5.2. The Fornell Model

Model, data, and scales. This model, the conceptual framework behind the American Customer Satisfaction Index (ACSI; Fornell et al. 1996), proposes that cus-

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[14] This characteristic of CVSEM becomes most clearly visible in the link between PRI to RQ, for which the CVSEM path coefficient (.77) exceeds the correlation between construct means (.65).

Model Construct	R^2				AVE		
	CVSEM	PLS	USM	Multiple Regression	CVSEM	PLS	USM
Perceived relationship investment (3 items)	.446	.389 (.384)	.469	.378	.811	.876 (.876)	.876
Relationship quality (3 items)	.591	.431 (.558)	.595	.425	.715	.813 (.814)	.810
Behavioral loyalty (2 items)	.212	.193 (.219)	.230	.192	.731	.849 (.842)	.822
Direct mail (3 items)	-	-	-	-	.814	.876 (.876)	.850
Preferential treatment (3 items)	-	-	-	-	.724	.809 (.811)	.876
Interpersonal communication (3 items)	-	-	-	-	.735	.822 (.823)	.813
Tangible rewards (3 items)	-	-	-	-	.775	.850 (.851)	.818
Overall goodness of fit							
CVSEM	.562						
PLS		.533 (.571)					
USM			.601				

Notes: AVE = Average variance extracted. Numbers in parenthesis refer to the full model.

Table 4: Fit Measures for the De Wulf Model

tomer satisfaction results from customers' expectations, perceived quality, and value perceptions and in turn influences perceptions of loyalty and complaint handling (see Figure 5; the USM specification matrix is in the Appendix). We use a random sample of 250 customers of a mobile phone provider, whose data were collected through personal CATI telephone interviews.[15] Previously, PLS has been used to analyze the customer satisfaction index data (Fornell 1992; Fornell et al. 1996).

Except for complaint handling and expectations, which are operationalized with a single item, all construct measurements use reflective multi-item scales (Tenenhaus et al. 2005), with alpha scores greater than .70.[16]

[15] This data set is freely available for academic purposes from the SmartPLS Web site (http://www.smartpls.de).

[16] The item for complaint handling is: "How well or poorly was your most recent complaint handled?" (respondents who had complained within the last 12 months) or "How well do you expect the company to handle a potential complaint?" (all other respondents). For expectations, we delete two of the original three items because of their low scale reliability and use only the item, "Expectations for the overall quality of [mobile phone provider] at the moment you became a customer of this provider."

Impact of	on	USM (OEAD/ t-value)	USM (ß)	CVSEM (OEAD)	CVSEM (ß/t-value)	PLS[†] (OEAD)	PLS[†] (ß/t-value)
Theoretically Proposed Relations							
Expectations	Perceived quality	.194** (5.30)	.440	.215	.464** (6.78)	.191 / .191	.437** (6.68) / .437** (7.08)
Expectations	Perceived value	.022 (1.27)	-	.009	-.014 (.23)	.026 / .026	.047 (.71) / .047 (.70)
Perceived quality	Perceived value	.327** (7.89)	.564	.449	.683** (7.53)	.319 / .319	.565** (7.87) / .565** (8.06)
Expectations	Customer satisfaction	.007 (.60)	-	.035	-.042 (.91)	.014 / .014	.019 (.43) / .019 (.44)
Perceived quality	Customer satisfaction	.514** (9.41)	.618	.649	.785** (8.07)	.490 / .490	.661** (12.72) / .660** (12.58)
Perceived value	Customer satisfaction	.141** (4.17)	.225	.183	.221** (3.34)	.159 / .159	.214** (3.74) / .215** (3.64)
Customer satisfaction	Complaint handling	.181** (3.12)	.314	.355	.596** (8.59)	.279 / .131	.528** (9.89) / .286** (2.87)
Customer satisfaction	Customer loyalty	.382** (6.30)	-	.612	.779** (6.57)	.383 / .273	.610** (9.68) / .509** (5.03)
Complaint handling	Customer loyalty	.101** (2.87)	.119	.020	.026 (.39)	.058 / .045	.092 (1.64) / .084 (1.38)
Theoretically Unproposed Relations							
Expectations	Complaint handling	.000 (.01)	-	n.i.	n.i.	n.i. / .032	n.i. / -.070 (1.12)
Perceived quality	Complaint handling	.152** (3.32)	.261	n.i.	n.i.	n.i. / .151	n.i. / .331** (3.15)
Perceived value	Complaint handling	.011 (.50)	-	n.i.	n.i.	n.i. / .005	n.i. / .007 (.08)
Expectations	Customer loyalty	.004 (.42)	-	n.i.	n.i.	n.i. / .014	n.i. / .027 (.45)
Perceived quality	Customer loyalty	.004 (.21)	-	n.i.	n.i.	n.i. / .019	n.i. / -.036 (.38)
Perceived value	Customer loyalty	.053 (1.23)	-	n.i.	n.i.	n.i. / .105	n.i. / .196 (1.61)

[†] Numbers before the slash refer to the theoretically proposed model; numbers after the slash to the full model.
** $p < .05$. * $p < .10$.
Notes: OEAD = Overall Explained Absolute Deviation; the OEAD values for CVSEM and PLS is calculated by dividing a path coefficient by the sum of path coefficients linked at the "dependent" construct and multiplying the outcome by the construct's R^2. ß = standardized path coefficient. n.i. = path was not included in model estimation. The t-values for PLS and USM are calculated by a bootstrapping routine with 200 samples.

Table 5: Results for the Fornell Model

Comparison of results. Again, we apply CVSEM and PLS to both the original model and the "full" model. As in the case of the De Wulf model, testing the full model is possible only with PLS. The OEAD values, path coefficients, and significance levels for the customer satisfaction model with all three methods appear in Table 5. Similar to our previous analysis, all relationships found significant by CVSEM and PLS are also significant in the USM estimation and vice versa. The only exception is the path from complaint handling to customer loyalty, which is only significant in the USM estimation (but close to significance in PLS). Thus, USM again does not overfit the data but instead provides stable and generalizable estimates. Moreover, we again find that the original model structure is incomplete. Specifically, the USM results show that customers' evaluations of complaint handling are influenced by not only satisfaction with the service but also the service quality perceived by the customer. This relationship is significant and strong, with an OEAD of .15. As a result, the impact of satisfaction on complaint handling is overestimated by the original model specification, which does not include this path.

Once more, USM reveals some hidden nonlinear and interactive model relations. With regard to nonlinearity, as we show in the lower part of Figure 4, satisfaction affects loyalty in a nonlinear way, following a degressive growth function, a finding consistent with previous research (Hennig-Thurau and Klee 1997; Zeithaml, Berry, and

Parasuraman 1996). The existence of an interaction effect of customer value and satisfaction on customer loyalty, which is relatively strong and significant ($IE^{Loy}_{Val/Sat}$ = .14; t = 8.49), also is visible in Figure 4 (see also Agustin and Singh 2005). The three-dimensional interaction surface graphic illustrates that a saturation level exists for the effect of satisfaction on loyalty; after a critical level of loyalty, an increase in satisfaction does not transform into higher loyalty rates. As we can derive from the interaction graphic, this saturation level is lower when customer value is small and higher when that value is high. In other words, high loyalty can be achieved only when the customer is both highly satisfied with a product and assigns a high value to it. Another significant (though slightly smaller) interaction effect emerges between satisfaction and complaint handling, which influences customer loyalty ($IE^{Loy}_{Sat/Comp}$ = .06; t = 10.78). Specifically, if satisfaction is high, increased complaint handling does not lead to higher loyalty, whereas when satisfaction is low, complaint handling exerts a positive impact on loyalty.

The CVSEM-OEAD scores are substantially higher for several model paths than the PLS-OEAD and USM-OEAD scores (Table 6), because CVSEM assumes the structural model is correct and interprets measurement error in favor of the model (Fornell and Bookstein 1982). However, the GoF (which combines structural model and measurement model accuracy) is highest for the USM solution. When comparing the GoFs of USM and PLS

Model Construct	R^2				AVE		
	CVSEM	PLS	USM	Multiple Regression	CVSEM	PLS	USM
Perceived quality (7 items)	.215	.191 (.191)	.194	.190	.506	.577 (.577)	.574
Perceived value (2 items)	.458	.345 (.345)	.349	.323	.720	.849 (.849)	.845
Customer satisfaction (3 items)	.866	.663 (.663)	.663	.654	.563	.693 (.693)	.680
Customer loyalty (2 items)	.632	.441 (.457)	.544	.390	.576	.762 (.767)	.761
Complaint handling (1 item)	.355	.279 (.317)	.344	.280	1.00	1.00 (1.00)	1.00
Expectations (1 item)	-	-	-	-	1.00	1.00 (1.00)	1.00
Overall goodness of fit							
CVSEM	.557						
PLS		.522 (.529)					
USM			.582				

Notes: AVE = Average variance extracted. Numbers in parenthesis refer to the full model.

Table 6: Fit Measures for the Fornell Model

for the full model, the variance explanation and overall model fit remain highest for USM.

5.3. Discussion: Identifying Hidden Paths, Nonlinearity, and Interactions in Field Data

Our application of USM, CVSEM, and PLS to two field data sets carries important implications for testing structural models in marketing and related disciplines. We find that USM can identify different kinds of theoretically unproposed model structures, which we believe may help marketing researchers develop better structural models, namely "hidden" paths, nonlinearity, and interactions.

Hidden paths. In both field data sets, we find theoretically unproposed relationships among the model variables, whose inclusion changes the relative strength of other relationships. As a consequence, some of the results gained through confirmatory SEM methods overestimate the strength of some construct interrelations while overlooking others. As is the case for the De Wulf model, the USM results show that the proposed fully mediating role of perceived relationship investment, which is confirmed by LISREL, should be reconsidered.

Hidden nonlinearity. We find nonlinear interrelationships in both the De Wulf and the Fornell models, which are overlooked by CVSEM and PLS. When data contain nonlinear paths, a potential consequence of using traditional SEM methods is the erroneous rejection of research hypotheses. This issue has obvious importance for marketing.

Hidden interactions. In both field data sets used herein, we find significant interaction effects among model variables that were not theoretically proposed. Although these interactions differ in strength, their omission would distort the results of CVSEM and PLS structural model testing and, similar to an omission of model paths or nonlinear relations, could lead researchers to draw misguided conclusions.

6. Implications for Marketing Research: How to use USM

We believe that as marketing researchers, we should be aware that when we test a structural model, our knowledge is not always sufficient to exclude alternative explanations and the existence of hidden structures. Although the two field data sets used herein do not represent a random sample of academic studies in marketing, our analyses suggest that the existence of hidden structures is a regular circumstance in the discipline. This commonality generates the need to complement widely used confirmatory methods of structural model testing with exploratory methods that can identify hidden structures. We introduce Universal Structure Modeling (USM) as a candidate for such exploratory analyses of structural models in marketing.

Using two sets of synthetic data and two field data sets, we demonstrate that USM provides stable and reliable estimates and does not overfit the data. When confronted with a fully linear data set that contains no interactions, USM results are similar to those of traditional SEM methods. Furthermore, USM can identify in an exploratory sense

- Interrelationships among model variables that are not expected by the researchers,

- The nonlinear character of model paths that has not been theoretically predicted by researchers, and

- Interactive effects of two model variables on other variables of the model that are not anticipated by researchers.

Accordingly, we believe that researchers who plan to test a structural model can benefit from complementing traditional SEM methods with USM. Specifically, USM might serve as a "forerunner" of more restrictive methods to explore the potential existence of theoretically unexpected effects. If USM does not identify hidden structures, researchers might replicate the USM findings with traditional SEM methods such as CVSEM and PLS. Although USM performs adequately when exposed to a linear data set, we recommend the use of confirmatory methods, such as CVSEM and PLS, when the linearity of the model relations is assured.

If USM locates hidden structures, the appropriate reaction differs depending on the kinds of structures revealed. In the case of hidden paths, researchers might go back to their theoretical model development and determine whether they can justify additional paths by the theories underlying the proposed model and, if so, incorporate the new paths into the model. Such a recursive procedure should be reported. If USM finds a nonlinear path, however, researchers might try to transform their data to allow for a traditional model test with PLS or CVSEM with nonlinear effects (e.g., logarithmic transformation). Please note that this approach is only possible if no other (e.g., linear) relations are affected by the transformation. Of course, theoretical arguments should support such a nonlinear relationship to avoid atheoretical data-driven model development.

Finally, if interactions among model constructs emerge from USM, we recommend that researchers who want to replicate USM results with CVSEM and PLS should incorporate the interactions into their model. In both methods, certain interactions can be incorporated through multigroup analysis or the inclusion of interaction terms. Again, these model extensions should be accompanied by a discussion of the theoretical mechanisms underlying the interaction effects. In summary, USM can contribute to an improved theory development process in marketing by combining exploratory and confirmatory elements. The method offers the potential to highlight weaknesses in theoretical model developments and can help prevent model misspecifications and misleading results.

Some aspects and limitations of USM require additional research. One of them is the effect of sample size on the stability of USM results. Similar to PLS, USM uses a "partial" optimization approach but draws on the Bayesian neural network framework, so its minimum sample size requirements are basically the same as those for PLS when the true relations are linear and additive (i.e., 5–10 times the largest number of incoming paths for a latent model variable or formative items for a construct; Bentler and Chou 1987). Although nonlinearity and interactive effects require larger samples, our experiments give us the confidence to state that USM can locate nonlinearity and interactions with sample sizes of less than 250 cases. The version of USM introduced herein is limited insofar as the measurement model only allows for linear relations between latent variables and manifest items. Extending the flexibility of the structural model to the measurement model would be desirable, because it might increase the explained variance in a model. Although we show that models exist in marketing research that contain hidden paths and would benefit from the use of USM, we cannot provide insight into the extent of these misspecifications in marketing science. We consider this point another challenge for further research. Finally, more extensive testing is necessary to explore the full power of USM and identify potential limitations.

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